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ADVANCES IN Banking Technology and Management

Impacts of ICT and CRM

VADLAMANI RAVI

Advances in Banking Technology and Management:
Impacts of ICT and CRM

Vadlamani Ravi
Institute for Development and Research in Banking Technology, India

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Chapter XVIII
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This chapter presents an overview of credit scoring models in banking and the applications of data mining in credit scoring in credit card, mortgage and small business lending. A review of the use of data mining techniques to credit scoring is presented. The chapter concludes by highlighting the merits and demerits of credit scoring.

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Foreword

The rapid strides made in the information and communication technology (ICT) arena have tremendously impacted the way banking is done worldwide. Nowadays, the customer does not have to enter the brick-and-mortar structure of the bank in order to get serviced by the bank. He or she can get all the services right at his or her doorstep on his or her desktop. Such is the quintessential influence of ICT on banking that all major operations/decisions with regard to deposits, withdrawals, and investments can be made at the click of a mouse on a computer or at an automatic teller machine (ATM). Another important fallout of this ICT-driven revolution in banking is that, thanks to the advances made in data mining and customer relationship management (CRM), banks can reap profits by increasing their service pie in a manner, which was unthinkable a decade ago. Consequently, the banks on their part can tailor their products to suit the customer needs and even pinpoint the customers who would purchase their products.

The banks are continuously striving hard to bring the state-of-the-art ICT innovations to make banking an even more convenient and pleasurable experience, and in the bargain attract more and more customers, thereby increasing the banks' profits. Consequently, the banks have dumped their traditional *product-driven* strategy to embrace the more logical and profitable *customer-driven* strategy. On the other hand, customers have also become hungrier and want the banks to become a one-stop-shop for all their financial and investments needs. This two-way demand and supply equation has not yet reached equilibrium, and this precisely has given rise to an increasingly difficult set of managerial problems for the banks to grapple with.

In this edited book, Dr. Vadlamani Ravi has succinctly captured these managerial problems in three dimensions, which he calls services management, business management, and risk management. This categorization, I believe, is logical and operationally sufficient. Services management takes care of technology-driven issues. Business management pertains to segmenting and identifying the right customer base for the right products. Finally, risk management attempts to measure and mitigate the associated finance and technology associated risks, namely, credit risk, market risk, and operational risk.

There is a right balance in the organization of the chapters in the book. All the important issues such as service quality in banks; technology acceptance of smart cards, Internet banking, and electronic purses; mobile banking and mobile commerce; information assurance in Internet banking; the usefulness of CRM and customer value dynamics in the banking industry; data warehousing and data modeling; data mining for risk management in credit cards; credit scoring, bankruptcy prediction, and foreign exchange forecasting; new computational model for value-at-risk; and software agent-based banking application architectures are covered in the book in great detail.

That the topic of this book is of paramount importance can be seen by the fact that the academics, researchers, and professionals from all over the world have contributed to it. This shows how relevant and contemporary the theme of the book is. Dr. Ravi must be congratulated for venturing into an undertaking as difficult as editing this book. Full credit to him for bringing the seemingly unrelated disciplines under one roof. I have no hesitation in suggesting this book to MBA students in finance, financial engineering, and information systems at any university. I am sure this book would also be of immense use to technology, business, and risk management professionals in the banking industry.

Professor M. Rammohan Rao
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M. Rammohan Rao *is the dean of the Indian School of Business (ISB). In his role as the dean, he focuses on bringing cutting-edge global research to ISB and helps in building the school as an academic institution of global repute. An illustrious academic, renowned worldwide for his research and teaching capabilities, Dean Rao has taught as a tenured professor of operations research at the Stern School of Business, New York University. He has also taught at the Graduate School of Management, University of Rochester as an associate professor and as a visiting faculty member at the University of Tennessee. He has held various positions at the IIM-B, including those of professor, visiting professor, dean, and director. His current teaching and research interests are in the areas of optimization, corporate finance, and financial derivatives. Dean Rao has published more than 85 articles in various professional journals. He has won several prestigious awards conferred on him by leading institutions across the world. He holds a PhD in Industrial Administration from the Graduate School of Industrial Administration, Carnegie-Mellon University, USA.*

Preface

Although 'banking' is an old activity and has its roots in economics, finance, and commerce, the concept of 'banking technology' is of recent origin. To many people 'banking technology' means the use of computers and related hardware to streamline and automate banking operations. This book attempts to demystify 'banking technology' and offer a much broader meaning and more realistic and operationally sufficient perspective on 'banking technology'.

Universally conducting efficient banking operations and associated business involves managing:

1. The information and communication technology that drives the banks' core business.
2. Customer relationships.
3. Risks associated with conducting business with customers and other banks and financial institutions.

Therefore the book is categorized according to the three focal areas: services management, business management, and risk management.

Successful banks all over the world have invested considerably in information and communication technologies, which in turn would increase banks' profits considerably on one hand and improve the convenience and comfort levels of their customers in doing business with them on the other. Further, such banks are very sensitive to the risks they face in dealing with money in the form of credit risk or market risk or operational risk. Banks continuously embrace, with great fervor, the latest developments in information and communication technologies and customer relationship management in order to service customers better and reap more profits. If banks employ cutting-edge technologies to service their customers effectively and efficiently, regulatory requirements such as Basel II also force the banks to implement these technologies to enable uniform banking services throughout the world.

This book brings together research contributions from several academics and industrial professionals in all three aspects mentioned above, and it conveys the message that banking technology and management emerged as a new discipline in its own right over the last decade and a half.

The foreword of the book by M. Rammohan Rao, dean of the Indian School of Business, highlights the nature of the demand and supply equation that exists between the banks as service providers and the customers and the resulting explosion of research opportunities. The division of chapters into three areas is operationally sufficient.

In **Chapter I**, Ravi introduces an overview of banking technology, its various facets, and the evolution of banking. Banking technology is introduced as a consortium of several disparate disciplines such as finance and risk management, information technology, communication technology, computer science, and marketing science. The influence of all these disciplines on various aspects of modern banking operations is clearly explained. Nowadays, banks and their customers are in a win-win situation where banks offer more and more services under one roof with impeccable reliability in a fairly secure manner resulting in more profits, and customers on the other hand can feel the pleasure and convenience of banking.

In **Chapter II**, Bellini and Pereira discuss various aspects of service quality for customers in the banking industry. They study the quality of banking services on the basis of the perception of 11,936 customers of a major Brazilian bank, and they identify five drivers that could explain customer satisfaction in an indirect way. These are: (1) business and financial transactions, (2) customer relationship, (3) information technology, (4) branch, and (5) image. They argue that these factors would help bank executives make strategic decisions in addressing a bank's customers.

In **Chapter III**, Carr reviews important theories in information systems—namely, the diffusion of innovations theory, the theory of planned behavior, and the technology acceptance model—that explain the adoption and diffusion of Internet banking. Empirical works investigating these theories are discussed. Carr also highlights the theoretical and methodological limitations of these models. Approaches that complement or challenge positivistic methodologies that are interpretive are presented in a case study. This chapter also discusses future trends in Internet banking that could include populations not included in the modern electronic financial systems.

In **Chapter IV**, Makris, Koumaras, Konstantopoulou, Konidis, and Kostakis describe the factors that affect the customer acceptance of Internet banking with the help of a case study of ALPHA Bank in Greece, which pioneered e-banking services in Greece. The authors also present a thorough analysis of the case study with the help of factor analysis on customer questionnaires in order to quantify the various variables that affect the use of an Internet banking system. They infer that although Internet banking in Greece is steadily penetrating, factors like security, ease of use, and perceived usefulness of a system continue to affect the customer's decision to adopt an Internet banking system.

In **Chapter V**, M'Chirgui and Chanel present the electronic purse as one of the latest smart card applications. This chapter explores and models the factors—economic, technological, and social—and forces driving the adoption and use of the Moneo electronic purse in the south of France. An empirical study presented analyzes the determinants of the probability of adoption for consumers and retailers, and of the frequency of use for consumers. The authors found that the frequency of use of Moneo is influenced by relative advantage, cost, visibility, security, income, and gender. Finally, the reasons why Moneo seems to have met with failure are determined, and solutions to help reach the required critical mass are proposed.

In **Chapter VI**, Patra proposes a novel hybrid service-oriented agent architecture for developing software in the banking industry as a possible solution to the growing issues of inter-and intra-bank operations. He cites the issues of interoperability, scalability, maintainability, and security as the challenges for the banking industry. He argues that the hybrid architecture can seamlessly integrate business functions across organizational boundaries. He illustrates the proposed service-oriented agent architecture with the help of a few banking applications.

In **Chapter VII**, Wonglimpiyarat, introduces a smart card (ATM/cash card, credit card, EFTPOS/debit card) application in the banking industry as a system innovation, where several parties join hands together and make it a success. The chapter elucidates the network nature of smart cards. The author argues that unless innovators in the smart card industry realize the advantages of collaboration, the diffusion of smart cards may not happen.

It is well known that Internet or electronic banking is vulnerable to cyber threats and attacks that would help the hacker or fraudster steal a customer's complete data in no time. Consequently, information assurance is of paramount importance to e-banking services. In **Chapter VIII**, Gupta, Rao, and Upadhyaya present an interesting state-of-the-art survey on the important issue of information assurance in electronic or Internet banking security. The survey highlights the critical aspects of information assurance that would be needed to design, develop, and assess an adequate electronic security infrastructure.

After Internet banking, the next big wave in e-banking includes mobile payment systems (m-payment systems) and mobile commerce (m-commerce). The paradigmatic shift from physical to virtual payment systems has been beneficial to both customers and merchants. For customers it affords ease of use. For mobile operators, mobile payment systems facilitate to consolidate their central role in the m-commerce value chain. Financial organizations view mobile payment and mobile banking as a new way of providing added convenience to their customers along with an opportunity to reduce their operating costs. **Chapter IX** by Nambiar and Lu presents all these issues along with an overview of competing mobile payment solutions that are found in the market today. It also reviews different types of mobile fraud in the m-commerce environment and solutions to prevent such fraud.

In **Chapter X**, Mantrala, Krafft, Dong, and Raman present ideas and concepts taken from marketing research literature for a successful CRM implementation in retail banking. They describe a framework for conceptualizing, operationalizing, and measuring CRM process implementation, and illustrate its use to identify activities that must be performed for successful CRM. They explain the proposed framework in the context of a case study of CRM implementation at a European bank. They also describe the importance of customer response to self-service banking technologies to CRM managers at banks. This chapter is a contribution on the operational and managerial aspects of CRM.

In **Chapter XI**, Rajagopal discusses a model that analyzes the variables associated with customer value. The model combines customer value, competitive efficiency, and profit optimization through a set of linear equations The framework is based on the theory of competitive advantage and customer lifetime value, so as to maximize the potential of the organization to create and sustain satisfied customers. The chapter also analyzes the main criteria for a successful Internet banking strategy and brings out benefits of e-**banking** from the point of view of banks, their technology, and customer values, and concludes that there is increasing returns to scale in the bank services in relation to the banking products, new technology, and customer value.

In **Chapter XII**, Narayanan presents the fundamental concepts of a data warehouse and its usefulness in banks. He argues that they are important if banks are to achieve sustainable competitive advantage against competing banks. Using data warehousing and analytics, it is possible for the banks to understand the behavior of their customers, which in turn helps them improve interaction with customers. The author argues that the same infrastructure can be used for multiple business applications.

In **Chapter XIII**, Narayanan presents the implementational details of data warehousing and analytics in the banking industry with the help of a real-life case study. Data warehousing represents one of the foremost technologies that can be used by banks to obtain sustainable competitive advantage. The author argues that adopting the right implementation methodology is important to ensure successful implementation, and he describes alternate implementation methodologies, typical challenges in implementation, and critical success factors.

While developing data warehouses for banks, an important aspect is the development of a logical data model, and the entire success of a data warehouse depends heavily on, among other things, the logical data model conceived and used. In **Chapter XIV**, Mauser describes a data model called SKO-Datenmodell, for a savings bank, Sparkassen-Organization, in Germany. The data model with 17,490 well-defined modeling objects was initially developed 15 years ago based on the financial services data model (FSDM) of IBM. SKO-Datenmodell is specially designed for Sparkassen-Organization. The different levels of SKO-Datenmodell and their uses are described in this chapter.

In **Chapter XV**, Ravi, Kumar, Srinivas, and Kasabov present an algorithm to train radial basis function neural networks (RBFNs) in a semi-online manner and demonstrate its effectiveness on bankruptcy prediction in banks. The authors employ the online, evolving clustering algorithm in the unsupervised training part of the RBFN and the ordinary least squares estimation for the supervised training part.

They compare its performance with a multi-layer perceptron, an adaptive neuro-fuzzy inference system (ANFIS), TreeNet, a support vector machine (SVM), a radial basis function neural network (RBFN), a rough set-based expert system (RSES), and an orthogonal RBFN. The authors conclude that the proposed semi-online algorithm for RBFN is better than other neural networks when area under the ROC curve (AUC) is taken as the performance metric.

In **Chapter XVI**, Yu, Wang, and Lau present a thorough literature review on the applications of neural network models to foreign exchange rates forecasting. Further, they propose a novel support vector regression (SVR)-based nonlinear ensemble forecasting model for foreign exchange rates forecasting. The ensemble comprises single neural network models as its constituent members, which are selected based on a conditional generalized variance approach. For illustration purposes, four typical foreign exchange rate series are used for testing. The authors compare several nonlinear ensemble methods for forecasting foreign exchange rates with the proposed SVR-based ensemble with respect to the measures such as normalized root mean square error and directional change statistics. Results obtained indicate that the proposed nonlinear ensemble model can improve the performance of foreign exchange rates forecasting.

In **Chapter XVII**, Samanta presents a procedure for the measurement of a value-at-risk parameter for a portfolio using historical returns. The main issue here is the estimation of suitable percentile of the underlying return distribution. When returns are normal variates, it is a very simple task. But it is well known that financial market returns seldom follow normal distribution. So, one has to identify suitable non-normal distribution for the returns and find out the percentile of the identified distribution. The class of non-normal distributions, however, is extremely wide and one has to identify the best distributional form from such a wide class. In order to handle the non-normality, he adopts a transformation-based approach originally proposed in 2003. The performance of the transformation-based VaR models is compared with two widely used VaR models. The author concludes that the transformation-based approach is a useful alternative.

The usefulness of data warehousing and data mining in banking industry is very well known. In **Chapter XVIII**, Felsövàlyi and Couran highlight the importance of data mining in risk management in lending and credit card activities at Citigroup. The authors focus attention on corporate lending based on Citigroup's own practices. They describe various aspects of risk management and assessment, early warning models, measuring loss, and also consumer lending with reference to credit cards.

In **Chapter XIX**, Bose, Pui Kan, King Tsz, Wai Ki, and Cho Hung present an overview of credit scoring models in banking and the applications of data mining in credit scoring. The applications of credit scoring presented include credit card, mortgage, and small business lending. A detailed discussion and review of the use of various data mining techniques to credit scoring are presented. A method to estimate the default probability is also presented. The chapter concludes by highlighting the merits and demerits of credit scoring.

This book is useful to the undergraduate and graduate students of an MBA program in financial engineering at any university. The book can also be used as reference book by researchers of financial engineering and banking executives.

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Chapter I
Introduction to Banking Technology and Management

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ABSTRACT

This chapter introduces banking technology as a confluence of several disparate disciplines such as finance (including risk management), information technology, computer science, communication technology, and marketing science. It presents the evolution of banking, the tremendous influence of information and communication technologies on banking and its products, the quintessential role played by computer science in fulfilling banks' marketing objective of servicing customers better at less cost and thereby reaping more profits. It also highlights the use of advanced statistics and computer science to measure, mitigate, and manage various risks associated with banks' business with its customers and other banks. The growing influence of customer relationship management and data mining in tackling various marketing-related problems and fraud detection problems in the banking industry is well documented. The chapter concludes by saying that the banking technology discipline is all set for rapid growth in the future.

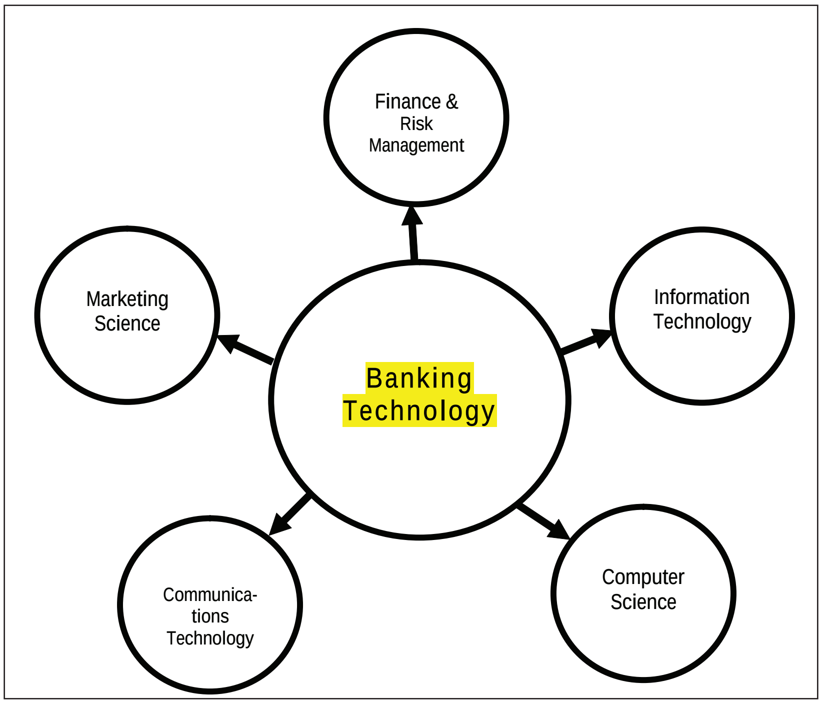
INTRODUCTION

The term "banking technology" refers to the use of sophisticated information and communication technologies together with computer science to enable banks to offer better services to its customers in a secure, reliable, and affordable manner, and sustain competitive advantage over other banks. Banking technology also subsumes the activity of using advanced computer algorithms in unraveling the patterns of customer behavior by sifting through customer details such as demographic, psychographic, and transactional data. This activity, also known as data mining, helps banks achieve their business objectives by solving various marketing problems such as customer segmentation, customer scoring, target marketing, market-basket analysis, cross-sell, up-sell, customer retention by modeling churn, and so forth. Successful use of data mining helps banks achieve significant increase in profits and thereby retain sustainable advantage over their competitors. From a theoretical perspective, banking technology is not a single, stand-alone discipline, but a confluence of several disparate fields such as finance (subsuming risk management), information technology, communication technology, computer science, and marketing science.

Figure 1 depicts the constituents of banking technology. From the functional perspective, banking technology has three important dimensions, as follows:

1. The use of appropriate hardware for conducting business and servicing the customers through various delivery channels and payment systems and the associated software constitutes one dimension of banking technology. The use of computer networks, security algorithms in its transactions, ATM and credit cards, Internet banking, telebanking, and mobile banking are all covered by this dimension. The advances made in information and communication technologies take care of this dimension.
2. On the other hand, the use of advanced computer science algorithms to solve several interesting marketing-related problems such as customer segmentation, customer scoring, target marketing, market-basket analysis, cross-sell, up-sell, and customer retention faced by the banks to reap profits and outperform their competitors constitutes the second dimension of banking technology. This dimension covers the implementation of a data warehouse for banks and conducting data mining studies on customer data.

Figure 1. Different constituents of banking technology



3. Moreover, banks cannot ignore the risks that arise in conducting business with other banks and servicing their customers, otherwise their very existence would be at stake. Thus, the quantification, measurement, mitigation, and management of all the kinds of risks that banks face constitute the third important dimension of banking technology. This dimension covers the process of measuring and managing credit risk, market risk, and operational risk. Thus, in a nutshell, in 'banking technology', 'banking' refers to the economic, financial, commercial, and management aspects of banking, while 'technology' refers to the information and communication technologies, computer science, and risk quantification and measurement aspects.

Evolution of Banking

Despite the enormous changes the banking industry has undergone through during the past 20 years—let alone since 1943—one factor has remained the same: the fundamental nature of the need customers have for banking services. However, the framework and paradigm within which these services are delivered has changed out of recognition. It is clear that people's needs have not changed, and neither has the basic nature of banking services people require. But the way banks meet those needs is completely different today. They are simply striving to provide a service at a profit. Banking had to adjust to the changing needs of societies, where people not only regard a bank account as a right rather than a privilege, but also are aware that their business is valuable to the bank, and if the bank does not look after them, they can take their business elsewhere (Engler & Essinger, 2000).

Indeed, technological and regulatory changes have influenced the banking industry during the past 20 years so much so that they are the most important changes to have occurred in the banking industry, apart from the ones directly caused by the changing nature of the society itself. In this book, technology is used interchangeably with information and communication technologies together with computer science. The relationship between banking and technology is such that nowadays it is almost impossible to think of the former without the latter. Technology is as much part of the banking industry today as a ship's engine is part of the ship. Thus, like a ship's engine, technology drives the whole thing forward (Engler & Essinger, 2000).

Technology in banking ceased being simply a convenient tool for automating processes. Today banks use technology as a revolutionary means of delivering services to customers by designing new delivery channels and payment systems. For example, in the case of ATMs, people realized that it was a wrong approach to provide the service as an additional convenience for privileged and wealthy customers. It should be offered to the people who find it difficult to visit the bank branch. Further, the cost of delivering the services through these channels is also less. Banks then went on to create collaborative ATM networks to cut the capital costs of establishing ATM networks, to offer services to customers at convenient locations under a unified banner (Engler & Essinger, 2000).

People interact with banks to obtain access to money and payment systems they need. Banks, in fact, offer only what might be termed as a secondary level of utility to customers, meaning that customers use the money access that banks provide as a means of buying the things they really want from retailers who offer them a primary level of utility. Customers, therefore, naturally want to get the interaction with their bank over as quickly as possible and then get on with doing something they really want to do or with buying something they really want to buy. That explains why new types of delivery channels that allow rapid, convenient, accurate delivery of banking services to customers are so popular. Nowadays, customers enjoy the fact that their banking chores are done quickly and easily (Engler & Essinger, 2000).

This does not mean that the brick-and-mortar bank branches will completely disappear. Just as increasing proliferation of mobile phones does not mean that landline telephone kiosks will disappear, so also the popularity of high-tech delivery channels does not mean that physical branches will disappear altogether. It has been found that corporate and older persons prefer to conduct their business through bank branches (Engler & Essinger, 2000).

The kind of enormous and far-reaching developments discussed above have taken place along with the blurring of demarcations between different types of banking and financial industry activities. Five reasons can be attributed to it:

1. Governments have implemented philosophies and policies based on an increase in competition in order to maximize efficiency. This has resulted in the creation of large new financial institutions that operate simultaneously in several financial sectors such as retail, wholesale, insurance, and asset management.
2. New technology creates an infrastructure allowing a player to carry out a wide range of banking and financial services, again simultaneously.
3. Banks had to respond to the increased prosperity of their customers and to customers' desire to get the best deal possible. This has encouraged banks to extend their activities into other areas.
4. Banks had to develop products and extend their services to accommodate the fact that their customers are now far more mobile. Therefore demarcations are breaking down.
5. Banks have every motivation to move into new sectors of activity in order to try to deal with the problem that, if they only offer banking services, they are condemned forever to provide only a secondary level of utility to customers (Engler & Essinger, 2000).

ROLE OF ICT IN BANKING

Technology is no longer being used simply as a means for automating processes. Instead it is being used as a revolutionary means of delivering services to customers. The adoption of technology has led to the following benefits: greater productivity, profitability, and efficiency; faster service and customer satisfaction; convenience and flexibility; 24x7 operations; and space and cost savings (Sivakumaran, 2005). Harrison Jr., chairman and chief executive officer of Chase Manhattan, which pioneered many innovative applications of ICT in banking industry, observed that the Internet caused a technology revolution and it could have greater impact on change than the industrial revolution (Engler & Essinger, 2000).

Technology has been used to offer banking services in the following ways (Sivakumaran, 2005):

- *ATMs* are the cash dispensing machines that can be seen at banks and other locations where crowd proximity is more. ATMs started as a substitute to a bank to allow its customers to withdraw cash at anytime and to provide services where it would not be viable to open another physical branch. The ATM is the most visited delivery channel in retail banking, with more than 40 billion transactions annually worldwide. In fact, the delivery channel revolution is said to have begun with the ATM. It was indeed a pleasant change for customers to be in charge of their transaction, as no longer would they need to depend on an indifferent bank employee. ATMs have made banks realize that they could divert the huge branch traffic to the ATM. The benefits hence were mutual. Once banks realized the convenience of ATMs, new services started to be added.

- The phenomenal success of ATMs had made the banking sector develop more innovative delivery channels to build on cost and service efficiencies. As a consequence, banks have introduced telebanking, call centers, Internet banking, and mobile banking. *Telebanking* is a good medium for customers to make routine queries and also an efficient tool for banks to cut down on their manpower resources. The *call center* is another channel that captured the imagination of banks as well as customers. At these centers, enormous amount of information is at the fingertips of trained customer service representatives. A call center meets a bank's infrastructural, as well as customer service requirements. Not only does a call center cut down on costs, it also results in customer satisfaction. Moreover, it facilitates 24x7 working and offers the "human touch" that customers seek. The call center has large potential dividends by way of improved customer relationship management (CRM) and return on investment (ROI).
- With the Internet boom, banks realized that *Internet banking* would be a good way to reach out to customers. Currently, some banks are attempting to harness the benefits of Internet banking, while others have already made Internet banking an important and popular payment system. Internet banking is on the rise, as is evident from the statistics. Predictions of Internet banking to go the ATM way have not materialized as much as anticipated; many reasons can be cited for this. During 2003, the usage of the Internet as a banking channel accounted for 8.5%. But this was due to the false, unrealistic expectations tied to it. Some of the factors that were detrimental in bringing down, or rather, not being supportive, are low Internet penetration, high telecom tariffs, slow Internet speed and inadequate bandwidth availability, lack of extended applications, and lack of a trusted environment**.**
- *Mobile banking* however is being regarded in the industry as "the delivery channel of the future" for various reasons. First and foremost is the convenience and portability afforded. It is just like having a bank in the pocket. Other key reasons include the higher level of security in comparison to the Internet and relatively low costs involved. The possibility that customers will adopt mobile banking is high, considering the exponential growth of mobile phone users worldwide. Mobile banking typically provides services such as the latest information on account balances, previous transactions, bank account debits and credits, and credit card balance and payment status. They also provide their online share trading customers with alerts for pre-market movements and post-market information and stock price movements based on triggers.

Another fallout of the ICT-driven revolution in the banking industry is the Centralized Banking Solution (CBS). A CBS can be defined as a solution that enables banks to offer a multitude of customer-centric services on a 24x7 basis from a single location, supporting retail as well as corporate banking activities, as well as all possible delivery channels—existing and proposed. The centralization thus afforded makes a "one-stop" shop for financial services a reality. Using CBS, customers can access their accounts from any branch, anywhere, irrespective of where they physically opened their accounts. The benefits offered by CBS are:

- Offer a "one-stop" IT management shop.
- Make banks prepared for current as well as future requirements.

- Decrease the risks arising from solutions requiring multiple components and multiple vendors.
- Improve the returns via seamless integration of software and hardware services.
- Provide a greater choice through the availability of an array of technologies (Sivakumaran, 2005).

Information technology has not only helped banks to deliver robust and reliable services to their customers at a lower cost, but also helped banks make better decisions. Here a data warehouse plays an extremely important role. It essentially involves collecting data from several disparate sources to build a central data warehouse to store and analyze the data. A data warehouse in a bank typically stores both internal data and data pertaining to its competitors. Data mining techniques can then be applied on a data warehouse for knowledge discovery (Hwang, Ku, Yen, & Cheng, 2004). Data warehousing also allows banks to perform time series analysis and online analytical processing (OLAP) to answer various business questions that would put the banks ahead of their competitors.

Apart from the market-driven reasons, compliance-driven reasons are also there behind banks establishing a data warehouse. Basel II accord is one such compliance. Basel II is one of the largest financial shake-ups in recent times; it will eventually lead to new rules and regulations for the banking industry worldwide. Banks were supposed to have their processes and systems in place by the start of 2007, which was when the Basel Committee on Banking Supervision planned to implement the Accord. The crux of Basel II is to ensure that financial institutions manage risk so that they have the adequate capital to cover exposure to debt. Banks will have to carry out a fundamental review and overhaul of their processes and systems in order to achieve compliance. Technology will be at the core of their strategies to meet Basel II requirements. The construction of a historical data store is a key IT initiative that must be pursued on a priority basis within Basel II programs. This will collect up to three years of operational risk data and up to seven years of credit risk data, and will act as a stepping stone towards a 'single customer view' for managing risk at an individual customer level (Porter, 2003).

The next wave in ICT-driven banking resulted in the creation of the Society for Worldwide Interbank Financial Telecommunication (SWIFT), which is a financial-industry-owned cooperative organization. SWIFT provides secure, standardized messaging services and interface software to 7,650 financial institutions spread over 200 countries. SWIFT's worldwide community includes banks, broker/dealers, and investment managers, as well as their market infrastructures in payments, securities, treasury, and trade. Establishment of SWIFT is a landmark development in worldwide payment systems in banks and financial institutions. SWIFT, through its comprehensive messaging standards, offers the financial services industry a common platform of advanced technology and access to shared solutions through which each member can communicate with its counter party. SWIFT works in partnership with its members to provide low-cost, competitive financial processing and communications services of the highest security and reliability. It contributes significantly to the commercial success of its members through greater automation of the end-to-end financial transaction process, based on its leading expertise in message processing and financial standards setting. Thus SWIFT is another important product of the applications of information and communication technologies in the banking industry (Graham, 2003).

Negative Effects of ICT in Banking, and Solutions Offered by ICT

While ICT provides so many advantages to the banking industry, it also poses security challenges to banks and their customers. Even though Internet banking provides ease and convenience, it is most vulnerable to hackers and cyber criminals. Online fraud is still big business around the world. Even though surveillance cameras, guards, alarms, security screens, dye packs, and law enforcement efforts have reduced the chances of a criminal stealing cash from a bank branch, criminals can still penetrate the formidable edifice like the banking industry through other means. Using Internet banking and high tech credit card fraud, it is now possible to steal large amounts of money anonymously from financial institutions from the comfort of your own home, and it is happening all over the world (Graham, 2003).

Further, identity theft, also known as phishing, is one of the fastest growing epidemics in electronic fraud in the world. Identity theft occurs when “fraudsters” gain access to personal details of unsuspecting victims through various electronic and non-electronic means. This information is then used to open accounts (usually credit card), or initialize loans and mobile phone accounts or anything else involving a line of credit. Account theft, which is commonly mistaken for identity theft, occurs when existing credit or debit cards or financial records are used to steal from existing accounts. Although account theft is a more common occurrence than identity theft, financial losses caused by identity theft are on average greater and usually require a longer period of time to resolve (Graham, 2003).

Spam scams involve fraudsters sending spam e-mails informing customers of some seemingly legitimate reason to login to their accounts. A link is provided in the e-mail to take the user to a login screen at their bank site; however the link that is provided actually takes the user to a ghost site, where the fraudster can record the login details. This information is then used to pay bills and or transfer balances for the fraudster’s financial reward (Graham, 2003).

Card skimming refers to the use of portable swiping devices to obtain credit card and EFT card data. This data is rewritten to a dummy card, which is then usually taken on elaborate shopping sprees. As the fraudster can sign the back of the card himself or herself, the merchant will usually be unaware that they have fallen victim to the fraud.

One can curb these hi-tech frauds by using equally hi-tech security mechanisms such as biometrics and smart cards. The key focus in minimizing credit card and electronic fraud is to enable the actual user of the account to be correctly identified. The notion of allowing a card to prove your identity is fast becoming antiquated and unreliable. With this in mind, using biometrics to develop a more accurate identification process could greatly reduce fraud and increase convenience by allowing consumers to move closer to a “no wallet” society. The main forms of biometrics available are fingerprint identification, palm print identification, facial recognition, iris recognition, voice recognition, and computer-recognized handwriting analysis (Graham, 2003).

Many industry analysts such as the American Bankers Association are proposing that the smart payment cards are finally poised to change the future of electronic payments. The smart card combines a secure portable payment platform with a selection of payment, financial, and non-financial applications. The reach of the smart card potentially goes beyond the debit and credit card model. Instead of a smart card, ISO uses the term ‘integrated circuit card’ (ICC), which includes all devices where an integrated circuit is contained within the card. The benefits provided by smart cards to consumers include: convenience (easy access to services with multiple loading points), flexibility (high/low value payments with faster transaction times), and increased security. The benefits offered to merchants include: immediate/guaranteed cash flow, lower processing costs, and operational convenience (Graham, 2003).

CRM THROUGH DATA MINING

Despite investing enormously into the ICT paraphernalia for providing better services to customers, banks cannot take their customers for granted. Unlike olden days, the customers have become more demanding. In other words, if customers are dissatisfied with the services of a particular bank, they immediately shift loyalties to its competitors. Hence, like in other businesses such as retail and insurance, banks have made a paradigmatic shift in their marketing strategies. Consequently, the age-old product-focused strategy has given way to a customer-focused strategy. Hence, building profitable and long-lasting relationships with customers has become paramount to banks. This is precisely where CRM plays a critical role. The main objective of CRM is to make long-lasting and profitable relationships with customers.

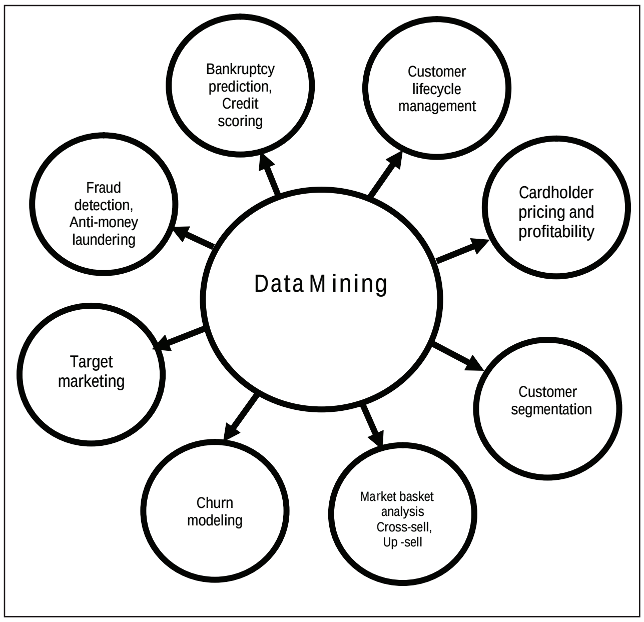
The successful adoption of IT-enabled CRM redefines the traditional models of interaction between a business and its customers both nationally and globally. CRM promises achieving corporate objectives, which involves continuous use of refined information about current and potential customers. With IT and communication technologies, banks can offer their customers a variety of products, lower prices, and personalized service. The effective management of information and knowledge is important to CRM for product tailoring and service innovation. It provides a single and consolidated view of the customer, calculating the value of the customer, establishing a strategy for multi-channel-based communication with the customer, and designing personalized transactions. CRM together with data mining helps banks improve their marketing policies to attract more customers and thereby increase their profit. Customer knowledge is recognized as an asset. IT is the enabling technology for discovery and management of customer knowledge (CRM in UK ref). With the IT-enabled CRM, relationship marketing has become a reality in recent years to gaining competitive advantage (Rygielski, Wang, & Yen, 2002).

Data mining tools can answer business questions very quickly and accurately now due to the information available, but in the past that was time consuming to pursue. The advent of the Internet has undoubtedly contributed to the shift of marketing focus, as online information is more accessible and abundant. Collecting customer demographic and psychographic data and its analysis makes target marketing possible. Knowledge discovery in databases (KDD) or data mining activities can be categorized into three major groups: discovery, predictive modeling, and forensic analysis. Data mining performs analysis that would be too complicated for traditional statisticians (Rygielski et al., 2002). Most of the banks are investing large amounts of money to collect and store transactional, demographic, and psychographic data of customers. The emphasis is now on how to effectively utilize the customer databases to manage the customer relationship. The potential difficulty of converting data into profits lies in obtaining relevant information from the data and customize the marketing mix policies to satisfy the consumer's wants and needs (Li, Xu, & Li, 2005).

Banks employ data mining for the following tasks:

1. **Card marketing:** By identifying optimal customer segments, card issuers and acquirers can improve profitability with more effective acquisitions and retention programs, targeted product development, and customized pricing.
2. **Cardholder pricing and profitability:** Card issuers can take advantage of data mining to price their products so as to maximize profit and minimize loss of customers. They can also perform risk-based pricing.
3. **Predictive lifecycle management:** Data mining helps banks predict each customer's

Figure 2. Applications of data mining in banking



lifetime value and to service each segment appropriately.

4. **Forensic analysis:** It is unusual to employ data mining for forensic analysis in many domains, but in banking it is a common practice, to look for deviations in the data for fraud detection. Businesses must have to use technology responsibly in order to achieve a balance between privacy rights and economic benefits. Current CRM solutions are not ensuring customer information privacy fully (Rygielski et al., 2002).
5. **Cross-sell/up-sell:** Using data mining, banks can cross-sell or up-sell their products to customers.
6. **Customer churn modeling:** Customer churn modeling is an important problem for banks and financial institutions to grapple with. Churn happens when existing customers become disgruntled with some aspects of the service of a given bank and shift loyalties to one of its competitors. Data mining techniques are extremely useful in identifying potential churners and giving banks early warning signals. Once potential churners are identified, banks take remedial actions to prevent such customers from leaving. This is because acquiring new customers is time consuming and more expensive than retaining the existing customers.
7. **Anti-money laundering:** Money laundering, considered a major financial crime, is the process of illegally transferring money from one country to another in an innocuous manner so that it goes undetected by law enforcement agencies. With development of global economy and Internet banking, it is predicted that money laundering crimes will become more prevalent, more difficult to investigate, and more detrimental to the economy and financial systems. The investigation of money laundering crimes involves reading and analyzing thousands of textual documents to generate crime group models (Zhang, Salerno, & Yu, 2003).

The use of international trade to transfer money undetected between countries is an old technique to bypass the government scrutiny. This is achieved by either overvaluing imports or undervaluing exports. This approach of money transfer need not be used to fund terrorist activities alone, but also can be used to evade taxes (Zdanowicz, 2004). Data mining is extremely useful in tackling the problem, and techniques like Web mining, text mining, collaborative filtering, social network analysis, and link discovery based on correlation analysis are nowadays used to trace the links between transfer of high-value amounts (Zhang et al., 2003). Figure 2 succinctly captures various applications of data mining in banking and finance.

Business process re-engineering is increasingly important as a way for companies to remain competitive. Process orientation combined with IT can yield tremendous performance improvements in companies. The banking sector is also demanding reengineering due to changes in economic setting, consumer needs, and market competition, and requires a redesign of current account-oriented and product information technology systems to customer-oriented systems. The majority of current banking IT systems adopt an account-oriented approach, thus limiting flexibility either to create strong relationships with their existing customers or to attract new ones with increased marketing efforts. Hence, there is a practical need for re-engineering of both banking business processes and their associated information systems. It was found that object-oriented methods are useful for business process reengineering as they can form a basis for representing banking business processes and information systems (Mentzas, 1997).

ROLE OF COMPUTER SCIENCE IN RISK MANAGEMENT IN BANKING

The quantification, measurement, mitigation, and management of risks occurring in banks while conducting their business are an integral part of successful and efficient banking operations. Risk is defined as the potential for realization of unwarranted consequences of an event. In view of the foregoing discussion in previous sections, it is clear that IT has become essential for the smooth running of the banks' operations. Even in the area of risk management, various areas of computer science are employed like never before and the growth has been tremendous. Various statistical and computer science algorithms are used for quantifying the risk whose information can then be used by the management team in hedging the risk through various countermeasures as applicable. In the banking scenario, risks can be broadly classified into three categories: credit, market, and operational risks. Credit risk is the risk of a counter party not meeting its obligations. Various credit-scoring models are developed in order to evaluate a counter party's creditworthiness, whose information can be very valuable when the management makes the decision of whether or not to grant a loan to a counter party.

In the past decade, many modeling alternatives, like traditional statistical methods, non-parametric methods, and artificial intelligent techniques, have been developed in order to successfully handle credit scoring tasks. Discriminant analysis and logistic regression are the most commonly utilized statistical credit scoring techniques, though often being criticized due to their strong model assumptions and poor credit scoring capabilities. On the other hand, the artificial neural networks are attractive alternatives in handling credit scoring tasks due to their associated memory characteristic, generalization capability. Even with the above-mentioned advantages, neural networks are criticized for long training process in designing the optimal network's topology and difficulties in interpreting the knowledge learned by the weights of the network. Li et al. (2003) reported that classification trees are more suitable than logistic regression in credit scoring applications. Later hybrid models involving multivariate adaptive regression splines (MARS) and neural networks (Lee et al., 2005), a new fuzzy support vector machine (Wang, Wang, & Lai, 2005), genetic-fuzzy and neuro-fuzzy classifiers (Hoffmann, Baesens, Martens, Put, & Vanthienen, 2002), backpropagation neural networks with discriminant analysis (Lee et al., 2002), clustering and neural networks (Hsieh, 2005), radial basis function network with softmax activation function (Sarlija, Bensic, & Zekic-Susac, 2006), and two-stage genetic programming (Huang, Tzeng, & Ong, 2005) were proposed for credit scoring problems.

According the Basel Committee, operational risk is defined as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events." This kind of risk is most difficult to anticipate and hence manage because of its unpredictable nature. Many sophisticated methodologies have been proposed in order to quantify operational risk in recent times. The methodologies range from simple mathematical methods to sophisticated soft computing methods. Scandizzo (2003) discussed the use of fuzzy logic in the measurement of operational risk. He developed a clustering algorithm based on a fuzzy algebra that produces a ranking of the business units within a financial institution.

Both linear and non-linear models have been developed for the measurement of operational risk. Linear models include regression models, discriminant analysis, and so forth. The non-linear models, based on artificial intelligence, try to capture the non-linearities in operational risk. Neural networks are an alternative to non-parametric regressions. Bayesian belief networks have attracted much attention recently as a possible solution to the problems of decision support under uncertainty. Bayesian networks provide a lot of benefits for data analysis. Firstly, the model encodes dependencies among all variables and it also handles missing data. Secondly, they can be used to learn causal relationships and hence used to gain an understanding of problem domains and to predict the consequences of intervention.

Data mining can be extremely useful in estimating hidden correlations and patterns of losses related to operational risk in large organizations, where these operational losses can be correlated to a number of unimaginable factors. And the simplest correlation techniques might not work efficiently or uncover hidden patterns or correlations. Fuzzy set theory facilitates decision making where there are vague or subjective judgments as inputs to the decision process. In banks in which less sophisticated techniques have been put in place, fuzzy logic can help in optimizing tasks such as the classification or ranking of operational risk, or even in allocating a certain capital to complex transactions where a history of losses may be very difficult to collate (Scandizzo, 2003).

Market risk can be broadly classified into interest rate risk, foreign exchange rate risk, and liquidity risk. Interest rate risk and foreign exchange rate risk are modeled and predicted by using time series methods, neural networks, decision trees, and so forth.

ROLE OF IT IN DATA STORAGE AND INFORMATION SECURITY IN BANKING

An interesting and useful way of storing information for banks with business presence in several countries is with a storage area network (SAN). A SAN is a dedicated, centrally managed, secure information infrastructure, which enables any-to-any (n-to-n cardinality) interconnection of servers and storage systems. Using SAN, banks can store their wealth of information in an organized, secure, and easily accessible manner. SAN offers the following advantages:

- It provides the connectivity of SAN with an ATM or a Gigabit Ethernet.

- It also facilitates true fiber channel and SCSI (Small Computer System Interface) internetworking and conversion.
- If a third-party copy agent is introduced, then it also reduces the backup many of them have on a daily basis.
- Another major advantage with a SAN is that it can interoperate with RAIDs (redundant array of inexpensive disks), tape storage, and servers.
- A SAN provides comprehensive Web-based and SNMP (simple network management protocol) management (Tanna, 2002).

Having stored a lot of sensitive and confidential financial data about their customers in information systems, the banks have to worry about making them secure enough, because the customers ultimately trust the banks for the safety of their information. There is a great chance for data to be misused when transactions are made on the Internet. To avoid such catastrophic developments, the banks must deploy a very powerful and reliable mechanism for securing the data. Some of the ways to introduce security in a bank using cryptographic algorithms are as follows (Tanna, 2002):

- **Restricted access:** Allowing only genuine people to enter the bank premises by having a physical security check. This can prevent unwanted people entering into the bank.
- **Authentication/authorization:** This is a standard protocol to verify whether the correct user is accessing the information (authentication by a valid username) and whether he himself is the authorized person who is actually using the information by making him enter a password (authorization).
- **Encryption/decryption of sensitive/crucial data:** The final step in the process would be to encode the sensitive data so that irrelevant people do not have access to it, while the data is in transit or when it is stored permanently.

Techniques for making the sensitive data secure are:

- **Encryption systems:** These are systems that use various encryption algorithms to secure the information.
- **Digital signatures:** This is a useful technique to secure information when there is a need to transfer critical documents across networks to combat with snooping and manipulation of the same. The signature is sensitive to the contents of the file and the signature is sent along with the file for verification (e.g., MD5).
- **Digital certificates:** These powers are built into today's browsers (e.g., Internet Explorer, Netscape) to employ SSL (Secure Socket Layer) security via *shtml* (Secure HTML) pages. The area of cryptography encompasses several algorithms to ensure safe encryption, decryption, and authentication.

ROLE OF IT IN BCP/DR IN BANKING

Business continuity planning and disaster recovery is very much critical to ensure successful and continuous operations in banks and financial institutions. Business disruptions occur for both foreseeable and unforeseen reasons, such as terrorist attacks, floods, earthquakes, and landslides. While the probability of occurrence of any individual event may be negligibly small, the business impact of disruptions can be immense. To survive, banks must protect their business against crises. This is not simply by taking property and casualty insurance on capital items and human resources, but by preparing comprehensive and robust business continuity plans (BCPs) that ensure business operations are resilient, the impact on customer service is minimized, financial losses are reduced, and regulatory compliance is maintained in the event of crisis. Customer loyalty, business reputation, and public trust must be protected by an effective and actionable BCP when a disaster strikes. Business continuity planning is about maintaining, resuming, and recovering business operations—not just the recovery of the information system. The planning process should include: risk and business impact analyses; risk management and crisis response action plans; monitoring and testing of operations, regulatory compliance, and recovery plans; awareness planning; and periodic reviews and revisions. Physically, banks can have a mirror site, which will act as a hot redundant unit to the original site where disaster may strike and business can be conducted as usual in a seamless way. However, software solutions to BCP are also possible. Software solutions provide support throughout the BCP process, enhancing banks' existing assets and capabilities with proven products and services that help banks in assessing likely impacts, avoiding known risks, planning recovery options, managing and implementing recovery mechanisms, monitoring the health of banks' operations, and automating action and awareness activities (Business Continuity Planning for Banking and Finance, 2007).

CONCLUSION

This chapter describes in a nutshell the evolution of banking and defines banking technology as a consortium of several disciplines, namely finance-subsuming risk management, information and communication technology, computer science, and marketing science. It also highlights the quintessential role played by these disciplines in helping banks: (1) run their day-to-day operations in offering efficient, reliable, and secure services to customers; (2) meet their business objectives of attracting more customers and thereby making huge profits; and (3) protect themselves from several kinds of risks. The role played by smart cards, storage area networks, data warehousing, customer relationship management, cryptography, statistics, and artificial intelligence in modern banking is very well brought out. The chapter also highlights the important role played by data mining algorithms in helping banks achieve their marketing objectives, fraud detection, anti-money laundering, and so forth.

In summary, it is quite clear that banking technology has emerged as a separate discipline in its own right. As regards future directions, the proliferating research in all fields of ICT and computer science can make steady inroads into banking technology because any new research idea in these disciplines can potentially have a great impact on banking technology.

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Section I
Services Management

Chapter II
Service Quality in Banks:
What are the Factors Behind Performance and Customer Satisfaction?

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ABSTRACT

Quality in servicing customers is an important marketing construct for banks, but idiosyncrasies in the definition of service quality and customer satisfaction, as well as in adapting current instruments to measure them in the international banking industry, constitute major constraints to research and practice. This chapter conceptualizes the quality of banking services based on the perception of 11,936 customers of a major Brazilian bank. Five drivers of banking service quality are developed and argued to be a proxy for customer satisfaction: (1) business and financial transactions, (2) customer relationship, (3) information technology, (4) branch, and (5) image. The resultant framework is expected to serve bank executives when making strategic decisions on how to address their clientele.

INTRODUCTION

The search for high levels of quality in delivering services has a tradition in industry (Zeithaml, Parasuraman, & Berry, 1990). According to Parasuraman, Zeithaml, and Berry (1985), service quality was a focus just after the concern on improving the quality of products emerged, and services are indeed increasingly important in the global economy—regarding the participation in the GNP and job creation, for instance. Information technology (IT) plays an important role in this, since it changes the economy into one that is based on services (Fitzsimmons & Fitzsimmons, 2000).

Competition has obliged service organizations to look for an effective way to differentiate in the market and augment the likelihood of customer satisfaction. Strategic quality management in services is therefore improving in industry, and this includes the banking sector (Soteriou & Stavrinides, 2000; Bhat, 2005; Bexley, 2005). However, service quality in banks was not always targeted when looking for the mediating factors towards financial performance (Mukherjee, Nath, & Pal, 2003), and financial institutions struggle to find or develop instruments to measure the quality of their services (Bahia & Nantel, 2000; Bhat, 2005). Delivering quality services is in fact an important marketing strategy (Berry & Parasuraman, 1991; Ray, Muhanna, & Barney, 2005; Voss, Roth, Rosenzweig, Blackmon, & Chase, 2004), but difficulties in defining *service quality* and *customer satisfaction,* as well as problems in deploying current instruments for measuring such constructs to specific contexts, represent important constraints for organizations to address their markets. Notwithstanding, only by measuring levels of quality it is possible to make improvements (Gardner, 2001).

In this chapter, we develop a framework to address the quality of banking services primarily in the Brazilian context. The framework is based on a preliminary quanti-qualitative study carried out by a consultant firm (of which the authors did not take part) with customers of the foremost Brazilian bank in terms of number of customers. Differently, though, from adopting the SERVQUAL rationale (Parasuraman et al., 1985, 1988; Parasuraman, Berry, & Zeithaml, 1993) for assessing quality—like the consultants did—we applied SERVPERF (Cronin & Taylor, 1992) to questionnaires received from the same respondents (11,936 in total), and so we were able to re-interpret the results. The new approach empowered us to propose five basic constructs to measure the quality of banking services in Brazil: (1) *business and financial transactions,* (2) *customer relationship,* (3) *information technology,* (4) *branch,* and (5) *image.*

The chapter is structured as follows: first, we introduce the Brazilian banking sector; second, we briefly discuss services management in banking and how to measure service quality by means of two widely known marketing scales; third, the research methodology is presented (both the consultant firm's and the authors' procedures), as well as the instrument developed for measuring service quality in the Brazilian banking sector; fourth, results from one application of the instrument are discussed, with special focus on five quality drivers; and fifth, we proceed to concluding remarks about the research, particularly highlighting insights for the Brazilian banking industry.

THE BRAZILIAN BANKING SECTOR

The business environment marked by fierce competition and continuous changes in the relationship between companies and customers sets the scene for the Brazilian banking industry. According to the Brazilian federation of banks (Febraban, 2006), this industry was characterized in the last few years by mergers and incorporations,

Table 1. Banks sorted by ownership (Febraban, 2006)

	2000	2001	2002	2003	2004	2005	Variation 2004-2005
Private national banks	105	95	87	88	88	84	-4.5%
Private foreign banks	70	72	65	62	62	63	1.6%
State banks	17	15	15	15	14	14	0.0%
Total	192	182	167	165	164	161	-1.8%

by a decrease in the number of private national banks, and by the stability in the number of private foreign banks operating in Brazil (see Table 1). Besides the stability in the number of banks, the sector is continuously improving performance. The Basel-II index is well above the minimum recommended by the Central Bank of Brazil (11%) and the international level (8%), notwithstanding the decrease from 24.3% to 22.3% between 2004 and 2005. The good results suggest the robustness of the sector, as well as the potential for increasing credit in the coming years.

Another key feature of the sector in Brazil is that there was a substantial improvement in the fulfillment of services, particularly in terms of enabling the electronic transactions. Internet banking, for instance, increased by 45.3% between 2004 and 2005; currently, 26.3% of all banking customers perform transactions via the Internet in Brazil. Nevertheless, the traditional channels for servicing customers are still much needed in the country.

In what comes to products offered to the individual customer, there was an increase of 4.3% in savings accounts (70.8 millions in total) and an increase of 5.4% in current accounts (95.1 millions in total). Such an increase followed the evolution of credit in Brazil, which was also expressive; indeed, the proportion between bank credits and the GNP grew from 27% to 31.3%, exceeding the 30% level for the first time since 1995. This expansion was the norm in all segments, but especially in those with higher legal guarantees, such as leasing (56.25%) and consigned credit (84.3%). Finally, social strata that were never introduced to the financial system were remarkably benefited.

In order to continuously improve quality, customer satisfaction polls are frequently performed in the Brazilian banking sector. In 2005, 46.3% of banks performed some sort of data collection with such methods as focus groups and surveys. Moreover, customer support services are hopefully effective in the sector (see Table 2).

SERVICES MANAGEMENT IN BANKING

Assorted research on banking service quality has been done over the last decade. Although there is always the assumption that institutionalization plays an important role in the overall performance of organizations (DiMaggio & Powell, 1983), quality is mandatory for a company to achieve profits (Soteriou & Zenios, 1997), and it effectively represents the single most important factor that mediates the selection of a bank by the prospecting customer (Bexley, 2005).

According to Bellini, Lunardi, and Henrique (2005), banks must be trustworthy and understand the current and future needs of their customers, thus making customers believe that they are supported by the best financial managers available in the industry. In fact, among the most important attributes for the perception of banking service quality, one finds the effective fulfillment of services and related issues like the politeness of employees during front-end servicing.

Table 2. Customer support (Febraban, 2006)

	2005	2004	2003
Number of telephone calls to customer support service	67,144,747	51,146,418	31,800,219
Proportion of complaints	2.2%	2.1%	2.9%
Average waiting time on the phone until support begins	56 seconds	31 seconds	180 seconds
Number of innovations introduced due to customer feedback	278	110	185

Information technology (IT) quite remarkably changed the financial sector (Currie & Glover, 1999), and the Internet in particular seems to be the new channel for banks (Mavri & Ioannou, 2006). IT reduced the contact between the bank and the customers, and by having lowered the information costs, it enabled individuals and companies to efficiently compare portfolios of investments between banks, and even invest directly. In general, IT provided banks with the ability to introduce new products, increase productivity, operate geographically dispersed, and compete on a global scale (Cooke, 1997). However, with new computer and telecommunications technologies and increasingly sophisticated management and control systems, sound investments in personnel training and development are necessary.

Issues related to the physical branches are also of concern for quality. For instance, the access to the facilities (e.g., parking lot attributes and the mobility of people inside the rooms) and concerns on safety and convenience of location make customers assess quality on a tangible basis (Castro, 1997). Quality drivers also include the branches' external and internal architecture, the provision of ATMs, and the availability of human attendants (Lovelock, 1996).

Advertising practices in the mass media and the institutionalized reputation and image within the community may also have an impact in the perception of a bank's quality. Horovitz (1987) makes the point, however, that the communication strategy must not promise to the customer a performance level for the service that cannot be later actually perceived; otherwise, customers are likely to leave the bank (Bexley, 2005). One strategy for developing a good image within the market is, according to Compton (1991), the decision to diversify the portfolio of services, inasmuch as those who use many banking services are not likely to move to another bank. Sponsoring cultural activities and sports can also be deployed.

SCALES FOR SERVICE QUALITY

Most studies on service quality make use of the SERVQUAL framework (Parasuraman et al., 1985, 1988, 1993), which measures a customer's perception of quality from comparing his or her expectations of an excellent service with the perception he or she has about the actual performance of the same service. Then, if the perceived service matches or exceeds the expected service, that customer would be motivated to contact the service organization again (Kotler & Armstrong, 2001). SERVQUAL, however, suffers several criticisms (e.g., Cronin & Taylor, 1992; Van Dyke, Kappelman, & Prybutok, 1997), mostly for trying to generalize assumptions to any type of service and for addressing service quality by contrasting customer expectations with customer perceptions about performance—which frequently poses validity problems in research instruments (Peter, Churchill, & Brown, 1993).

Cronin and Taylor (1992), on the other hand, developed the SERVPERF framework, which is based on the assumption that a service's perceived performance would be *per se* a good predictor of quality. Therefore, scores computed from differences—like in SERVQUAL—are discarded, which makes SERVPERF more efficient by reducing to half the items under analysis. Moreover, it is assumed that service quality precedes customer satisfaction, and that satisfaction strongly impacts the purchase intentions.

According to Teas and DeCarlo (2004), however, SERVPERF is more effective in predicting perceived value and purchase intentions, while SERVQUAL performs better in predicting customer satisfaction. Further discussions of conceptual and empirical issues of the two frameworks can be found in Cronin and Taylor (1992), Teas and DeCarlo (2004), Franceschini, Cignetti, and Caldara (1998), and in a series of information systems articles in the top journal

MIS Quarterly (Pitt, Watson, & Kavan, 1995, 1997; Van Dyke et al., 1997; Kettinger & Lee, 1997, 2005; Watson, Pitt, & Kavan, 1998; Jiang, Klein, & Carr, 2002).

Our study adopts SERVPERF to address the quality of banking services, like Al-Hawari, Hartley, and Ward (2005) did to measure the quality of automated banking services, and differently from procedures in Angelis, Lymperopoulos, and Dimaki (2005) to understand service quality according to bank ownership. Some research perspectives (e.g., Soteriou & Zenios, 1997) conceptualize service quality as exhibiting objective attributes along with perceptual ones, like waiting times, incident duration, and credit approval rates, but we are interested solely in the subjective interpretation of customers about bank performance, irrespective of attributes being somehow considered elsewhere directly measurable or not. More on service quality frameworks can be found in Chowdhary and Prakash (2005), and an interesting chronology of service quality research is available in Bexley (2005).

THE RESEARCH

The development of the model for studying the quality of banking services started with marketing research performed by a consultant firm hired by the most prestigious Brazilian bank. By the time this chapter was written, the bank had 24 million customers with financial applications, some US$63 billion in deposits, approximately 15,000 branches in Brazil and other countries, 42,000 ATMs, and 87,000 employees (Torres & Kischinhevsky, 2006).

The consultants identified theoretical quality indicators for banking services. They were also responsible for applying a survey questionnaire to customers of that Brazilian bank dispersed over the whole country, as well as for formatting the answers in an SPSS™ database. The authors of this chapter, in turn, performed: (a) the theoretical framework for service quality in the banking sector, (b) the validation and improvement of the questionnaire, and (c) the analysis of the data collected by the consultant firm.

Data collection performed by the consultants gathered 11,936 valid questionnaires (completely answered and with no typos). Before data collection, however, the following methodological procedures have been performed (here only briefly presented for the reader to know how the first version of the instrument was developed by the consultants):

1. Several focus groups with people carefully selected to make emerge relevant attributes to be included in the instrument.
2. Content analysis of the writings from the previous step, in order to sort the attributes and to format them into more appropriate technical terms.
3. Pre-test of the attributes as a questionnaire with 800 customers.
4. Adjustments to the instrument, which grouped together 43 structured questions about the perceived performance of banking services, answers given on a nominal five-point Likert scale from "I totally disagree" to "I totally agree."

Therefore, *perceived service performance* is defined by the degree to which the customer assesses the service as effective or not. Demographic data were also collected for the customer profile (age, gender, region of the country, etc.), in order to build clusters of customers within the population. Finally, one specific question to measure each customer's *overall satisfaction with the bank* was included; it was measured by a five-point Likert scale from "totally unsatisfied" to "totally satisfied."

From the consultants' database of answers, we initially performed a literature review on service quality, customer satisfaction, and the banking sector, in order to effect construct validation of the instrument (Churchill, 1979; Boudreau, Gefen, & Straub, 2001). Five factors were identified as key for assessing the services of a bank (some theoretical sources clearly rooted their exhortations in the SERVQUAL framework):

- *Business and financial transactions* (B&FT), that is, attributes of the ultimate purpose of the bank, that of collecting financial resources from customers, making investments, and distributing financial benefits to customers and shareholders (e.g., Castro, 1997; Neuberger, 1998; Mukherjee et al., 2003).
- *Customer relationship* (CR), that is, attributes of the relationship between the bank and its customers for service fulfillment (e.g., Castro, 1997; Martins, 1996; Soteriou & Zenios, 1997; Mukherjee et al., 2003).
- *Branch* (Brn), that is, attributes of the physical environment where services are performed, like comfort and ease of access (e.g., Lovelock, 1996; Castro, 1997; Soteriou & Zenios, 1997; Mukherjee et al., 2003).
- *Information technology* (IT), that is, how technology supports customers in their needs in services (e.g., Albertin, 1998; Drucker, 2000; Lovelock, 1996; Mukherjee et al., 2003; Al-Hawari et al., 2005).
- *Image* (Img), that is, how the bank presents itself to society (e.g., Horovitz, 1987; Compton, 1991).

Therefore, (1) the services of a bank (2) are offered to its customers (3) in physical branches (4) supported by the information technologies, and (5) the services are made known to the community by the image gradually developed within a group of customers and other people. These findings and assumptions adequately represent the main components of a banking service.

Exploratory factor analysis was performed in order to address construct validation—the degree to which the instrument measures the implied concepts (Churchill, 1979; Boudreau et al., 2001). Prior to extracting factors, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy for factor analysis was applied to the answers, and the present case (11,936 performance perceptions on 43 indicators) reached the excellent 0.976 level (within a 0-to-1 range). Another preliminary test performed was Bartlett's test of sphericity (BTS), which checks whether the correlation matrix approximates the identity matrix, unveiling correlations among items. To a significance level of 1% ($p<0.01$), the null hypothesis of non-existing significant correlations among items was rejected.

The next step was to conceptually analyze the instrument. After pre-test, the instrument consisted of 43 questions, meaning that 43 variables should be scrutinized in the attempt of grouping them into key conceptual factors. The result was that the five factors developed from the literature review were also found in the conceptual grouping of items—but some items happened to seem irrelevant, and as such they should be tried in further tests.

With the five conceptual factors in hand, principal component analysis (PCA) was performed in order to measure the mathematical correlation among items, thus verifying the plausibility of reducing the 43 original items to only five—the five factors. There would be, of course, as many components as the original items, but only the components explaining the largest amount of the total variance of the measures would be considered as principal components. A criterion for setting an acceptable level for explaining the total variance by a principal component would be that this component should explain at least what would be expected from it in terms of explanation if all items had the same statistical power for the measures. That is, if n is the number of items, then the last principal component should explain, at the very least, $100/n$% of the total variance, thus exhibiting an eigenvalue equal to or greater than 1. This principle can be deployed

Table 3. Exploratory factor analysis

Item	B&FT	CR	IT	Brn	Img
It is a bank where you can easily get a loan.	.47				
There is a private room where you can do business with the manager.	.47				
You can make all sorts of banking transactions using the call center.	.48				
The bank invests automatically the money in your current account.	.55				
The bank helps you decide what to do with your money.	.56				
It is the bank with the lowest tariffs.	.57				
The bank has managers who know your needs.	.58				
The more you use the bank, the less you pay tariffs.	.60				
The manager gets in touch with you to monitor and inform about investments and loans.	.65				
You can use the overdraft checking account during some days without paying interest.	.68				
All customers are serviced equally.		.42*			
The security force is trained to service customers politely.		.49			
You are proud of owning an account in the bank.		.62			
The branch's personnel is informed and competent.		.64			
The bank is trustworthy.		.65			
The employees are polite and courteous.		.66			
Statements are simple and easy to understand.			.40		
It is easy to use the bank through the Internet.			.44		
The bank has exclusive ATMs.			.48		
It is easy to get checks at the branch.			.53		
ATMs inside the branch are easy to use.			.56		
You can make all sorts of transactions with the ATMs.			.60		
The bank has exclusive ATMs to print checks.			.64		
The branch has enough tellers for the customers.				.39*	
The branch has enough space for the customers in its parking lot.				.46*	
The branch displays appropriate directions for the customers.				.46	
The branch's security doors work well and enable customers to get in and out easily.				.49	
The branch offers seats, water, coffee, and air-conditioner.				.54	
The branch is spacious.				.57	
The bank provides a complete portfolio of products and services.					.40
The bank acts closely to the community, helping people to solve problems.					.46*
The bank advertises its products and services.					.50
The bank sponsors sport activities, live shows, and theater plays.					.76

** Items moved between factors due to conceptual reasons.*

when the number of items ranges from 20 to 50 (Hair, Anderson, Tatham, & Black, 1998), which was our case (43).

When extracting the principal components from the 43 questions and applying the orthogonal rotation Varimax to help discriminate the variables in each component, six components emerged—and not the five previously identified in the conceptual stage. Nevertheless, PCA and Varimax are mathematical procedures not sufficient for building the factors; in fact, the researcher's subjective judgment plays an important role in this regard, thus being his or her responsibility to ultimately decide on the whole set of factors and items. Besides the analyst's subjective interpretation, it is common to have items with low correlations with some or even with all factors, this being another reason for moving items across factors or excluding them.

Therefore, items not conceptually coherent with the component to which they were mathematically correlated were assessed again. The first procedure was to check their loads in other components with which they had stronger theoretical ties, in a way that they could join those other factors if their loads were not really low; or it was even assumed that an item could be deleted from the analysis if it could not be moved from one component to another. Numerous extractions of principal components were performed—each time moving some items across factors—until 10 items were considered useless for the questionnaire.

At each removal of items from the instrument and subsequent new calculation of principal components, KMO and BTS tests were performed. For the final instrument with 33 items in Table 3, the values for both tests were respectively 0.969 and a significance level of 1%, indicating adequacy for factor analysis.

Although the final factors present a conceptually valid structure and the tests for sample adequacy show that the database is appropriate for factor analysis, the 10 items excluded led to a situation where only three components out of the five in Table 3 had eigenvalues higher than 1, with statistical power of only 39.13% of the total variance. However, if all the five components developed conceptually are included, the explanation amounts to 45.07%, with the two less powerful components presenting eigenvalues close to 1 (0.988 and 0.97). We believe that this procedure (of including the fourth and the fifth principal components into the framework) does not harm in any way the generalization of findings; on the contrary, it puts together the theoretical factors and the first five principal components statistically extracted.

Finally, in order to address the instrument's reliability, Cronbach's alpha was assessed—the higher the value, ranging from 0 to 1, the higher the reliability that can be assigned to the set of measures. Nevertheless, it is difficult to set minimum levels for the alpha, since such a value is highly dependent on the nature of the research (Hoppen, Lapointe, & Moreau, 1996); we assume

Table 4. Cronbach's alphas for the factors

Factor	Cronbach's Alpha
Business and Financial Transactions	0.84
Customer Relationship	0.79
Information Technology	0.71
Branch	0.70
Image	0.61
Questionnaire	**0.92**

that values starting from 0.6 or 0.7 are acceptable (Hair et al., 1998). If this is the case, the current instrument is reliable—numbers were 0.92 for the whole instrument, and between 0.61 and 0.84 for each factor (see Table 4).

RESULTS

Although ownership matters for bank performance, mainly when contrasting the efficiency of private and state banks (Bonin, Hasan, & Wachtel, 2005) and given that our research was carried out with customers of a single bank, we believe that the findings can be amplified to some extent for the whole sector—at least in Brazil. The main reason for this is that, beyond the significant sample of almost 12,000 respondents, many interviewees were also customers of other banks with different ownerships, thus being able to subjectively compare performances.

The descriptive analysis showed that the *overall satisfaction* of the bank's customers with the services was 3.87 (scale ranging from 1 to 5). In what comes to the top-two-box index (Marr & Crosby, 1993), which deals with the percentage of satisfied or totally satisfied respondents regarding the overall perception, a level of 75.4% was reached. The *average performance* perceived by the customers for the five factors ranged from 3.39 to 4.26 (also on a 1-to-5 scale), with 3.96 representing the instrument's average score (see Table 5). Although these are not directly comparable scales, it is interesting to note that, from the customer's ability to use a five-point scale, the bank's average performance in services looks similar to the overall satisfaction with the same services; if service performance (and not the difference between performance and expectation) is truly a proxy for service quality, and if service quality precedes customer satisfaction, the results are theoretically supported by SERVPERF.

The performance of each factor in Table 5 reflects the sum of the average performance of each of its items. In terms of *information technology* (see Table 6), emphasis is put on the bank's exclusive ATMs (4.46) and the ease in using them (4.46), as well as on the simplicity of the account statements (4.44). On the other hand, Internet banking (3.84) scored low. During the last two decades, the financial sector developed greatly in terms of size, industry structure, and the variety of consumer products and services offered. IT has been responsible for maintaining banking services running at the same pace or even better than previously. Internet banking, on the other hand, faced some difficulties before becoming popular in Brazil; issues about access, security, and user-friendliness were not addressed properly a few years ago, driving customers away. By means of technical improvements and huge investments in advertising, some problems were mitigated, and Internet banking now seems to grow steadily.

The indicators of trust (4.53)—best performance for the whole instrument—and employee politeness (4.36) had the best performance for *customer relationship* (see Table 7). High levels of

Table 5. Performance of the factors

Factor	Performance
Information Technology	4.26
Customer Relationship	4.21
Image	4.03
Branch	3.91
Business and Financial Transactions	3.39
Questionnaire	**3.96**

trust may lead to high levels of customer loyalty, unfolding the possibility of strengthening the customer relationship with the bank. Employee performance is important since employees constitute the front-end interface between many, if not most, customers and the bank; moreover, there are people who still prefer human interaction when transacting with the bank. However, the impartiality in servicing averaged far lower (3.62) than the other indicators. This attribute should be worked out with care by the bank executives, given that it may cause disruptions in trust.

Regarding the bank's *image* (see Table 8), the portfolio of products and services and the advertisement policies are positively noteworthy (4.30), whereas both the sponsoring of sports and cultural activities and the relationship between the bank and the outer community (3.63) had low performances. What seems interesting in these findings is that the business issues of the image—the portfolio of products and services—performed far higher than the actual services offered (as discussed below), what urges managers to align promises and offerings.

The *branch* (see Table 9) shows high levels for the security doors (4.35) and the internal signaling for customers (4.31), but the number of tellers (3.39) and the available space in the parking lot (3.23) averaged among the least performing indicators of the whole instrument. Branch location, especially in big cities, is critical, since customers need to be served in a traffic-efficient manner; in order to help solve this demand, Internet technologies and self-service machines within third-party

Table 6. Information technology

Item	Performance
The bank has exclusive ATMs.	4.46
ATMs inside the branches are easy to use.	4.46
Statements are simple and easy to understand.	4.44
It is easy to get checks at the branch.	4.27
You can make all sorts of transactions with the ATMs.	4.18
The bank has exclusive ATMs to print checks.	4.16
It is easy to use the bank through the Internet.	3.84
Factor	**4.26**

Table 7. Customer relationship

Item	Performance
The bank is trustworthy.	4.53
The employees are polite and courteous.	4.36
The branch's personnel is informed and competent.	4.28
The security force is trained to service customers politely.	4.24
You are proud of owning an account in the bank.	4.23
All customers are serviced equally.	3.62
Factor	**4.21**

Table 8. Image

Item	Performance
The bank provides a complete portfolio of products and services.	4.30
The bank advertises its products and services.	4.30
The bank sponsors sport activities, live shows, and theater plays.	3.88
The bank acts closely to the community, helping people to solve problems.	3.63
Factor	**4.03**

Table 9. Branch

Item	Performance
The branch's security doors work well and enable customers to get in and out easily.	4.35
The branch displays appropriate directions for the customers.	4.31
The branch is spacious.	4.17
The branch provides seats, water, coffee, and air-conditioner.	4.00
The branch has enough tellers for the customers.	3.39
The branch has enough space for the customers in its parking lot.	3.23
Factor	**3.91**

Table 10. Business and financial transactions

Item	Performance
There is a private room where you can do business with the manager.	3.70
It is a bank where you can easily get a loan.	3.67
You can make all sorts of banking transactions using the call center.	3.64
The bank has managers who know your needs.	3.55
The bank helps you decide what to do with your money.	3.51
The bank invests automatically the money in your current account.	3.47
It is the bank with the lowest tariffs.	3.30
The more you use the bank, the less you pay tariffs.	3.29
The manager gets in touch with you to monitor and inform about investments and loans.	3.15
You can use the overdraft checking account for some days without paying interests.	2.63
Factor	**3.39**

facilities strategically located near workplaces and domiciles are an alternative. But a number of customers still need intense human interaction, and those perceive that the number of tellers to service them is not enough—unfortunately, the number of bank personnel continues to decrease due to the controversial efficiency imperative applied to the salaries.

Maybe surprisingly, the *business and financial transactions* (see Table 10)—the bank's *raison d'être*—grouped some of the poorest indicators of all. Indeed, all items in this factor performed lower than the instrument's average, while the pro-activity of the manager in updating the customer about his or her investments and loans (3.15) and using the overdraft checking account for some days without paying interests (2.63) were the worst performing indicators. Interestingly, the best performing indicator—the opportunity of talking privately with the manager—scored below the average of all other factors (3.70). We believe that institutionalization factors (DiMaggio & Powell, 1983) as revealed when comparing the performance of the business issues of image and actual transactions, and some industry practices (e.g., all federal organizations and many other companies require that their employees have an account in the bank) are among the reasons why the bank exhibits a healthy financial performance notwithstanding its poor technical performance.

Multiple regression analysis (MRA) was carried out to show the influence of the factors on the customers' *overall satisfaction* with the services. Although explaining somewhat poorly the dependent variable ($r^2=0.315$; $p<0.0001$), the analysis enabled insights to be developed for understanding that satisfaction. All five factors were significant for $p<0.0001$.

MRA resulted in $S=3.87+0.314a+0.408b+0.144c+0.128d+0.116e$, where S is the customers' overall satisfaction with the bank's services, a is the perceived performance of the business and financial transactions, b is the perceived performance of customer relationship, c is the perceived performance of the information technology, d is the perceived performance of branches, and e is the perceived performance of the image.

Customer relationship is perceived as the factor with the highest impact on the overall satisfaction (0.408), even if compared to the main purpose of the bank—to perform *business and financial transactions* (0.314). This is in line with Angelis et al. (2005), who suggest that the technical characteristics of bank products declined in importance as compared to how the bank addresses customer care, and with Strandvik and Liljander (1994), for whom the relationship between banks and customers is very strong. For the surveyed bank, it is positive to see that the most valued factor operates at high performance (4.21); on the other hand, the second factor in importance for satisfaction—*business and financial transactions*—is the worst in performance (3.39), urging the bank's executives to address this more carefully.

The fact that the *information technology* is perceived to be the best in performance (4.26) validates what Drucker (2000) says about the banking industry maybe being the most prominent in deploying IT. However, being the third in importance for satisfaction (0.144) seems to be explained by the understanding that the bank customer does not see IT as a distinctive feature anymore, but a commodity—more on the relation between IT and competitiveness can be found in Tan and Teo (2000). Donald Feimberg from the Gartner Group in Latin America even suggests that IT is not a tool for the bank, but the bank itself (Febraban, 2002); indeed, there is a general belief that information systems and business processes can be arguably taken as synonyms (Alter, 1996).

Finally, *branch* and *image* were the least relevant for the customers regarding the impact on satisfaction (0.128 and 0.116, respectively). The bank's *image*, however, deserves special attention for having been the third factor in performance (4.03); nevertheless, the effort that the bank is making to promote its brand does not seem to influence customer satisfaction as intensively as other factors do—and this poses issues on prioritizing resource allocation.

Ongoing analyses of variance between subgroups of respondents are puzzling and did not reveal any findings worthy of discussion so far.

CONCLUSION

This chapter discussed the development of a framework for measuring the quality of banking services in Brazil, starting from a preliminary study carried out by a consultant firm contracted by the most prestigious Brazilian bank. As compared to that firm's procedures, we applied a different theoretical perspective (SERVPERF instead of SERVQUAL) for interpreting the data collected in a survey on the perception of 11,936 customers about that bank's services. We also built a compact theoretical model on banking services and performed assorted statistical procedures to understand the empirical data.

The present study is original due to the validation of factors to address service quality in Brazilian banks: (1) *business and financial transactions,* (2) *customer relationship,* (3) *information technology,* (4) *branch,* and (5) *image*. An important implication in the domain of quality in banking services is that the perceived performance levels for the factors conveniently gauge the quality of services, with no clear need for contrasting between perceived performances and customer expectations (as in SERVQUAL).

In terms of implications for management, it is worth noting that customer relationship is the most important quality driver as perceived by the market, even if compared to the financial organization's utmost purpose of generating business and financial transactions. It is also meaningful that this most valued factor performed high in the surveyed bank. According to reports from the Brazilian finance newspaper *Gazeta Mercantil* (1999), research developed by the *Eurogroup* with 17 Brazilian banks in 1998 showed that retail banks were accustomed to losing 18% of their customers per year, two-thirds due to service problems. Moreover, employing people to sell products and services seems to be much more efficient than the deployment of any technology. All this deals with the relation between the bank and its customers.

On the other hand, the second dimension in importance—business and financial transactions—needs a really careful analysis by the executives of the surveyed bank, given that it was the poorest factor in performance. It seems that the contrast between service levels and tariffs may be at the root of the problem, and this is exacerbated for customers who are coerced by their employers to have an account in the bank. Additionally, given the still unsolved problem in Brazil of banks not easily granting credit for micro and small enterprises, as well as the fact that the Brazilian interest rates are the highest in the world—which contributes to the pandemic lack of monetary resources in the population—any difficulty in getting loans would be naturally perceived as an ineffective fulfillment of service.

The fact that IT is perceived to be the best performing factor acknowledges the surveyed bank for its efforts in deploying high technology. Even in the poorest Brazilian regions, it is usual to see the local communities making use of the bank's ATMs and even the Internet to process their banking transactions. The effectiveness with which IT is being deployed by the bank may also have a positive effect on the assessment made by customers about the physical branches, given that IT—and the Internet in particular—is reducing the demand for the traditional channels for service fulfillment. However, given that Brazil still struggles against a blatant informational and digital divide, bank managers cannot ignore the threats to implementing most of the technology.

The bank's image deserves some reinterpretation for having been the third in performance, but also the less influential on customer satisfaction. Indeed, the bank supports many high-profile activities, but it should be investigated further, whether this is regarded as appropriate or even necessary by the customers. We cannot conclude on this from the available database.

Finally, bank managers are now safeguarded by our findings to deploy SERVPERF instead of the less efficient SERVQUAL framework to assess the quality of services. This is not to say that SERVQUAL should be discarded, but that, according to previous assumptions in the literature confirmed in our research, there is maybe a more economic route to understand how the clientele assesses the fulfillment of services in the banking sector.

It is of importance to say that the suitability of the data for today's analyses should be interpreted with care, especially for the performance of the IT indicators. Indeed, data on banking service performance and customer satisfaction are expected to change as a result of the continuous improvements in the sector, the technological innovations, and the institutionalization of a bank's image. Moreover, the source of our data poses threats to the external validity of findings, in the sense that since we had to start from an already accomplished survey, there was no room to add redundant questions that could otherwise test the respondents' comprehension and coherence, and thus strengthen the constitution of the final factors.

We suggest that the instrument as a whole be used and validated in other Brazilian and international banks, in order to be increasingly useful for measuring service quality in the sector. Since we normalized and translated the consultants' instrument, it is of pressing need to verify its suitability for English-speaking nations. Additionally, an arresting theme for further research is to understand the very nature of the drivers of performance and satisfaction, in order to conclude on their transitoriness or not in explaining the banking services—and for this to be achieved, one should first conclude on the role played by banks in current society.

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Chapter III
Adoption and Diffusion of Internet Banking

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ABSTRACT

This chapter reviews important theories—the diffusion of innovations theory, the theory of planned behavior, and the technology acceptance model—in information systems that explain the adoption and diffusion of new technological innovations especially in the context of Internet banking. These theories taken together provide us with psychological models that influence the adoption of a new delivery channel for banks, that is, Internet banking. Empirical works that have investigated these theories are discussed. A critical perspective is offered that highlights the theoretical and methodological limitations of these models. Newer and richer models that take into account the socio-historic contexts of technology adoption are called for. Approaches that complement or challenge positivistic methodologies that are interpretive are presented in a case study. Relating theory to practice this chapter discusses possible future trends in Internet banking that could make an attempt to include populations that are not included in the modern electronic formal mainstream financial systems.

INTRODUCTION

Internet banking is an emerging technology that permits conduct of banking transactions through the Internet. "Internet banking" refers to systems that enable bank customers to access accounts and general information on bank products and services through a personal computer (PC) or other intelligent device. Internet banking products and services can include wholesale products for corporate customers as well as retail and fiduciary products for consumers. Soon, the products and services obtained through Internet banking may mirror products and services offered by other bank delivery channels such as traditional branch banking, automated teller machines, phone banking, and call centers (Gartner, 2003). Banks with a physical brick-and-mortar presence or virtual banks can offer Internet banking. Virtual, branchless banks can also offer Internet banking, although virtual banks without physical offices may offer their customers the ability to make deposits and withdraw funds via branches or ATMs owned by other institutions (Gopalakrishnan, Daniel, & Damanpour, 2003).

With the widespread growth of the Internet, customers can use this technology anywhere in the world to access to a bank's network. The Internet, as an enabling technology, has made banking products and services available to more customers and eliminated geographic and proprietary systems barriers. With an expanded market, banks also may have opportunities to expand or change their product and service offerings. Global Internet access had exceeded more than one billion people by December 2005 (Lichenstein & Williamson, 2006). In 2005 India recorded 38.5 million users until November. India now accounts for 50.6 million Internet users and ranks as the fourth largest among the global Internet users after the United States, China, and the European Union (Hindustan Times, 2006). This figure is up by a substantial 54% from 25 million in 2004. A broadband policy and other initiatives by the IT and Telecom Ministry in India have encouraged increased adoption of the Internet. Today, a monthly broadband subscription costs as little as 199 rupees (US$4.50). The room for "prospective customers" is quite high.

This chapter focuses on adoption studies in Internet banking. There are push factors and pull factors that enable adoption of Internet banking, though adoption delays and realization delays exist. The second section begins with a brief description of Internet banking which provides a Web interface to a bank. This section addresses issues such as economic benefits and profitability gains in introducing Internet banking for banking establishments, and the structural and technical preconditions necessary for Internet banking to be adopted by banking customers (the access to and the pervasive presence of basic Internet resources). The third section deals with the problem of trust in electronic commerce. The reason why electronic commerce has not succeeded is due to the fact that there are not sufficient institutional and social frameworks that guarantee a trustworthy electronic environment to the customer. A review of trust literature is made and Internet banking is examined in this context as security and privacy concerns emerge when financial transactions are made over the Internet medium.

The fourth section reviews state-of-the-art research in the adoption of Internet banking through three different theoretical lenses. First, the diffusion of innovations theory is outlined. Next the theory of planned behavior and the technology acceptance model are described. This is followed by an analytical discussion of recent research work in this domain. In the fifth section, two case studies, one each from New Zealand and Australia, are discussed. A brief section on possible future trends in Internet banking is included, and the last section concludes this chapter.

ISSUES AND TRENDS IN INTERNET BANKING TODAY

Internet banking provides competitive advantage to banks. Customers today not only expect but demand Internet banking facilities when they open new accounts. This situation is particularly true in developed economies. This section provides a description of Internet banking facilities, the economic benefits of introducing Internet banking, and the physical infrastructure requirements or enabling technologies necessary for Internet banking.

Internet Banking

Internet Banking allows customers of banks to:

- Do balance enquiry, for example, online enquiries of current checking or savings account balances.
- Transfer funds electronically, for example, transfer funds between one's own accounts or external accounts.
- Pay bills, for example, utility bills or insurance premiums, or buy railway and air tickets, and so forth.
- Make loan applications, for example, applications for car loans, housing loans, personal loans, and so forth.
- Make investments, for example, create fixed deposits and so forth.
- Trade in shares and securities.

There are different types or levels of Internet banking. The basic level of Internet banking is primarily informational. The bank's Web site has marketing information about the bank's products and services. The second level is communicative where the Web site allows interaction between the bank's system and the customer such as account inquiry, loan applications, or static file updates (name and address changes). At the third level bank customers have more power to operate their accounts. This is the transactional level where customers have the ability to execute transactions like paying bills, transferring funds, making fixed deposits, and so forth. Most banks offer balance enquiry and funds transfer capabilities through the Internet today. It is expected that more banks will develop the facilities for bill payment, credit applications, new account setup, cash management, and fiduciary and insurance services through Internet banking (Furst, Lang, & Nolle, 2000).

Cost Benefits of Internet Banking to Banks

Organizations experience efficiency gains through lower costs in the first phase of technological application. There are significant performance improvements in deploying Internet banking over alternative delivery mechanisms. Baras (1986) has found that the Internet significantly lowers the cost of distribution of banking products and services. The cost per transaction of various delivery channels tells us that face-to-face banking costs $1.07, telephone banking $0.54, automated teller machines (ATMs) $0.27, and Internet banking $0.02 (Gopalakrishnan et al., 2003). In India the banking industry estimates teller cost at Re.1/- (US$0.022) per transaction, ATM costs Re. 0.45/- (US$0.0099), phone banking Re.0.35/-, and Internet banking Re. 0.10/- per transaction (Indian Express, 2004). For banks, introducing Internet banking as a new delivery channel is a cost-effective and revenue-generating venture.

The capital investment to deploy Internet banking is relatively low compared to opening a new branch or even installing an ATM. In spite of the low costs, all banks do not adopt Internet banking speedily. This is primarily due to environmental factors (the level of penetration of the Internet), the industry-level factors (basic computerization of banks), and firm-level factors (individual bank strategies to introduce Internet banking). In retail banking, the degree of risk that banks undertake in becoming an Internet bank also depends on bank size, profitability, and the amount of investment necessary to transfer activities to the Internet.

The Development of Enabling Technologies for Internet Banking

Gopalakrishnan et al. (2003) identify three major external processes as environmental factors that enable the creation and diffusion of a new technological application in any industry:

1. The development of a new enabling technology.
2. The availability of complementary assets and ancillary systems.
3. The existence of a critical mass of users and providers.

Sahal's (1981) two key ideas are that technological change occurs as a result of incremental performance enhancers and a series of improvements in many technological areas. The technology development process can be seen as a series of disjoint developments in different fields. In the case of Internet banking, this boils down to key complementary technological assets such as encryption technology that permits online security systems, increased Internet access for individual users through Internet service providers (ISPs), and benefits from advances in basic telecommunications technologies such as faster connections through modems or through new developments in communications infrastructure such as an integrated services digital network (ISDN) or digital subscriber line (DSL) and cable modems. Technologies like data compression, voice over Internet protocol (VoIP), and other related technologies that have emerged now make the Internet a medium for communication and commerce. This has facilitated firms to communicate with their customers directly over the Internet using rich media like voice and video.

Only when critical masses of people are acquainted with new technologies do emerging technological applications in industries become viable. It is important from an economic and social viewpoint that a critical mass of users exists. The potential market size increases when a greater number of users adopt a technological application. Only this facilitates an economic viability of a new technological innovation. This wide social base makes it possible for new types of interaction to take place. It even gives rise to new social systems as the technology opens up spaces for new types of relationships.

However, there was considerable delay during the early years in adoption of Internet banking due to the need for attainment of technical feasibility in the first instance and the economic feasibility of adopting the technology within the user industry consequently (Rosenberg, 1982). The capital investment related to the adoption of Internet banking both at the level of the individual user and the bank has been relatively low compared to other technologies or delivery channels (e.g., ATMs). This low capital investment cost has significantly reduced the delay in adoption of the Internet and its applications like Internet banking.

Consumer Trust in Internet Banking

The Internet medium is the mediator between a customer and a bank in Internet banking. The medium itself being not completely secure and the dealing with a non-face-to-face transaction raise the question of trust. Trust in electronic transactions has been studied from various perspectives. Here an outline of trust studies is given and it is applied to the context of Internet banking.

Trust has been defined in various ways. Here is a commonly accepted definition of trust in the literature:

The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party. (Mayer, Davis, & Shoorman, 1995)

Lewicki and Bunker (1995) identify three ways of arriving at trust. Trust can be arrived at based on calculation (some perceived benefits outweighing perceived risks), knowledge (e.g., understanding the security features of the technology), or on the basis of empathetic identification (sharing of similar values). Trust can be seen as a psychological state (belief, confidence, positive expectations, or perceived probabilities). An individual's disposition to trust emerges during early childhood from caregivers. This disposition is extended to other people and situations as one grows up. An individual learns to trust in systems and processes. While attempting to bank electronically, the subjective attitude towards banking convenience, its usefulness, and social approval of Internet banking determine adoption. Consumer trust is also mediated by individual characteristics of consumers such as past purchasing behavior, personal values, gender, age, and education, which influence the decision to shop or bank online (Chen & Dhillon, 2003).

Castelfranchi, Falcone, and Pezzulo (2003) approach the study of trust from a socio-cognitive perspective. Various internal and external attributions to trust beliefs derive a degree of credibility of the vendor (in this case the bank). Trust is basically derived from various beliefs (about vendors) from different belief sources (various people in the social network). Trust is broken into its cognitive constituents: trustworthiness of the subjective evaluation of the belief sources (reputation) by the one who trusts, the content of the belief, how the source evaluates the belief, and who or what the source of the belief is. The quantitative dimensions of the trust are based on the quantitative dimensions of its cognitive constituents. This is demonstrated using cognitive fuzzy maps.

Good Web site features such as layout, appeal, ease of use, graphics, and readability have been known to attract consumers. Other characteristics such as reliability, usability, efficiency, and likeability also influence the popularity of a bank's Web site (Chen & Dhillon, 2003). The presence of an Internet banking Web site and its infrastructure, consumer characteristics, characteristics of the bank, and repeated interaction with the bank's Web site lead to a correlation between competence, integrity, and benevolence of the bank which in turn lead to overall trust. Consumer characteristics include propensity to trust. While the bank's credibility, consumer characteristics, and Web site characteristics are major determinants of trust in electronic banking, these would assume lesser significance if the risks involved in an electronic transaction could be completely mitigated. However, these characteristics will still play an important role in order to realize successful business even under conditions of no risk.

The product or the complexity of service offered through the Internet may vary in its economic significance and therefore in the level of risk. The level of financial risk involved varies the level of risk taking. Noteberg, Christiaanse, and Wallage (2003) have established that ordering a book, a video camera, a vacation package, or trading in securities have different levels of risk and benefit. People may adopt different features of Internet banking based on the levels of risk involved, for example, they may only inquire about balances, which is relatively safer than electronic transfer of funds.

Trust is developed under specific conditions—risk and interdependence. The level and form that trust takes depends on the variations in risk and interdependence. It is a question of assessment of risks involved. While entering into a relationship, there are perceptions of hazards and probable negative consequences. Trust is a psychological state of mind when the person is willing to assume the risks involved. When the perceived risk and the benefits of entering into a relationship are weighed against each other and the perception of benefits outweigh the risks in the relationship, the person enters into a trusting relationship (Kim & Prabhakar, 2000). Chen and Dhillon (2003) identify that "trust would not be needed if actions could be undertaken with complete certainty and no risk."

McKnight, Cummings, and Chervany's (1998) initial trust model has quickly become one of the more widely cited models in trust literature. Initial trust is defined as trust in an unfamiliar object, dealing with a relationship in which the trusting subject does not have credible, meaningful experience, knowledge, or affective bonds with the trusting object. Figure 1 provides an overview of this trust model.

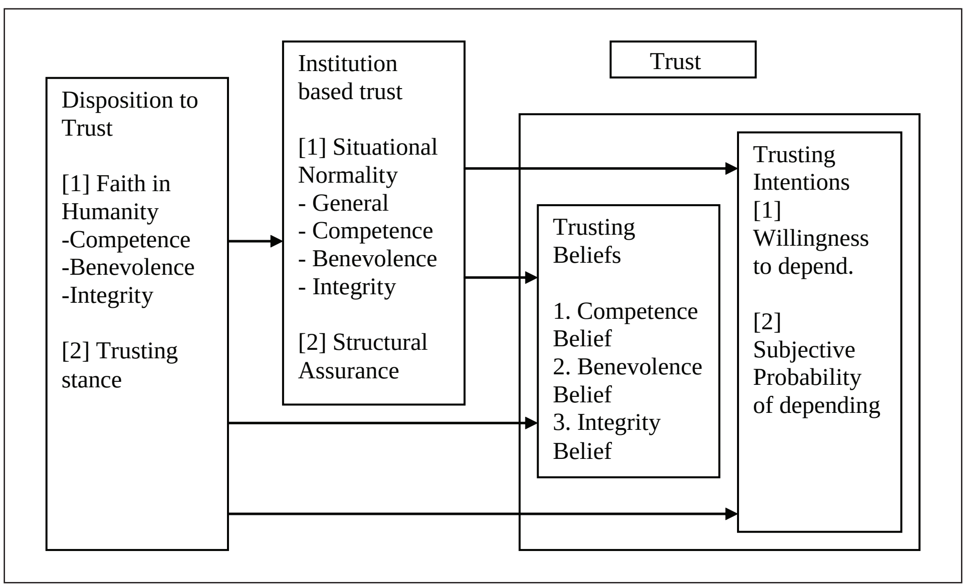
In the McKnight model, the construct of trust was divided into two components. The first component is trusting beliefs and the second is trusting intentions. Trusting beliefs are trusting a subject's perception that the trusting object has attributes that are beneficial to the trusting subject. This component is represented in the model by three categories of beliefs, the trusting subject's perceptions of an object's:

1. Competence (trusting an object's ability to do what the subject needs)
2. Benevolence (trusting an object's caring and motivation to act in the subject's interests).
3. Integrity (trusting an object's honesty and promise keeping).

Two underlying sources of trust are identified in the model as disposition to trust and institution-based trust. In each of these sources, trust emerges based on three categories: competence, integrity, and benevolence. Institution-based trust refers to structural conditions that enhance trust like guarantees, regulations, promises, legal recourse, or other procedures in place. Institution-based trust, along with word-of-mouth referrals and a trustor's propensity to trust, form the basis of initial trust in Internet banking leading to its adoption and use (Kim & Prabhakar, 2000).

The extent to which customers trust in Internet banking correlates with their overall trust in the electronic system (Kwok, Lee, & Turban, 2001). Performance measures that customers use to evaluate Internet banking Web sites include network and download speed, navigability, reliability, and availability (Lichtenstein & Williamson, 2006). Customers' technology orientation and perception of the technological competency of the electronic communication system is very important in their information processing behavior and perceived trust. Reputation is another dimension of trust. If an Internet banking Web site has a poor reputation, then customers will not visit that site. Trust is formed (building trust), trust endures over a

Figure 1. McKnight's initial trust formation model



period of time (stability), and ultimately trust declines (Rousseau, Sitkin, Burt, & Camerer, 1998). Finally, trust in Internet banking is gained through long-term usage and it has been influential in the adoption of Internet banking (Gartner, 2003).

RESEARCH CONTRIBUTIONS IN ADOPTION OF INTERNET BANKING

The Reserve Bank of India, in its report "Trends and Progress in Indian Banking, 2001-2002," says Internet banking has failed to take off due to a combination of psychological, technological, and socioeconomic factors. There are many reasons why Internet banking has not been readily accepted by banking customers. Some of these are:

- Slowness of adopting Internet banking in the 40+ age group.
- Lack of a critical mass of early adopters.
- Lack of a strong trust environment.
- Hesitation of low-income groups to engage in Internet banking since they basically cannot afford an Internet infrastructure at home.

Researchers have applied a variety of models and methods to study why adoption of Internet banking has been gradual, along with the factors that influence adoption. In this section we summarize the major research models and discuss the findings of recent research as well the theoretical and empirical applicability of the outcomes.

Diffusion of Innovations Theory

Rogers' diffusion of innovations (DoI) theory is a broad social psychological/sociological theory that studies the diffusion of new technologies. The theory has potential application to information technology ideas, artifacts, and techniques. The theory attempts to describe the patterns of adoption, explain the mechanism of adoption, and help in describing whether and how any new invention will be adopted in the market. According to DoI, technological innovation is communicated through particular channels, over time, among the members of a social system. The **phases** through which a technological innovation moves are:

- **Knowledge** (exposure to its existence, and understanding of its functions).
- **Persuasion** (the forming of a favorable attitude to it).
- **Decision** (commitment to its adoption).
- **Implementation** (putting it to use).
- **Confirmation** (reinforcement based on positive outcomes from it).

Rogers (1995) identifies operative forces in consumer Internet banking adoption. The five main variables that are considered in the DoI are:

1. Relative advantage (the degree to which it is perceived to be better than what it supersedes).
2. Compatibility (the degree to which the service is consistent with the customer's values, experiences, and needs).
3. Complexity (the difficulty of understanding and use).
4. Trialability (the degree to which the service can be experimented with prior to making a decision whether to adopt).
5. Observability (the degree to which the service can be observed successfully being used).

Different **adopter categories** are identified as:

- **Innovators** (venturesome)
- **Early adopters** (respectable)
- **Early majority** (deliberate)

- **Late majority** (skeptical)
- **Laggards** (traditional)

Early knowers generally are more highly educated, have higher social status, are more open to both mass media and interpersonal channels of communication, and have more contact with change agents. **Mass media channels** are relatively more important at the knowledge stage, whereas **interpersonal channels** are relatively more important at the persuasion stage.

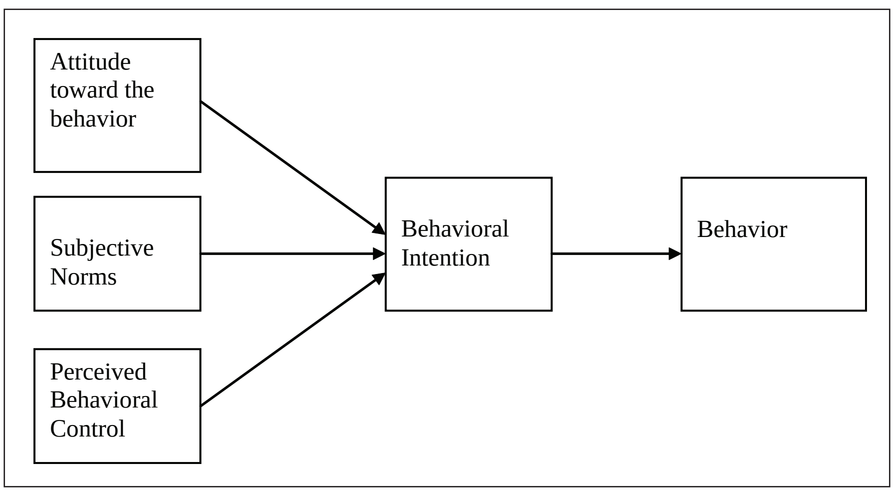
Earlier adopting individuals tend not to be different in age, but tend to have more years of education, higher social status, and upward social mobility; be in larger organizations; have greater empathy, less dogmatism, a greater ability to deal with abstractions, greater rationality, greater intelligence, a greater ability to cope with uncertainty and risk, higher aspirations, more contact with other people, greater exposure to both mass media and interpersonal communications channels; and engage in more active information seeking.

However, the diffusion of innovations theory has its limitations. Many of its elements are particularly specific to the culture in which it emerged (North America in the 1950s and 1960s), and hence less relevance in, for example, African, Asian, and Pacific countries. Moreover, DoI is a very good descriptive tool, but it does not have as much strength as an explanatory theory. This theory is not so particularly useful when predicting technology adoption outcomes. Also, it does not provide guidance on how to accelerate the pace of adoption of a particularly new innovation like Internet banking.

Theory of Planned Behavior (TPB)

The theory of reasoned action (TRA) is a psychological model created by Ajzen and Fishbein in 1980. Later on, perceived behavioral control (Ajzen, 1985) was added as a variable in the model, as behavior appeared not to be totally voluntary and under control. This resulted in the creation of the theory of planned behavior, used to identify the attitudinal, social, and perceived behavioral control factors that influence the adoption of Internet banking (Tan & Teo, 2000). The framework postulates that a person's intention to adopt Internet banking (dependant variable) is determined by three factors (independent variables):

Figure 2. Theory of planned behavior



1. *Attitude,* which describes a person's affect towards Internet banking.
2. *Subjective norms,* which describe the social influence that may affect a person's intention to use Internet banking.
3. *Perceived behavioral control,* which describes the beliefs about having the necessary resources and opportunities to adopt Internet banking.

The theory of planned behavior explains that only specific attitudes toward a behavior (e.g., adoption of Internet banking) can be expected to predict that behavior. The model enables measuring attitudes toward the behavior under consideration. To be able to understand someone's intentions and therefore predict his or her behavior, the theory identifies people's subjective norms as an antecedent of intention—that is, their beliefs about how people whom they hold in high esteem in their personal framework will view the behavior. Not only that, perceived behavioral control also influences intentions. Perceived behavioral control refers to people's perceptions of their ability to perform a given behavior, for example, their ability to operate a computer or 'surf' the Web. The third predictor is attitude, which reflects a positive or negative affect towards the behavior in question. All three predictors lead to intention.

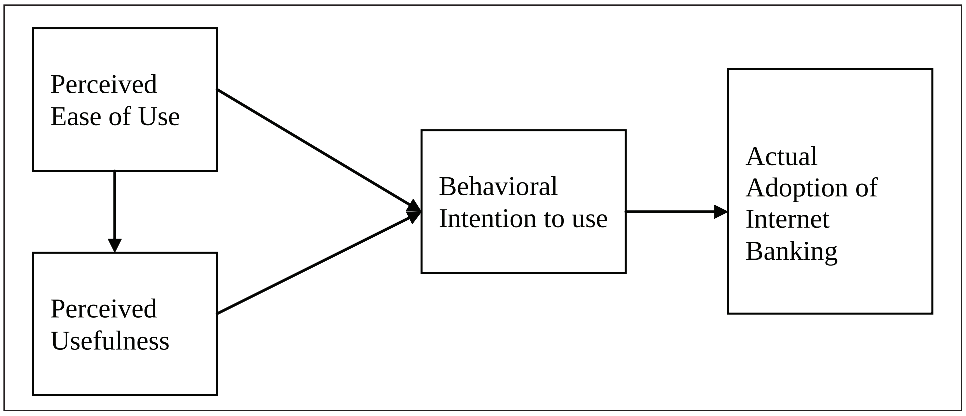
This model tells us that the more the perceived behavioral control and the subjective norm, and the more favorable the attitude, the stronger would be the person's intention to perform the behavior under consideration—that is, adoption of Internet banking. TPB has been successfully applied in various fields like medicine and health (see http://people.umass.edu/aizen/tpbrefs.html for a detailed bibliography).

Technology Acceptance Model (TAM)

TAM is a well-established, powerful, and parsimonious tool for predicting user acceptance in the literature. The technology acceptance model, an adaptation of theory of reasoned action, gives us two important variables that influence the behavioral intention to use Internet banking (Davis, 1989):

- **Perceived usefulness (PU):** This was defined by Davis as "the degree to which a person believes that using a particular system would enhance his or her job performance."
- **Perceived ease-of-use (PEOU):** Davis defined this as "the degree to which a person believes that using a particular system would be free from effort."

Figure 3. Technology acceptance model



TAM has been used to examine the possible antecedents of perceived usefulness and perceived ease of use toward microcomputer usage. However, a criticism of TAM is that there are very few studies that study the factors that affect PEOU and PU (Gefen & Keil, 1998).

Discussion of Theories

This section outlines the work of empirical validation of the theoretical models described in the section above. A brief discussion of the research process is followed by an analytical discussion. Table 1 outlines the sources of the research contributions considered here for discussion.

The diffusion of innovations theory is a theoretical descriptive framework, and not much empirical work has been done based on it. Most studies in TPB and TAM undertaken recently are replication studies, with some minor variations that confirm the basic pure form of the models. Essentially these are positivist approaches. The research models derived from TPB and TAM measure psychometric variables that influence adoption behavior. Measurements of variables and constructs (data) are tested, using methods such as factor analysis or structural equation modeling, to confirm or disconfirm hypotheses derived from the theoretical models. Data is collected usually using a survey instrument (questionnaire) that is administered either by phone, mail, online, or personal interview (Table 2 shows instruments administered and the demographic details of respondents for the various studies considered here). As in all science, we do not have definite and absolute empirical certitude for the theoretical models, as they have varying degrees of fit (Table 3 shows the degrees of fit for the hypothesized models) and different levels of confidence. There is always a possibility that other models can fit the same data.

We can only state that these are non-disconfirmed models.

Almost all authors discussed in this section have assessed the reliability of their measurement instruments mathematically using Cronbach's α. It is necessary to assess the reliability of an instrument when variables developed from summated scales (like the Likert scale) are used as predictor components in theoretical models. It is quite important to know whether the same respondents would give the same responses for the same set of items if the same questions are rephrased and re-administered. Variables derived from measurement instruments are said to be reliable only when they provide consistent and similar responses over a repeated administration of the test. Cronbach's α gives an index of reliability (varies from 0 to 1) associated with the variation in the true score of the "underlying construct" (see Cronbach, 1951, for a detailed discussion and computational formula). The generally accepted

Table 1. Recent research contributions on the adoption of Internet banking

Model	Authors
M1	Tan & Teo (2000)
M2	Wang, Wang, Lin, & Tang (2003)
M3	Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila (2004)
M4	Shih & Fang (2004)
M5	Chan & Lu (2004)
M6	Lai & Li (2005)

Table 2. Profiles of respondents

Model	**Geographical Area**	**Instrument Administration**	**Age Group**	**Number of Respondents**	**Demographic (%)**	
					Male	**Female**
M1	Singapore	Online Questionnaire	20-40	454	-	-
M2	Taiwan	Personal Interview	20-40	123	55	45
M3	Taiwan	Survey	-	425	49	51
M4	Finland	Survey	29	268	55	45
M5	Hong Kong	Survey	-	634	51.5	48.5
M6	Hong Kong	Questionnaire	20-45	247	49.4	50.6

Table 3. Fit indices

Model		$\chi^{2/df}$	**GFI**	**AGFI**	NFI	**NNFI**	**CFI**	**RMSR /RMSEA**
M1		-	-	-	-	-	-	-
M2		3.00	0.90	0.85	0.96	0.96	0.97	0:027
M3	M3a TRA	1.25	-	-	0.98		0.99	0.029
	M3b TPB	1.55	-	-	0.96		0.97	0.043
	M3c Decomposed TPB	1.80	-	-	0.94		0.95	0.054
M4		-	-	-	-	-	-	-
M5		3.26	0.84	0.81	0.90	_	0.93	0.067
M6		2.01	0.89	0.84	0.95	0.96	0.96	0.08

$\chi^{2/df}$–Ratio of Chi-square to degrees of freedom
GFI–Goodness of Fit Index
AGFI–Adjusted Goodness of Fit Index
NFI–Normed Fit Index
NNFI–Non-Normed Fit Index
CFI–Comparative Fit Index
RMSR–Root Mean Square Residual
RMSEA–Root Mean Square Error of Approximation

level of the reliability coefficient is 0.7 or above, although lower thresholds have also been admitted (Nunnaly, 1978; Santos, 1999).

Construct validity is measured using convergent and discriminant validity. Table 4 overviews the different model descriptions and the corresponding research methods employed for investigation, and gives a very brief description of the various constructs employed by researchers. Table 5 summarizes the results of the investigations.

Across several studies, subjective norms—that is, the influence of friends, relatives, and peers to adopt Internet banking—do not have significant support (there is a geographical bias here that most of these studies emerge from the Asia Pacific region). Perceived risk is a variable that can have a negative influence on adoption behavior, but measurement of risk perception has been found to be difficult. The study by Lai and Li (2005) illustrates that TAM can be consistently applicable across all demographic populations. TAM remains invariant across factors such as gender, age, and differing levels of IT competence.

Ravi, Carr, and Sagar (2006) attempted to profile Internet banking customers with variables from these models using intelligent techniques such as ANN, SVM, CART, and Logistic Regression. With evidence collected through questionnaires administered to Internet banking users and non-users in India, they were able to rank the variables as *intention, beliefs, subjective norms, trust in the bank, attitude, perceived usefulness, security,* and *perceived ease of use,* in that order. This clearly demonstrates that adopting intention, belief systems of people, and social influence play a great role in the diffusion and adoption of Internet banking among South Asians.

TAM is a parsimonious tool that can be used to predict Internet banking usage (or any new technological innovation). It may be a very

Table 4. Variable/construct descriptions

Attitude (ATTITUDE): Positive or negative affect towards intended behavior.
Compatibility (COMPATIBILITY): Compatible with individual's jobs and responsibilities.
Complexity (COMPLEXITY): The level of technical skills required to operate the Internet banking site.
Computer Self-Efficacy (CSE): Individual's self-confidence in his or her ability to operate the computer.
Facilitating Conditions (FC): Ease of access to technological resources, government support, and so forth.
Information on Online Banking (INFO): Provision of information about Internet banking.
Intention to Use Internet Banking Services (INTENT): Intention to adopt Internet banking.
Image (IMAGE): The perception that using Internet banking will enhance one's status socially.
Perceived Usefulness (PU): Perceptions about how a behavior will enhance job performance.
Perceived Behavioral Control (PBC): Individual's perceptions about his or her ability to perform a behavior.
Perceived Credibility (PC): Perceptions about security and privacy concerns while doing Internet banking.
Perceived Ease of Use (PEOU): The extent to which the use of Internet banking is free from effort.
Perceived Enjoyment (PE): Perceptions about how enjoyable the Internet banking experience is.
Perceived Risk (PRISK): Perceptions about risks in Internet banking.
Quality of Internet Connection (IC): Whether using dial up, broadband, or corporate Internet.
Relative Advantage (RA): Financial reasoning, convenience.
Result Demonstrability (RD): Tangible demonstration of results of information technology.
Security and Privacy (SP): Concerns regarding secure transactions and loss of privacy.
Subjective Norm (SN): Perception about whether people important to the users advise the behavior or not.
Trialability (TRIALABILITY): Opportunity to experiment with a new technological innovation.
Usage of Internet Banking (ADOPTION): Active use Internet banking.

Table 5. Results of investigations

Model	Research Framework Investigated/Research Method	**Theoretical Model Description**	Direction	β	Research Results
M1	Decomposed TPB/ Multiple Linear Regression	RA→INTENT COMPATIBILITY→ INTENT COMPLEXITY→INTENT TRIALABILITY→ INTENT RISK→INTENT CSE→INTENT FC→INTENT ATTITUDE→INTENT SN→INTENT PBC→INTENT INTENT→ADOPTION	+ve +ve +ve +ve -ve +ve +ve +ve +ve +ve +ve	0.142 0.149 -0.29 0.321 -0.081 0.159 -0.021 -0.026	Confirmed Confirmed Confirmed Confirmed Confirmed Confirmed Confirmed Confirmed Rejected Confirmed Confirmed
M2	TAM/ SEM	CSE→PU CSE→PEOU CSE→PC PU →INTENT PEOU →INTENT PC →INTENT	+ve +ve -ve +ve +ve +ve	0.16 0.63 -0.21 0.18 0.48 0.24	Confirmed Confirmed Confirmed Confirmed Confirmed Confirmed
M3a	TRA/ SEM	ATTITUDE→INTENT SN→INTENT INTENT→ADOPTION	+ve +ve +ve	0.88 0.11 0.48	Confirmed Rejected Confirmed
M3b	TPB/ SEM	ATTITUDE→INTENT SN→INTENT PBC→INTENT INTENT→ADOPTION	+ve +ve +ve +ve	0.82 0.11 0.05 0.53	Confirmed Rejected Rejected Confirmed
M3c	Decomposed TPB/SEM	RADVANTAGE→ ATTITUDE COMPATIBILITY→ ATTITUDE COMPLEXITY→ ATTITUDE CSE→PBC FC→PBC ATTITUDE→INTENT SN→INTENT PBC→INTENT INTENT→ADOPTION	+ve +ve -ve +ve +ve +ve +ve +ve +ve	0.82 -0.02 -0.74 0.75 -0.14 0.57 -0.06 0.04 0.48	Confirmed Rejected Confirmed Confirmed Rejected Confirmed Rejected Confirmed Confirmed
M4	TAM/FA	PU→ADOPTION PEOU→ADOPTION PE →ADOPTION INFO→ADOPTION SP→ADOPTION IC→ADOPTION	+ve +ve +ve +ve +ve +ve	0.074 0.074 0.134 0.079 0.247	Confirmed Confirmed Confirmed Confirmed Confirmed Rejected

continued on following page

Table 5. continued

M5	TAM/CFA	SN→PU	+ve		Rejected
		SN→IMAGE	+ve	0.39	Confirmed
		IMAGE→PU	+ve	0.11	Confirmed
		RD→PU	+ve	0.40	Confirmed
		PRISK→PU	-ve		Rejected
		CSE→PEOU	+ve	0.63	Confirmed
		PU→INTENT	+ve	0.53	Confirmed
		PEOU→INTENT	+ve		Rejected

CFA–Confirmatory Factor Analysis
SEM–Structural Equation Modeling
β–Standardized Path Coefficients
A→B– Indicates the hypothesis that the independent variable (A) influences the dependent variable (B) either positively or negatively.
For descriptions of variables/constructs, see Table 4.

simplified representation of a complex reality dealing with only two cognitive components that mediate all other external variables. TAM's explanatory power relies on individual rational calculus of technology acceptance. It specifies the conditions that a technical innovation must meet (i.e., usefulness and ease of use) for it to succeed in the market.

Decomposed TPB gives a fuller understanding of usage behavior and intention to adopt Internet banking. TPB offers more effective guidance to IT managers who are interested in the implementation of information technologies (Taylor & Todd, 1995). While TAM provides utilitarian reasoning for acceptance of a technological innovation, TPB illuminates the personal aspects such as affect, social pressures and influence, and an assessment of personal capacities in the formation of intent to use a technological innovation. However, TAM and TPB do not fully reflect all the variables in the external environment that influence adoption.

One criticism that can be leveled against TPB and TAM studies is that some aspects may be tautological. If an individual has already adopted Internet banking and if you ask the respondent whether convenience (PU) was a factor, then obviously the response would be positive. Second, while causal relationships are empirically validated, the antecedent variables (cause) must be measured at a point of time before the consequent variables (effect) are measured. Most studies measure both variables at the same points in time using the same instrument. Thirdly, in the populations examined, important variables such as risk perceptions and computer anxiety (feelings of anxiety toward computers and computer use, e.g., techno phobia) have not been accommodated in models and investigated. The units of analysis for TAM and TPB are individuals. This gives rise to psychological models. But if we approach adoption studies from a perspective of social groups as units of analysis, we may come up with radically different models, for example, introduction of computerized systems in the banking industry in India faced organized, stiff resistance during the initial phases as bank employees had apprehensions of threats of job loss and retrenchment (Goodman, 1991). Technology adoption and usage must be treated as a complex social-psychological-economic phenomenon (Konana & Balasubramanian, 2005).

CASE STUDIES

Case studies throw light on factors that are significant in particular circumstances. Here two case studies are summarized. The first one is based in New Zealand (Chung & Paynter, 2002) and the second in Australia (Lichtenstein & Williamson, 2006). Following are highlights (excerpts) from their works.

A Quantitative Approach: New Zealand

New Zealand has already achieved a significant level of Internet penetration and usage. More than 50% of the population have Internet access, and 34% use it on a regular basis in New Zealand. In 2000, about 200,000 New Zealanders used the Internet for banking. The cost of New Zealand Internet service providers (ISPs) has declined significantly over the past four years. The costs of a personal computer and the costs of an Internet connection are still prohibitive for some segments of the population. There are still barriers for many people to use Internet banking because of high costs. Lowering ISP charges will further enhance Internet usage and facilitate Internet banking in New Zealand. Affordability of the Internet is a precondition for adopting Internet banking.

Marketing, delivery, and customer service are very important. The number of customers registered for Internet banking is growing, but some of those registered never use it, and some of those use it and then stop. More recently, banks have added services that customers need, such as the ability to change their address, request a copy of their statement, and order travelers' checks. It is believed that added functionality enhances Internet banking. Customer service support is also critical, as the Internet customer wants an immediate response to a request, for example, replacement for a forgotten or lost password.

An evaluation of New Zealand Internet banking Web sites and a survey of subjective customer opinions were taken. The study does a comparative Web site evaluation of Web sites and services offered by seven New Zealand banks. Absence or presence in the Web site of the following components were evaluated:

- **Information:** Regarding bank, customer, and financial products.
- **Legal statements:** Disclaimer, privacy policy, and security policy.
- **Order:** Account balance, funds transfer, open account, make payment, check book, loan application, change password, after-sales service (e.g., e-mail enquiries).
- **Ease of use:** Frequently asked questions, tutorials/demonstrations, search, help, navigation.
- **Aesthetic effects:** Graphics and animations.
- **Performance:** Update frequency, response time, technical problems.

Based on objective evaluation of the Web site and a survey of subjective opinions, the capabilities/offerings of seven banks were ranked. The survey results (correlations) indicated that *checking account balance, checking bank statements,* and *transfer of funds between accounts* were the most frequently used banking services in that order.

Customers also expressed concern about the security of online transactions. Security practices should be established and enhanced, especially when banks offer transaction-oriented services. Besides security of transactions, customers wanted up-to-date information, services free from technical problems, good response time, and download time.

Most banks tend to use the Internet to deliver services in a manner that is generally consistent with their business strategies. These banks have built upon their existing infrastructure and use online banking to defend, retain, and expand their existing customer base. Internet banking brings in more customers with ease. Some benefits reportedly associated with Internet banking include increased cross-selling of services to customers (i.e., Internet banking customers have a higher concentration of financial services purchased from the bank) and increased customer profitability and loyalty.

A Qualitative Approach: Australia

Lichtenstein and Williamson (2006) have made an interpretive study in the Australian banking context. The case study analyzes positivist studies of factors influencing consumer adoption of Internet banking. In particular it was found that most work is fragmented and the theoretical base is inconclusive:

- Adoption rose with higher levels of financial assets and education, but individual attitudes and beliefs were stronger than demographics (Kolodinsky, Hogarth, & Shue, 2000).
- Convenience (24x7 access factor) has been identified as an important factor and high levels of usage of Internet at the workplace. However, many believed they did not need this high level of convenience (Chung & Paynter, 2002).
- Internet banking has been treated as an innovation, and consequently the theory of planned behavior and Roger's theory of Innovation have been applied in this context. The main influences are: perceptions of relative advantage, compatibility, trialability, and risk. But lack of prior Internet usage inhibited adoption of Internet banking. Consumers were unaware of Internet banking and its benefits, and those who did not use the Internet did not feel any need to do so (Chung & Paynter, 2002).
- Adaptability, technical self-efficacy, and knowledge of Internet banking were individual differences that accounted for adoption decision (Thornton & White, 2001).
- Security, privacy, trust, and risk considerations affect adoption decisions.

As Lichtenstein and Williamson (2006) felt that the wide range of theories and factors in the Internet banking adoption literature is "insufficiently mature" and without "solid foundation," they opted to use an interpretive approach based on grounded theory. Purposive samples (in contrast to random sampling techniques by positivist theorists) were selected that reflected the demographic categories of Internet banking users as groups of males and females, of different ages, of different levels of education, income, and access to Internet. Data was collected through individual and focus group interviews. A semi-structured interview schedule was used which provided the possibility to explore deeper issues as they emerged as interviews progressed.

A theoretical framework evolved based on analysis of the interview results. The key factors in consumer adoption of banking were:

- Consumer *attention*, including high level of *accessibility* at home or work, *usability*, perceived competence—*self-efficacy,* and *convenience*.
- Relative advantage.
- Risks and costs.
- Knowledge and support.

The Australian case makes the following recommendations to banks based on the results of the field study:

- Improve marketing of Internet banking services to combat lack of awareness of Internet banking and its facilities.
- Establish kiosks in banks and public places, and develop cheaper mobile alternative technologies to provide for dedicated and unchallenged consumer Internet access.
- Offer Internet training among customers to overcome lack of Internet confidence.

- Streamline setup procedures and provide setup support so that initial setup procedures become easy.
- Improve screen design and navigation where people find it difficult to use.
- Make enhancements to retail banking by providing more functions.
- Lack of trust, security, and privacy risks—provide consumer reassurance and information, improve application security and privacy, and provide information on security and privacy. Assist consumers in developing secure Internet banking practices and risk management procedures.

Comments on Case Studies

The evils of specialization (Russell, 1946) have led to a plethora of quantitative results. Qualitative studies using interpretive methods are a welcome departure from traditional positivist approaches. However, one needs to understand the contexts and limitations of both quantitative and qualitative frameworks. The objective material world, where deterministic relationships (cause-effect) are the norm, needs to be approached with positivist methodologies. The socially constructed, intersubjective world (agreement reality) needs to be treated with interpretive approaches (Habermas, 1984). We need pluralist methodologies in a multidimensional world (Mingers, 2001).

FUTURE TRENDS

Adoption studies are important from a marketing perspective. Richer theoretical models that are more comprehensive and sophisticated than TAM and TPB are required. TAM is too parsimonious to be useful for IT managers and systems implementers. Although TAM has been demonstrated to be demographically invariant in the Hong Kong context, generalizing the results for all regions and populations needs to be done cautiously.

Newer technologies in banking are being introduced like mobile banking and consequently mobile-based payment systems. Appreciation of the factors that determine adoption of new innovations helps banks succeed in the market.

Specifically, as practitioners we need to be able to extend Internet banking to populations who are not familiar with English (possibly illiterate), who cannot operate computers comfortably (low IT competence), and who are not used to using usernames and passwords (culture-specific variables). Practitioners can think of designing electronic banking systems such as public Internet kiosks with touch screens and biometric identifications (coupled with smart cards) which will bring Internet banking to rural and other marginalized folk, and to those who cannot afford to have their own computer systems at home or in the workplace. This would bridge the digital divide.

CONCLUSION

This chapter introduced the features of Internet banking. It examined the infrastructure and institutional conditions necessary for adoption of Internet banking:

- The cost effectiveness for banks to introduce Internet banking as a new delivery channel and the convenience it offers to customers.
- The technical conditions needed, including prevalence of Internet connectivity in the population (broadband connectivity, DSL, etc.), and the technology for secure messaging over the Internet (like SSL).
- The need for consumer trust in Internet banking: the provision of institutional and structural safeguards.

Three major theories in information systems—the diffusion of innovations theory, the theory of planned behavior, and the technology acceptance model—in the context of adoption of Internet banking were reviewed. Studies that have empirically investigated the models derived from these theories were discussed. The methodology and the research process employed in these studies were elaborated. Limitations of these models and their methodological investigations were outlined. Two case studies were presented of which one took an interpretive approach in contrast to a positivist approach. Finally, a framework for future trends in Internet banking was presented on how to extend the reach of Internet banking through new technological innovations to large sections of the populations that are presently excluded.

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Chapter IV
Customer Acceptance of Internet Banking Services in Greece:
The Case Study of Alpha Bank

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ABSTRACT

This chapter deals with the factors that affect Internet banking customer acceptance. More specifically, it examines the case of an Alpha Bank branch in Greece which is a pioneer in introducing and applying e-banking services in Greece. In this framework, the chapter performs a factor analysis based on the gathered results provided by customer questionnaires in order to quantify the various parameters that affect the use of an Internet banking system (IBS). The findings of the analysis show that although IBS in Greece is steadily increasing its penetration, factors like security, ease of use, and perceived usefulness of a system continue to play a major role on the final decision of the customer to adopt an Internet banking system.

INTRODUCTION

A growing phenomenon in financial services is the rising use of sophisticated electronic means (e.g., communication and computer networks, mobile terminals, automatic teller machines, etc.) toward the development of novel financial services for processing electronic transactions, collaborating with business partners, or servicing customers, regardless of geographical and time limitations.

Especially lately, there is significant use of the Internet as a shared telecommunication channel for performing financial transactions and offering bank services. The Internet is a global network consisting of numerous discrete wide area networks that use a specific set of protocols in order to interchange data successfully. The Internet, in its current form, came up for public use in the mid-1990s, with the World Wide Web, a huge collection of hyperlinked documents located in Web servers around the world available for viewing or downloading.

The integration of the Internet—as a worldwide network infrastructure—with traditional banking services provided a new class of bank services, which are generally described as "Internet banking" (IB). Besides the many advantages, IB transactions imply significantly lower costs than traditional branch or even phone banking transactions, making them quite profitable and preferable for the banks. Thus, banks are moving towards the provision of multimodal Internet banking services, offering to customers innovative products with wider choices and at a lower cost.

On the other hand, most customers are accustomed to conducting traditional transactions instead of electronic ones. They are also accustomed to touching and examining a transaction receipt after its completion. Moreover, the face-to-face contact is related to trust in business deals and transactions, while in the new environment of faceless electronic transactions, the concept of trust must be reconsidered on a new basis, namely in terms of security issues like confidentiality, integrity, and authenticity. The penetration of the Internet as a useful tool in the hands of Greek people has risen significantly during the last five years.

The aim and objectives of this chapter are the identification and quantification of the factors that affect the adoption of Internet banking services (IBS) in Greece. More specifically, we examine the IB-customer acceptance of Alpha Bank.

The rest of this chapter is organized as follows. The next section initially presents some information related to Greek economy, and later discusses the Alpha Bank profile and some historical data about its activities in the Greek banking sector. Then, an extensive literature review is presented about IB acceptance, while the next section shows data collection analysis, which includes the research aims/objectives, the research design, and the research techniques. The chapter then deals with the findings, providing specific data in order to deduce important conclusions and recommendations, while the final section discusses the future trends of IB acceptance.

BACKGROUND

The Greek Economy

The Greek economy is in a fast growing track after the stabilization policies in recent years. Greece remains a net importer of industrial/capital goods, foodstuffs, and petroleum. Leading exports are manufactured goods, food/beverages, petroleum products, cement, chemicals, and pharmaceuticals. Greece achieved high rates of growth from the 1950s through the early 1970s due to large foreign investments. In the mid-1970s, Greece suffered declines in its GDP growth rate, ratio of investment to GDP, and productivity.

The evolution of the Greek economy in relation to that of Western Europe can best be represented by comparative measures of standard of living. The per capita income of Greece was 65% that of France in 1850, 56% in 1890, 62% in 1938, 55% in 1970 (Bairoch, 1976), and 77% in 2005 according to Eurostat. In 1981, protective barriers were removed when Greece joined the European Community. The government pursued expansionary policies, which fueled inflation and caused balance-of-payment difficulties. In 2001 Greece joined the Economic and Monetary Union (eurozone).

Alpha Bank

Alpha Bank was founded in 1879 and is the second largest bank in Greece, after the National Bank of Greece. In 1918 the banking department of the "J.F Costopoulos" firm was renamed to "Bank of Kalamata." In 1924 the bank's headquarters moved to Athens, and it was renamed "Banque de Credit Commercial Hellenique." In 1947 the title was changed to "Commercial Credit Bank," in 1972 to "Credit Bank," and finally in March 1994 to "Alpha Credit Bank." In 1999, the bank bought over 51% of Greek "Laiki Bank," and one year later acquired the entire "Laiki Bank." In 2002, the effort of Alpha Bank to merge with Ethinki Bank did not flourish.

Regarding its international expansion, an outline of its main actions is:

- In 1960, the Commercial Credit Bank founded a branch in Cyprus.
- In 1993, the Credit Bank, together with EBRD, founded "Banca Bucuresti" in Romania and started operations the next year. The Credit Bank owned a 50% share.
- In 1994, the Credit Bank acquired the Commercial Bank of London and renamed it into "Alpha Credit Bank London."
- In 1996, Alpha Credit Bank founded a branch in Tirana, Albania.
- In 1997, Alpha Credit Bank founded Alpha Credit Bank Jersey.
- In 1998, Alpha Credit Bank acquired 82.5% of Lombard.
- In 1999, Alpha Credit Bank acquired the 65% of Kreditna Banka in Skopje. Today this share reaches 84%.
- In 2000, Banca Bucuresti changed its name to Alpha Bank Romania (ABR). Monte dei Paschi di Sienna took over 5% of the shares. The Alpha Bank share was then 63%. After this, Alpha Bank Romania acquired a 12.5% share of Victoria Bank, the greater private bank of Moldavia.
- Alpha Bank also operates three branches in Serbia, and one at Sofia, Bulgaria.

With more than 450 branches, Alpha Bank Group is considered a significant international banking player, at present from Cyprus and South-eastern Europe to New York, London, and Jersey in the Channel Islands. It is acknowledged as an innovator in introducing new electronic services in the Greek market, such as: banking services over the phone, PC link, banking services through the Internet, and more recently, banking services over mobile phones.

Alpha Bank entered the online environment in 1999 and gradually offered a wide variety of services to its customers, such as:

- Account balance information.
- Statement information/request.
- Check book request.
- Stop check instructions.
- Fund transfer within own accounts.
- Fund transfer to third-party accounts.
- Telegraphic transfers.
- Demand drafts and cashier's orders.
- Foreign exchange rate enquiry and utility bill payments.

Especially during the last six years, Alpha has met great success and its IB market penetration is in continuous growth.

Customer Acceptance of Internet Banking

E-banking is a field where research has been focused on demonstrating the various benefits of it against the traditional transactions. Towards this, the main customer benefits (Aggelis, 2005) of IB are classified as:

- Service availability 24 hours/7 days a week.
- No delays and queues.
- Quick access to bank products.
- Reduction of paper usage.
- Online transfer of funds.
- Accessibility anytime and anywhere.
- Reduction of transaction costs due to automation/human-free of the required processes.
- Better utilization of time.

On the other side, the intention to transact online is closely related to the significant reduction in operational costs, due to the decrease of the branches and the minimization of the staff. It is widely accepted that online banking is the cheapest way for offering banking services once established (Sathye, 1999; Robinson, 2000; Giglio, 2002). More specifically, it has been estimated that the operational cost of a traditional bank transaction is approximately $1.07, while the equivalent cost through a phone transaction is almost half (i.e., $0.54); if the transaction is performed online, then the cost drops to only $0.001. (Mols, 1998; Robinson, 2000; Sheshunoff, 2000). Moreover, besides IBS being the most profitable and wealthiest segment of bank institutions (Mols, 1998; Robinson, 2000; Sheshunoff, 2000), it has been shown that IB also leads to higher levels of customer satisfaction and retention in comparison to the standard face-to-face financial services (Polatogly & Ekin, 2001).

Therefore, IBS (i.e., online transactions, payments, and money transfers) have recently increased in popularity around the world. According to Barwise (1997), it has been estimated that 60% of retail banking transactions will have been replaced by the corresponding online ones by 2007, while the total move from the traditional transactions to the electronic ones will be gradually completed, as 3G/4G mobile communication networks offer Internet access anytime, anywhere, and anyhow.

From a business perspective, emphasis has been put on researching the customer acceptance of IBS in correlation to economical, social, and psychological issues (Karjaluoto, Mattila, & Pento, 2002; Waite & Harrison, 2002; Brandley & Stewart, 2003). One of the earliest works in this field was conducted among Denmark citizens and showed that the IBS-registered bank customers are generally more satisfied than non-IBS registered customers for the same bank services (Mols, 1998). Similarly, another early work by Sathye (1999) showed that the main factors for the non-adoption of IBS by Australian customers are: (1) security concerns about the Internet, and (2) the lack of awareness about IBS.

These preliminary outcomes about IBS acceptance motivated the examination also of other aspects/factors that affect IB acceptance, such as compatibility, usefulness, and ease of use, as well as various demographic data (i.e., gender, age, marital status, ethnic background, and formal instruction of the customer) (Eriksson, Kerem, & Nilsson, 2004; Yoonhee, 2005; Shergil & Bing, 2005; Eun, 2001). Finally, relative advantage, complexity, compatibility, observability, and risk tolerance proved to play a crucial role in IB acceptance (Mattila, Karjaluoto, & Pento, 2003; Kolodinsky, Hogarth, & Hilgert, 2004).

Also, another parameter that influences the degree of IB adoption is the customer familiarity with the target-object/service, since it has been proven that experienced customers behave in a more positive way towards IB than inexperienced ones (Karjaluoto et al., 2002). Therefore, personalization, task familiarity, and accessibility seem to have significant influence on perceived usefulness and ease of use, which in turn are important factors in fostering a positive attitude toward accepting the services Therefore, the amount of information that customers receive about IB and its perceived usefulness have been identified as major factors of IB acceptance (Sathye, 1999**;** Beethika, 2004).

Similarly, security and privacy are considered to be closely related to IB acceptance (Sathye, 1999; Hamlet & Strube, 2000; Tan & Teo, 2000; Polatoglu & Ekins, 2001; Howcroft, Hamilton, & Hewer, 2002). Exploring the obstacles of IB customer acceptance in Australia, Sathye (1999) found that privacy and security were the major barriers against adoption. On the other hand, we can claim that it does not matter how secure the bank's computer systems are, if the customer's personal computer is infected by malicious software, making the security/privacy issues more fundamental.

From the customer point of view, security remains the vital factor of IB acceptance. Customers still remain skeptical about security, hacking issues, and personal data/information misuse by third parties (Kobsa, 2001; Kobsa, 2002). Going to an online/virtual banking environment, in contrast to a face-to-face transaction with a teller, the customer feels that he or she is open to numerous risks. According to a specific study about security, customers want to lead their own acts and be in the position to know the consequences and causes of their own decisions (Baronas & Louis, 1988; Karvonen, 1999).

However, there are also many other non-psychological factors that may negatively influence IBS adaptation, since a great portion of the potential or existing customers do not have access to the Internet, making it impossible for them even to try the online services. Also, another great portion of the customers have Internet access only at work/office, where content/access filtering rules deprive the IB use/acceptance.

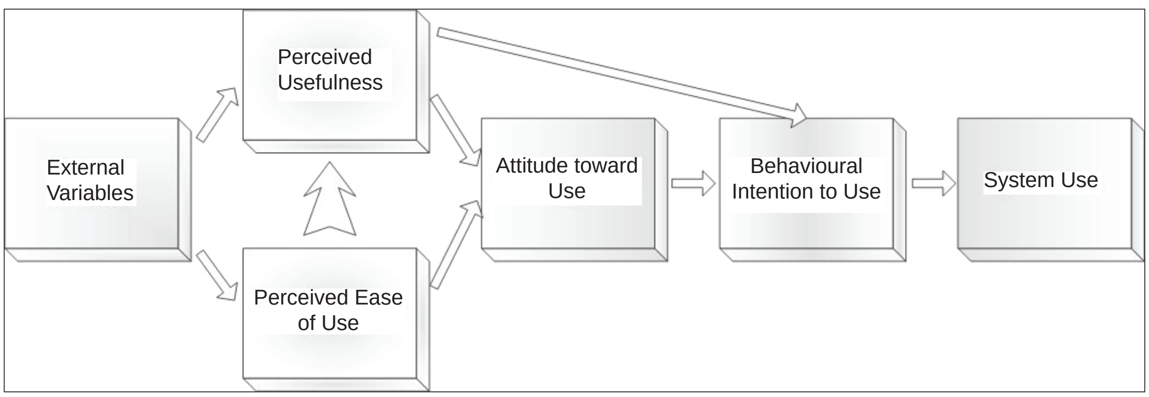
In the next section, we examine the IB acceptance of Alpha Bank in Greece, showing that, using an extended technology acceptance model (TAM), reliable quantitative results can be derived.

Research Methodology

Issues, Controversies, Problems

For the needs of this chapter, we explore one of the best known models in information technology systems (ITS): the technology acceptance model (Davis, Bagozzi, & Warshaw, 1989; Mathienson, 1991; Davis & Venkatesh, 1996).

Figure 1. Technology acceptance model (Davis et al., 1989)



According to TAM, which is depicted in Figure 1, the system use/acceptance (actual behavior) is determined by two factors: perceived usefulness (PU) and perceived ease of use (PEOU). These factors are related to the attitude toward the use, which in turn influences the behavioral intention to use an ITS. More specifically, PU is defined as "the degree to which a person believes that using a particular system would enhance his or her performance" (Davis, 1989), while PEOU is considered "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989).

TAM is based on the theory of reasoned action (TRA) model, which has been designed to predict and understand an individual's intended behavior (Ajzen & Fishbein 1980). According to Ajzen and Fishbein (see Figure 2): "An individual executes a unique behavior that was decided by his or her behavioral intention (BI) determined by their attitude (A) and a subjective norm (SN), including that some external variables are considered in TRA to be related to a person's behavior." In the TRA model, the term "actual use" is used in a similar way to "customer acceptance" of a specific service, since it describes the final customer decision on using a specific service.

Many related studies have used TAM to measure ITS acceptance, and have proven its validity and reliability (Mathieson, 1991; Davis & Venkatesh, 1996; Eriksson et al., 2004: Davis, 1989; Taylor & Todd, 1995), while some improvements have been proposed to it (Venkatesh & Davis, 2000). Moreover, Mathieson (1991) states that "TAM's ability to explain attitude toward using a new IT system is better than other models (e.g., TRA)."

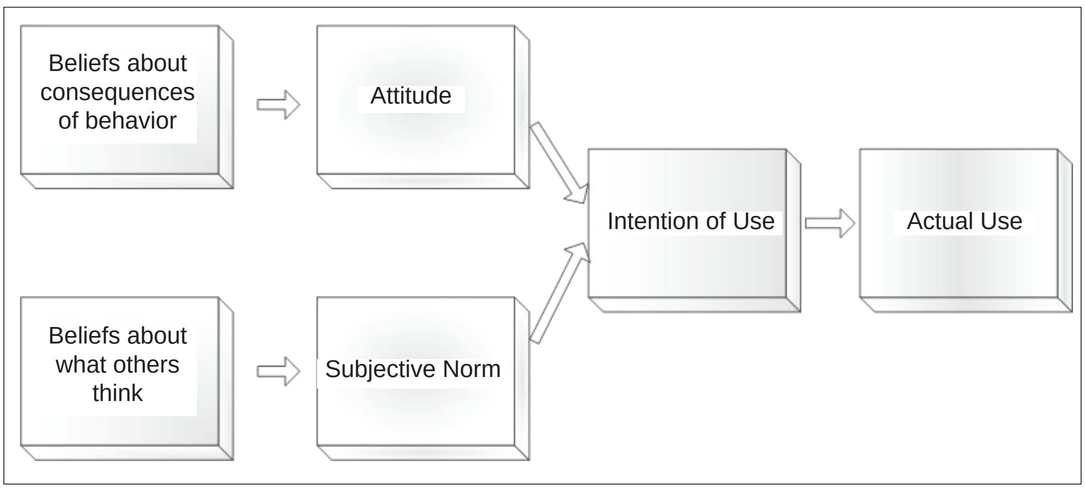
According to TAM, PU and PEOU are both critical factors that can affect IT acceptance (Davis et al., 1989). Therefore, an ITS that is believed to be easier than another is more likely to be accepted by customers. Keeping this statement in mind, we consider the following hypotheses H1 and H2:

H1: Perceived usefulness (PU) has a positive effect on customer acceptance of IB.

H2: Perceived ease of use (PEOU) has a positive effect on customer acceptance of IB.

Moreover, the amount of information that a customer receives about a product plays an important role in deciding to use it, since we assume

Figure 2. Theory of reasoned action (Ajzen & Fishbein, 1980)



that a well-informed customer tends to adopt/use a new service easier. In an empirical investigation among Australian customers, Sathye (1999) found that customers were totally unaware about the advantages and potential of IBS, and this proved to be an obstacle against using the system. Thus, we also involve the amount of information in our model with the following hypothesis:

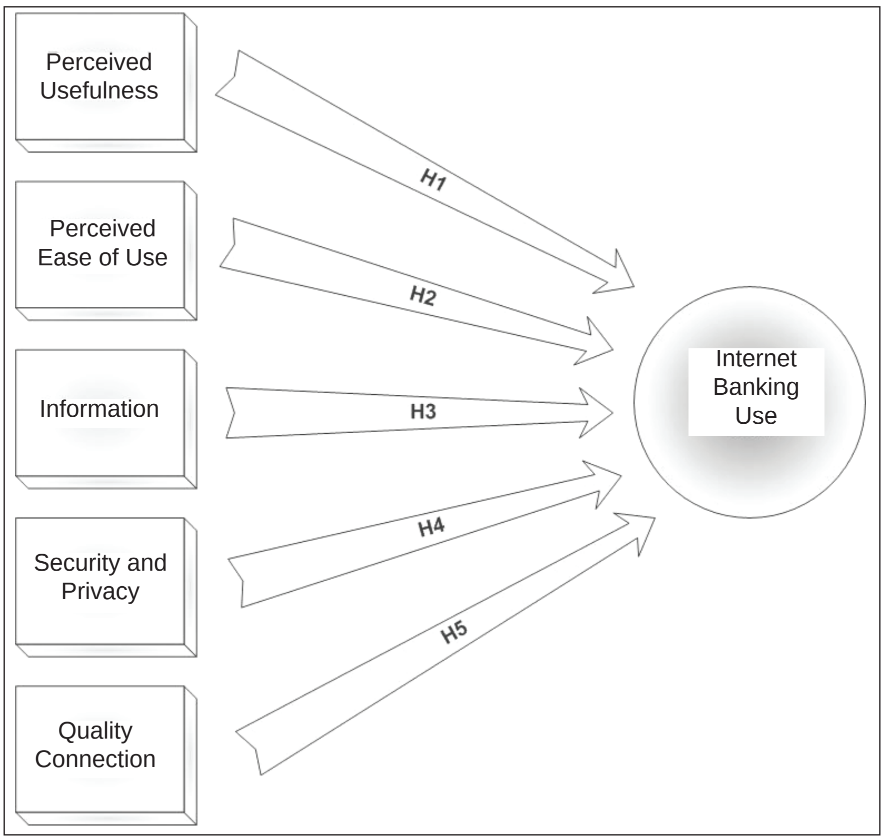
H3: The amount of information a customer receives about Internet banking services has a positive effect on customer acceptance of IB.

As mentioned before, the potential customers of IBS are concerned about security and privacy issues. Security is the primary factor that can prevent a customer from accepting an ITS. According to Kobsa (2001), customers want to control what kind of data is collected, for what purposes, for how long data will be processed, and by whom. Hoffman, Novak, and Peralta (1999) found that many customers are unwilling to give personal data over the phone or the Internet (e.g., credit card or Social Security numbers). In order to include these parameters in our model, we will use the following hypothesis:

H4: Security and privacy have a positive effect on customer acceptance of IB.

Finally, the quality of Internet connection may influence the adoption of IBS (Sathye, 1999; Polatogly & Ekins, 2001). So, our last hypothesis for the proposed research model is:

Figure 3. The proposed extended TAM model



H5: The quality of the Internet connection has a positive effect on customer acceptance of IB.

Consequently, the proposed extended TAM research model for measuring customer acceptance of Alpha Bank IBS is depicted in Figure 3, and it is based on the five previous hypotheses.

Considering the proposed extended TAM model, it can be derived that the TRA, which is the basis of the original TAM model, is strongly related to our five hypotheses since the five aforementioned hypotheses describe different aspects of the consumer's attitude and subjective norm.

In order to examine the impact of these factors on the acceptance of Alpha Bank IBS, we performed a questionnaire survey with Alpha Bank customers of three different branches in Greece (Chalandri, Spata, and Koropi). The procedure involved the collection of primary/personal data from the participants (i.e., attitudinal, motivational, behavioral, and perceptive aspects), in order to reassure the selection of a representative population sample, ensuring higher reliability than other survey techniques. The survey was conducted during the period of January–May 2006. A total of 200 questionnaires were delivered to respondents, of which 159 were returned, for a response rate of approximately 80%.

In order to quantify the positive/negative perception of the respondents, a Likert five-point ranking scale was used, ranging from "*strongly agree*" to "*strongly disagree*." The questionnaire included all five hypotheses of the proposed TAM model (i.e., perceived ease of use, perceived usefulness, quality connection, information and security concern) as well as some demographics data (i.e., background relation with Internet banking, concerning issues like: how they used to make online transactions, how often and what transactions were performed more regularly). The use of Internet banking was in our model as the dependent variable.

The aforementioned described collection of (among others) perceptual data related to IBS acceptance provides some information about how it must be bridged by the IT specialists, the gap between the actual reliability of an IT system, and the psychological/subjective sense of reliability as it is perceived by the customer. Thus, such data can provide hints of making consumer friendly a technologically efficient IB system. On the other hand, perceptual data are subjectively dependent, which sometimes imposes a limitation on the objectiveness of the collected data.

In the next section, we analyze the collected results, providing the factors and their impact on influencing Alpha Bank IB acceptance.

Solutions and Recommendations

In order to interpret the collected answers and measure the tendency of Alpha Bank customer towards IBS use, we used five independent factors (i.e., quality of Internet connection, amount of information, perceived usefulness, perceived ease of use, and security matters). The five-point Likert scale was used as a technique for the fulfillment of the questionnaires. Afterwards, we used the Principal Component Analysis with Varimax rotation for the computation.

We should infer that two of the variables from our model related to the quality of Internet connection were not included at the end, because the dispersion of the answers was not appropriate for the extraction of accurate conclusions. Due to this, hypothesis H5 was excluded from further analysis, since there was not a clear tendency from the customers. This may be explained by the fact that nowadays a typical Internet user has a reliable (either broadband or dial-up) connection, and thus that factor does not affect IBS adoption.

The mean age of the 159 respondents is 33.2 years, and gender is 61% male and 39% female. The average level of monthly income before taxation is: 25.7% less than 500€, 36.4% between 501€ and 2000€, and 37.9% greater than 2000€.

Initially, Bartlett's Test of Sphericity (BTS) showed that the variables within the same factors are strongly inter-correlated, being used to

Table 1. Descriptive statistics

Hypothesis	Item	N	Minimum	Maximum	Mean	Std. Deviation
Information	I have received enough information about IBS	159	3.00	5.00	4.0377	0.57243
	I have received enough information about the benefits of IBS	159	3.00	5.00	4.5849	0.63944
Perceived Usefulness (PU)	Using IB enables me to utilize services quickly	159	3.00	5.00	4.4906	0.72799
	Using IB improves my performance at utilizing IBS	159	3.00	5.00	4.7547	0.51209
	Using IB for my banking services increases my productivity	159	3.00	5.00	4.7101	0.61533
	Using IB enhances my effectiveness at utilizing IBS	159	3.00	5.00	4.8679	0.37506
	Using IB makes it easier for me to utilize IBS	159	3.00	5.00	4.7849	0.57701
	Overall, IB is useful for me to utilize IBS	159	3.00	5.00	4.7786	0.53229
Perceived Ease of Use (PEOU)	Learning to use IB is easy for me	159	2.00	5.00	3.3082	0.98050
	I find it easy to do what I want to	159	2.00	5.00	3.4151	0.90219
	My interaction with IB is clear and understandable	159	1.00	5.00	3.9308	1.44134
	I find IB to be flexible to interact with	159	1.00	5.00	4.6792	0.69647
	It is easy for me to become skillful at using IB	159	1.00	5.00	3.7421	1.07453
	Overall, I find IB easy to use	159	1.00	5.00	3.9245	1.38503
Security and Privacy	Using IB is financially secure	159	1.00	5.00	3.1698	1.66577
	I trust in the ability of IB to protect my privacy	159	1.00	5.00	3.0063	1.41196
	I trust in the technology IB is using	159	1.00	5.00	3.9686	1.43386
	I trust in IB as an actual bank	159	1.00	5.00	2.8679	1.27345
	I am worried about the security of IB	159	4.00	5.00	4.9371	0.24354
	Matters of security have great influence on me for using IB	159	3.00	5.00	4.9308	0.30020

determine whether the subgroup error variances were homogeneous. The null hypothesis being tested is: the error variances for the subgroups are statistically equal. This is a necessary and often ignored assumption, when moderated multiple regressions are used to evaluate moderating effects of categorical variables. BTS showed that it is unlikely that the correlation matrix is the 'identity', and thus the variance (and standard deviations) of the groups differ significantly.

The Kaiser-Meyer-Olkin (KMO) criterion was used to indicate a practical level of common variance. The KMO measure of sampling adequacy is an index for comparing the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. A large KMO measure means that factor analysis of the variables is efficient, since correlations between pairs of variables can be explained by the other variables. The KMO was calculated to be ≥ 0.5, indicating the sampling adequacy. Thus, based on KMO and BTS, we are sure that the data are adequate in order to proceed to further analysis.

Table 1 presents the descriptive statistics for all the variables under investigation (i.e., the mean, the standard deviation, and the number of respondents *N* who participated in the survey). Based on these statistics, the following outcomes can be derived about the statistically important variables that influence customers for or against IB use:

- Customers are worried about the security of IBS.
- Security plays an important role in accepting IBS.
- Perceived usefulness is an important factor in IB acceptance.

In order to identify and quantify the various parameters that affect the adoption of IBS, we used the descriptive statistics of Table 1 for factor analysis. From this procedure, Figure 4 was deduced, which depicts the *Scree Plot* of the collected data, demonstrating the corresponding eigenvalues of the factors. The graph is useful for determining how many factors to retain in the analysis. Towards this, the Kaiser criterion was applied, which is also known as the "eigenvalue-greater-than-1" method.

Figure 4. Scree plot

Table 2. Factor eigenvalues, extraction sums, and rotated sums of squared loadings

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	1.691	8.456	8.456	1.691	8.456	8.456	1.565	7.827	7.827
2	1.529	7.646	16.102	1.529	7.646	16.102	1.424	7.118	14.945
3	1.441	7.205	23.308	1.441	7.205	23.308	1.348	6.739	21.684
4	1.413	7.065	30.372	1.413	7.065	30.372	1.343	6.713	28.397
5	1.275	6.373	36.746	1.275	6.373	36.746	1.301	6.507	34.904
6	1.216	6.080	42.825	1.216	6.080	42.825	1.258	6.290	41.193
7	1.199	5.996	48.821	1.199	5.996	48.821	1.227	6.133	47.327
8	1.144	5.718	54.539	1.144	5.718	54.539	1.195	5.976	53.303
9	1.058	5.292	59.831	1.058	5.292	59.831	1.182	5.911	59.214
10	1.013	5.064	64.895	1.013	5.064	64.895	1.136	5.681	64.895
11	0.944	4.719	69.614	-	-	-	-	-	-
12	0.879	4.395	74.009	-	-	-	-	-	-
13	0.858	4.290	78.299	-	-	-	-	-	-
14	0.766	3.830	82.130	-	-	-	-	-	-
15	0.718	3.592	85.721	-	-	-	-	-	-
16	0.661	3.304	89.025	-	-	-	-	-	-
17	0.617	3.086	92.112	-	-	-	-	-	-
18	0.587	2.935	95.047	-	-	-	-	-	-
19	0.531	2.653	97.700	-	-	-	-	-	-
20	0.460	2.300	100.000	-	-	-	-	-	-

Thus, from Figure 4 it can be observed that the first 10 factors have eigenvalue greater than 1, while from factors 11-20 the eigenvalues are less than 1. So, 10 factors are retained for the representation of data.

Table 2 presents all the factors extractable for the analysis along with their eigenvalues, extraction, and rotated sums of squared loadings. The 10 factors account for 64.895% of the total variance, with Factor 1 accounting for 8.456% and Factor 10 for 5.064%. Only 35.105% of the total variance is attributable to the other factors. Thus, these 10 factors can satisfactorily represent the data.

Table 3 indicates the corresponding rotated component analysis. The idea of rotation is to reduce the factors on which the variables under investigation have high loadings. Rotation does not actually change anything, but makes the interpretation of the analysis easier. Also, from Table 3 it can be derived that factors 8 and 10 did not load any parameter on the specific variances, which leads us to exclude them from the specific factor analysis presented in this chapter.

Factor 1 accounts for the largest proportion of the total variance (8.456%). Table 3 shows that this factor consists of the eight variables with

Table 3. Rotated component matrix

Item	1	2	3	4	5	6	7	9
I have received enough information about IBS	0.709	-	-	-	-	-	-	-
I have received enough information about the benefits of IBS	-	-	-	-	-	0.861	-	-
Using IB enables me to use services quickly	-	-	-	-	-	-	-	-
Using IB improves my performance at utilizing IBS	0.815	-	-	-	-	-	-	-
Using IB for my banking services increases my productivity	0.798	-	-	-	-	-	-	-
Using IB enhances my effectiveness at utilizing IBS	0.845	-	-	-	-	-	-	-
Using IB makes it easier for me to utilize IBS	0.787	-	0.732	-	-	-	-	-
Overall, IB is useful for me to utilize IBS	-	-	-	-	-	-	0.696	-
Learning to use IB is easy for me	-	-	0.610	-	-	-	-	-
I find it easy to do what I want to	-	-	-	-	0.802	-	-	-
My interaction with IB is clear and understandable	-	-	-	0.771	-	-	-	-
I find IB to be flexible to interact with	-	-	-	-	-	-	-	0.797
It is easy for me to become skillful at using IB	-	-	-	-	-	-	-	0.587
Overall, I find IB easy to use	-	0.635	-	-	-	-	-	-
Using IB is financially secure	-		-	-	0.564	-	-	0.598
I trust in the ability of IB to protect my privacy	-	0.711	-	-	-	-	-	-
I trust in the technology IB is using	-	0.584	-	-	-	-	-	-
I see IB as an actual bank	0.768	-	-	-	-	-	-	-
I am worried about the security of IB	0.625	-	-	-	-	-	-	-
Matters of security have great influence on me for using IB	0.823	-	-	-	-	-	-	-

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 19 iterations.

factor loadings ranging from 0.625 to 0.845. Four of the eight items describe perceived usefulness (i.e., Using IB improves my performance at utilizing IBS; Using IB for my banking services increases my productivity; Using IB enhances my effectiveness at utilizing IBS; Using IB makes it easier for me to utilize IBS), and they suggest that the use of IB improves the performance of bank transactions; three factors are security-related (i.e., I trust in IB as an actual bank; I am worried about the security of IB; Matters of security have great influence on me for using IB), suggesting that a well-secured IBS is a crucial parameter to IB acceptance. Finally, the last factor (i.e., I have received enough information about IBS) regards the amount of information, showing that customers have already received enough information about IBS potentials and security level. Thus, according to this, the factor can be referred to as the *"Amount of information about perceived usefulness and security level."*

Factor 2, which accounts for 7.646% of the total variance, consists of three variables with factor loadings ranging from 0.584 to 0.711. One factor is related to perceived ease of use (i.e., Overall, I find IB easy to use), while the other two are security related (i.e., I trust in the ability of IB to protect my privacy; I trust in the technology IB is using), showing the importance of providing, on the one hand, a friendly user interface, and on the other hand, maintaining simultaneously at high levels the trust of the customer regarding privacy and IBS reliability. Thus, this factor can be named *"Friendly user interface, providing privacy and reliability."*

Similarly, Factor 3 accounts for 7.205% of the total variance. Table 3 shows that two items are loaded on this factor: one regarding perceived usefulness (i.e., using IB makes it easier for me to utilize IBS), and one about perceived ease of use (i.e., Lexruing to use IB is easy for me). Consequently, this factor is referred to as *"Easy use of IB and IBS utilization."*

On Factor 4, only one item is loaded about perceived ease of use (i.e., My interaction with IB is clear and understandable), which accounts for 7.065% of the total variance. Thus, this factor can be named *"Clarity between IB and customer interaction."*

Factor 5 accounts for 6.373% of the total variance. As presented in Table 3, this factor consists of two items with loadings ranging from 0.564 to 0.802. One factor is related to perceived ease of use (i.e., I find easy to do what I want to), while the other (i.e., Using IB is financially secure) is security related. This factor is referred to as *"Easiness to find and run securely a specific IBS financial process."*

Factor 6 accounts for 6.080% of the total variance. Table 4 presents the item which loads on this factor at 0.861. This item describes the amount of information regarding IBS benefits. Thus, this factor is referred to as the *"Amount of information about IBS benefits."*

Similarly, Factor 7 contains only one item with factor loading of 0.696, which is related to perceived usefulness (i.e., IB is useful for me to utilize IBS) and named *"IB usefulness on IBS utilization."*

Finally, Factor 9, which accounts for 5.292% of the total variance, includes three factors related to security and perceived ease of use. Therefore, this factor is referred to as *"Flexibility and ease of use of a secure IBS."*

To summarize, the eight factors and their factor names that affect Alpha Bank's IB acceptance are presented in Table 4, along with their share in variance. The main factors that seem to influence a customer towards or against using IBS are perceived ease of use and perceived usefulness, in combination with adequate security. In other words, customers seem to be willing to use a specific e-banking system if they have received adequate information about its benefits and potentialities, while the whole service is offered via a friendly, easy, and definitely secure interface.

RECOMMENDATIONS

This exploratory research has been conducted with the purpose of studying customer acceptance of Alpha Bank IBS in Greece. Towards this, we used a special expansion of the well-known technology acceptance model. The proposed model uses two standard variables (i.e., perceived usefulness and perceived ease of use) and three new variables: amount of information, quality of Internet connection, and security/privacy. From the proposed extended TAM, the parameter "quality of Internet connection" was excluded from the model, because it was not statistically significant based on its high variance. So, this factor is not regarded as influent in the case of adopting IBS.

Afterwards, factor analysis was performed with a sample of 159 customers. From this analysis, eight different factors emerged. By extrapolating the deduced factors, we can infer that: if customers trust in the security standards of an Internet banking system and are informed and believe that using it will increase their productivity and effectiveness, then the probability of adopting the particular system is high. So, bank managers should make efforts towards the following directions:

1. To improve security and privacy standards in order to be trusted by customers.
2. To refer and promote the benefits that stem from IBS use/adoption.
3. To increase the amount of information about IB and IBS benefits.
4. To offer IB through a user-friendly IBS interface.

FUTURE TRENDS

The evolution of mobile communication networks will gradually cause the migration of existing e-services of the Internet to our mobile terminals, exploiting the high communication speeds offered by 3G/4G networks. These new mobile e-banking services will initiate a new customer acceptance phenomenon, where all the existing models and studies should be extended and re-estimated in order to include the various parameters that will influence a possible customer for or against using the mobile services.

The adaptation of IBS to mobile communication networks will enable the customer to be able to perform his or her bank transactions anytime, anywhere, and anyhow, offering absolute mobility in contrast to the existing IBS through the Internet, where the customer must access the e-banking system via a personal computer or laptop equipped with Internet access.

On the other hand, the new mobile IBS will

Table 4. Deduced factors influencing IB acceptance

Factor	Factor Name	Variance
1	*Provision of information about perceived usefulness and security level*	8.456%
2	*Friendly user interface, providing privacy and reliability*	7.646%
3	*Easy use of IB and IBS utilization*	7.205%
4	*Clarity between IB and customer interaction*	7.065%
5	*Easiness to find and run securely a specific IBS financial process*	6.373%
6	*Amount of information about IBS benefits*	6.080%
7	*IB usefulness on IBS utilization*	5.996%
9	*Flexibility and ease of use of a secure IBS*	5.292%

also create new threats and customer biases against adapting to the new services. Thus, the IB institutions should initiate a new marketing plan in order to persuade the customers about the adequate security, the benefits, and the flexibility of the new mobile services.

Therefore, once the customers have accepted and adopted the e-banking services via the Internet, they will face a new challenge through the e-banking services via mobile phones. The existing customer acceptance studies may help the bank institutions toward the faster adaptation of the new services, but surely some extensions of the current models with new factors should be needed.

CONCLUSION

This chapter presented a study of Alpha Bank IBS customer acceptance in Greece. An extension of the technology acceptance model was used for the quantification of the parameters that influence the customer acceptance, which included two standard variables (i.e., perceived usefulness and perceived ease of use) and three new ones: amount of information, quality of Internet connection, and security/privacy.

Subsequently, we performed factor analysis with a sample of 159 customers. From this, eight different factors were deduced which are loaded with variables coming from the questionnaires and quantify the IBS customer acceptance. By extrapolating the deduced factors, we conclude that: if customers trust in the security of an Internet banking system and believe that using an IBS will increase their productivity and effectiveness, then the probability of using the particular system is higher.

Thus, bank institutions, in order to promote IBS use, must take actions in order to reassure possible customers about the high standards of the security and the potential that IBS use offers. The provision of consumer reassurance and information by improving IBS security and privacy would be beneficial towards IB acceptance. Towards this, the bank IT specialists should be aware of the various security and privacy risks, which will help them to develop more secure IB systems. On the other hand, the consumers should be also informed about various available risk-precaution practices and management procedures of an IBS, like not using a public computer to access an IB account, not providing personal data to spoof e-mails, and so forth.

Another parameter stemming from our quantitative results is that bank institutions should improve marketing of Internet banking services, in order to eliminate lack of awareness to potential users of IBS. Towards this, various IBS training sessions could be organized on the bank premises for customer to strengthen their confidence in using an IB system. Based on the perceived usefulness-related results, it is obvious that banks should provide through the IBS an efficient graphical user interface that will provide easy access and navigation among the various offered services.

Finally, according to our results, the amount of information that a consumer receives about an IBS plays a major role into adapting its use or not. Thus, by providing informative leaflets and advertisements relative to the alternative services and benefits of using an IBS, new users can be motivated towards IBS adoption.

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Chapter V
The Adoption and Use of Smart Card Technology in Banking:
An Empirical Evidence from the Moneo Electronic Purse in France

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ABSTRACT

The electronic purse is one of the latest smart card applications. It handles small payments and is complementary to other payment cards. However, there have been considerable obstacles to its widespread adoption and use by customers and retailers. This chapter explores and models the factors—economic, technological, and social—and forces driving the adoption and use of the Moneo electronic purse in the South of France. An empirical study on 200 individuals allows us to analyze the determinants of the probability of adoption for consumers and retailers (Logit models) and of the frequency of use for consumers (Poisson model). The latter is found to be significantly explained by four factors (relative advantage, cost, visibility, and security), income, and gender with the expected sign. Finally, the reasons why Moneo's introduction seems to have met with failure are determined, and potential solutions to help reach the required critical mass by redirecting marketing strategies are proposed.

INTRODUCTION

During the last 4,000 years, there have been only four major innovations in the process of making payments (see Evans & Schmalensee, 1999): coins (4,000 years ago), checks (800 years ago under the name of bills of exchange), notes (more than 100 years ago), and cards (more than 50 years ago).

Card use has expanded phenomenally in the past 10 years due to the development of the "chip," leading to smart cards. A smart card is a credit card-sized plastic card with an embedded chip that provides power for multiple uses (SIM cards for mobile phones, credit/debit cards such as Visa and MasterCard, health cards, etc.). The security of smart cards is enhanced by PIN verification and cryptography, and the size and power of the chip determine their storage and processing capacities. These types of cards are useful when a secure digital key or identity needs to be stored.

Innovative applications of the smart card have taken place in several sectors, like telecommunications, transport, finance, or health. Banking products currently offer several means of payment, including card-based payment transactions that were originally performed with magnetic stripe technology used for online authorization. With smart cards, the concept remains the same, but cards are reasonably flexible in their applications and more secure. There are three main types of electronic payment using smart cards: credit cards (in which payment is made after a service is rendered), debit cards (in which payment is made when the service is rendered), and electronic purses (in which payment is made before the service is rendered). Ranki and Effing (2000) give more details and an evaluation of the advantages and limitations of such payment systems.

In contrast to a debit card, the electronic purse contains an amount which can be topped up and is debited for each transaction when connected to a reader (payment terminal, automated teller machine, ATM). The transfer is made without direct involvement of a financial intermediary (in off-line mode), unlike purchases made with credit cards, debit cards, or checks, which require exchanges between the customer's and retailer's financial institutions. These exchanges increase the fixed costs associated with these types of payment, making them impractical for small payments. Because the sum is transferred directly from the customer to the retailer, the electronic purse appears to be a cheaper alternative to other existing payment cards and a solution to low-cost transaction problems. Both customers and retailers benefit from the advantages of the electronic purse.

The Danish Danmønt card tested in the city of Næstved as early as September 1992 was the first pilot trial of the electronic purse ever realized. Since then, several electronic purse projects have been developed in Europe (see Table 1), some of them being very successful (see for instance Clark, 2005, and Van Hove, 2000, who reviewed success as well as failure stories of adoption for respectively six and sixteen electronic purse schemes throughout the world). In Belgium, for instance, the electronic purse named Proton has known success since more than 30% of cardholders have activated the e-wallet function and realized 102 million operations in 2005, for an amount of € 486.6 million. This is mainly due to its economic and technological advantages. First, Proton does not support any fees for cardholders, a no-charge policy which allowed gaining an important number of holders who keep using it. Second, the payment is rapid because the reader is directly connected to the cash-box: merchants have to type out the price once which is a key ergonomic aspect. Finally, Proton cards can be used for public payphones[1] as well as in vending machines. This multi-application device greatly influenced the use of Proton.

France is both the leading country worldwide in number of payment card transactions per inhabitant and the first country in Europe where all cards were equipped with microchips. The most widely used card is a payment card (or bank card) that is accepted nationwide and is run by a central organization called *Groupement d'Intérêt Economique-Cartes Bancaires* (GIE-CB). This smart card already handles many off-line transactions and is also widely used in public telephones. The system is fully compatible and there are no standardization problems.

Table 1. Main electronic purse projects in Europe (Source: European Central Bank)

Country	Project
Belgium	Proton
France	Moneo
Germany	Geldkarte
Italy	Minipay
Netherlands	Chipknip
Luxembourg	Mini Cash

For all these reasons, France could have been expected to be a fertile ground for a successful launch of the electronic purse Moneo. However, in spite of the success of electronic purses in other countries (Proton in Belgium or Octopus in Hong Kong), there have been major obstacles to a massive and rapid adoption. Although more than 300 million Euros were invested by the banks directly and indirectly in the system, Moneo has not really taken off: 1.2 million Moneo cards are currently in circulation in France, compared with 45 million traditional bank cards (debit and credit cards). As a consequence, the annual number of transactions generated by Moneo is similar to that carried out in one day using bank cards.

The purpose of this chapter is to explore and model the processes and forces driving widespread and frequent use of the electronic purse as one of the lasting smart card banking applications. We propose a model in which exogenous and endogenous factors can influence customer and retailer decisions, subsequently providing empirical data based on the introduction of the electronic purse Moneo in the area of Aix-Marseilles in the South of France. The reasons why Moneo's introduction seems to have met with failure are determined, and potential solutions to help reach the required critical mass by redirecting marketing strategies are proposed.

The remainder of this chapter is structured as follows. In the following section, we present the theoretical foundations. The next section provides the research model, and then empirical results are described. We conclude with the main finding and offer solutions.

THEORETICAL FOUNDATIONS

Several articles over the past two decades have examined the problem of widespread adoption of electronic payment systems following the rapid growth of Internet and new card-based technology (particularly the smart card). On the one hand, the rapid growth of the Internet has greatly increased interest in electronic commerce (Dos Santos & Peffers, 1998; Eastin, 2002; Stroborn, Haitmann, Leibold, & Frank, 2004; Vesa & Heck, 2005). On the other hand, card-based technology has greatly increased interest in credit cards (Plouffe, Vandenbosch, & Hulland, 2001) and chip-based cards, known as smart cards. The economic theory on the adoption of products derived from the smart card is limited and recent (Aubert & Hamel, 2001; Truman, Sandoe, & Rifkin, 2003; Hui, Cheng, & Depickere, 2003). These empirical studies have been used to explain problems in attaining widespread adoption of new electronic payment products.

The main question they address is: how are users of innovative technology persuaded of its value? Their answers are largely based on work developed around innovation theory (Rogers, 1995; Moore & Benbasat, 1991) and network externalities (Farrel & Saloner, 1985; Katz & Shapiro, 1985), which are closely linked to customer behavior and marketing science literature (Mahajan, Muller, & Bass, 1990). However, to date, none of these studies has used all these approaches to account for the adoption and diffusion of new electronic payment instruments or smart card products. Taking all these approaches together, we endeavor in this chapter to explore and model the processes and forces driving the use of the Moneo electronic purse in the South of France.

Innovations Theory

There is a broad stream of literature on the diffusion of innovation, which covers several disciplinary boundaries. Innovation is defined as a new idea perceived by the individual (Rogers, 1995) or by the organization (Moore, 1994). It is a product, a service, an input, a process, or a technology. Diffusion is the process by which this innovation is spread through a population of potential adopters (Rogers, 1995). The dominant stylized fact concerning the use of new products or technologies over time indicates that the diffusion of innovation typically follows an S-curve. The literature examines the patterns giving rise to this S-curve by focusing on the diffusion of technology among firms or organizations on the one hand (Metcalfe, 1988; Baptista, 1999) and on the diffusion of products or information among individuals or firms on the other hand (Rogers, 1995; Moore & Benbasat, 1991; Mahajan et al., 1990). Moreover, research on products adoption and dominant designs are usually addressed within the context of the product lifecycle model (Abernathy & Utterback, 1978). Furthermore, such literature, particularly on dominant designs, emphasizes social factors (Anderson & Tushman, 1990), their lack of existence in some industries (Klepper, 1996), and problems with identifying them in many others until long after they have appeared (Utterback, 1994).

In this chapter we focus on the adoption of new electronic payment instruments in light of the product diffusion literature. In order to explain the diffusion process, this literature has tried to determine which characteristics of an innovation influence its adoption. Rogers (1995) points out that "the characteristics of innovations, as perceived by individuals, help to explain their different spleen of adoption" (p. 15). The author defines five characteristics that affect the adoption rate of an innovation: relative advantage, compatibility, complexity, triability, and observability. Relative advantage is the degree to which an innovation is perceived as better than the idea it supersedes. Compatibility is the degree to which an innovation is perceived as being consistent with existing values, past experiences, and needs of potential adopters. Complexity is the degree to which an innovation is perceived as difficult to understand and use. Triability is the degree to which an innovation may be experimented with on a limited basis. Observability is the degree to which the results of an innovation are visible to others. Thus, the innovations perceived by the individual must have high enough relative advantage, compatibility, triability, and observability, and low enough complexity to warrant a quick adoption. Similarly, Tornazky and Klein (1982) affirmed that among the characteristics of the innovation, relative advantage, compatibility, and to a lesser extent, complexity, constitute the most important predictors of adoption.

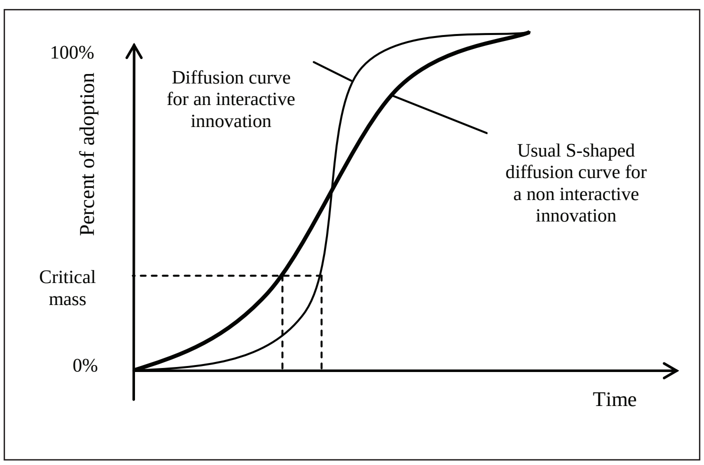
Based on Rogers' conceptual framework, Moore and Benbasat (1991) added new variables that can influence the widespread adoption of an innovation. The two authors developed a measurement instrument known as perceived characteristics of innovating (PCI). This instrument introduces further considerations influencing individual decisions to adopt the notions of visibility, result demonstrability, image, and voluntariness. Visibility is the extent to which an innovation is perceived to be in widespread use in the relevant adoption setting. Result demonstrability is the degree to which the unique features and benefits of an innovation are readily discerned by the potential adopter. In fact, these first two variables cover the concept of observability defined by Rogers. In addition, image represents the degree to which individuals believe that an innovation will increase their prestige or status in their relevant community or location. Finally, voluntariness reflects the extent to which the adoption of an innovation is perceived to be under an individual's volitional control.

Network Externalities

There is vast theoretical literature on adoption of new technologies involving network externalities and also network compatibility, the best known starting with Farrel and Saloner (1985) and Katz and Shapiro, (1985, 1986), which focus on the adopters' behavior in the network markets. Several studies on this field have highlighted network effects on the widespread adoption of means of electronic payment (Gowrisankaran & Stavins, 2004). The payment instruments are a network good because the benefit drawn from the good is related to the increase in the number of users. The fundamental feature of such markets, and in general, most markets with network externalities, is that they are two sided (Rochet & Tirole, 2003): customers and retailers are the principal users of means of payment, and each side is composed of only one of these groups. An increase in the number of retailers offering a new payment system benefits the customers, and the reverse. However, the corresponding externalities are not internalized by end users, unlike in the multi-product literature (the same customer buys the printer and the ink cartridges). This is closely related to the chicken and egg problem, since benefit to the customer depends directly on the number of retailers accepting the means of payment and only indirectly on the number of customers who adopt it or use it. Conversely, benefit to the retailers depends directly on the number of customers using the electronic purse and only indirectly on the number of retailers accepting it.

Another consequence of network externalities is that many potential users of the product might decide to wait for it to attain some initial success before entering the market. This delay occurs because early adopters will see few benefits from the product until its use is widespread. If a sufficient number of customers adopts a wait-and-see attitude, there may be insufficient demand to successfully launch the product. So achieving widespread adoption of the product depends on having a sufficient number of users: the critical mass (Oliver, Marwell, & Teixeira, 1985). Thus, the achievement of a critical mass of users (customers and retailers) is a prerequisite for market penetration by new payment systems, because market dynamics can considerably change once critical mass has been achieved. The market for network goods may grow slowly until it reaches

Figure 1. Diffusion curves for an interactive and non-interactive (bold) innovation (Adapted from Mahler & Rogers, 1999)



a critical mass, then suddenly begin expanding rapidly (generally, the process produces an S-shaped diffusion curve, see Figure 1). This makes it difficult to forecast the size of a market on the basis of growth rates before critical mass has been attained. Moreover, this will be more crucial for interactive innovation, contrary to non-interactive innovation, which diffuses relatively more slowly until a critical mass of adopters is reached (see Figure 1).

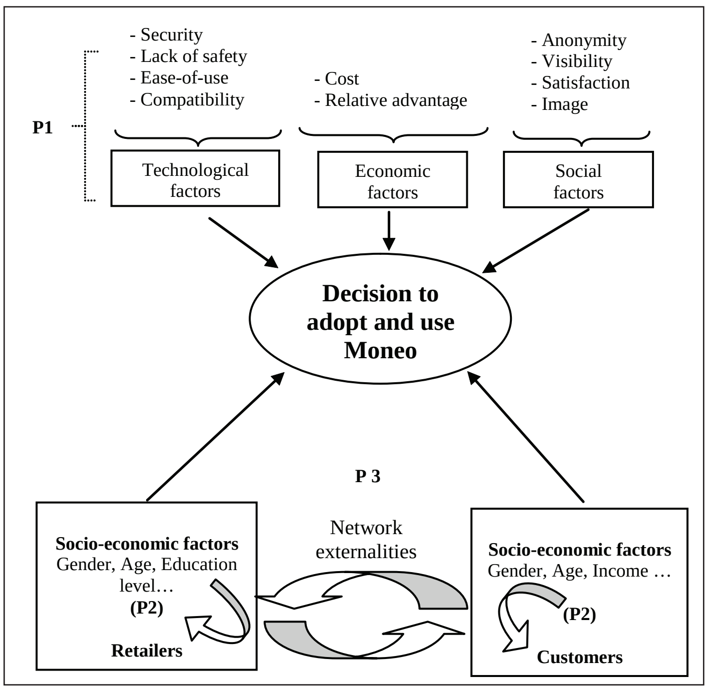
MODEL

Our purpose is to analyze the factors that explain the limited success of the Moneo purse despite its compatibility with the existing payment cards issued by the same organization (GIE-CB) and the high level of use of existing payment cards in France. In this section, we propose a model in which the use of the electronic purse depends on three kinds of processes. The first process (P1) underlines individual use factors of three main types: technological, economic, and social. The second process (P2) highlights individual socio-economic factors connected with customers or retailers. The third process (P3) presents use factors associated with network externalities—that is, interactions between customers, between retailers, and between customers and retailers. Figure 2 provides a general overview of the model. We develop in the following the issues related to the underlying factors of the P1 and P3 processes. The assumptions on their effects on the frequency of use are then formulated, and their validity will be ascertained empirically after that.

Factors of Individual Use (P1)

These factors are divided into three main groups: technological, economic, and social (Chou, Lee, & Chung, 2004; Yu, Hsi, & Kuo, 2002).

Figure 2. Model of widespread adoption of the electronic purse



Technological Factors

Security*:* Security is a major issue in payment systems since it is one of the main characteristics of card money and network money (Furche & Wrightson, 2000). The success of smart cards is primarily due to greater security for the banking community as well as for customers or retailers. Thus electronic purse systems generally use improved payment technology, offering increased protection against fraud and theft compared to traditional payment systems, like cash, checks, and older electronic payment structures (based on magnetic strip technology). However, the degree of security can be difficult to assess.[2]

Assumption 1: *A (perceived) high level of security offered by the electronic purse (system) leads to its increased use by customers (retailers).*

Reliability: The electronic purse payment system must work around the clock, without any risk of interruption, and without noticeable delays in authorization and clearing (Schmidt & Muller, 1999).

Assumption 2: *The absence of transaction failure when using an electronic purse (system) leads to its increased use by customers (retailers).*

Ease of use: Acceptance of the electronic purse is favored when the whole system (card and terminal) is easy to use. This greatly depends on the technology used. For instance, contactless technology, which takes only 0.3 seconds to register a payment, offers more ease of use than contact technology, which takes one or two seconds, not counting insertion and extraction times, and consequently brings an important ergonomic aspect.

Assumption 3: *A perceived easy-to-use electronic purse (system) leads to its increased use by customers (retailers).*

Compatibility: Compatibility represents the degree to which an innovation is perceived as compatible with existing products, and with the consumption patterns, the recent experience and the needs of the potential adopter. The electronic purse possesses one characteristic which is analogous to credit and debit card transactions: method of payment—that is, a card and a reader. So, the use of credit and debit cards improves the perception of the new product by potential adopters.

Assumption 4: *A new means of payment (system) compatible with already existing habits leads to its increased use by customers (retailers).*

Economic Factors

Cost: A fundamental criterion of choice, cost has been the subject of numerous studies on transactions demand for money, from the renowned works of Baumol (1952) and Tobin (1956) to more recent literature (Whitesell, 1992; Santomero & Seater, 1996; Shy & Tarkka, 2002). All the literature, based on the opportunity-cost approach, indicates that the cost of using a medium of exchange determines whether it will be used and for which goods it will be traded. Consequently, users usually compare costs and benefits before adopting a technology. The electronic purse system involves two types of costs:

1. *Initial costs* include the installation cost of the payment system (reader for retailers: 100 to 120 euros per terminal, plus 15 euros per month for leasing) or the annual customer subscription fee (between 6 and 10 euros in the case of Moneo).
2. *Operational or transaction costs* represent the commissions paid by the retailer on each transaction (0.3 % to 0.9 % per transaction).

Indeed, the cost of technology or innovation refers both to the initial cost and to the operational cost, and is usually assumed to be negatively related to the use and implementation of innovation.

Assumption 5: *Low costs for subscription (installation) lead to its increased use by customers (retailers).*

Relative advantage: Payment by electronic purse offers several advantages. In the perception of retailers and customers, these advantages must constitute improvements over already existing products: convenience of use, no need to carry change, a rapid transaction time, ability to fix and control expenditure by only topping up with the amount desired, advantages vis-à-vis competitors, and so forth. These relative advantages are related to the whole system (cards, readers, networks, etc.).

Assumption 6: *A high perception of the advantages of the electronic purse (system) leads to its increased use by customers (retailers).*

Social Factors

Anonymity: Anonymity of transactions constitutes a major consumer right (Goodhart, 2000). The identity of the customer should not be revealed to other parties, and business or financial institutions should not be allowed to trace user information. Moreover, financial institutions must protect the anonymity of the retailer during transactions. Electronic purses allow for the direct transfer of credit balances from purse to purse without immediate involvement of financial institutions. This is important because the most important distinction on this point between the characteristics of currency on the one hand and electronic transfers on the other is that currency is completely anonymous, whereas electronic transfers have facilitated and increased the recording of information on user behaviors.

Assumption 7: *A high degree of transaction anonymity leads to its increased use by customers (retailers).*

Satisfaction: We consider the degree of individual satisfaction on testing the innovation, which reflects the opinion both of customers and of retailers. Customer satisfaction reflects an emotional state in response to an evaluation of the quality of the services provided by the electronic purse. Thus, individuals with higher satisfaction are expected to use the innovation more frequently, whereas lower satisfaction often leads to the rejection of technology after a trial period.

Assumption 8: *A high degree of satisfaction with the electronic purse (system) leads to its increased use by customers (retailers).*

Visibility: Visibility is the extent to which an innovation is perceived to be in widespread use in an area. The adoption of Moneo can directly influence the way people pay for their purchases in everyday life. This concept of visibility can be interpreted in two ways. First, it is related to the social influence aspect—that is, the fact that adopters can influence non-adopters towards using the innovation. Second, it deals with the role of a network externality to reach critical mass. Here, visibility addresses the former aspect whereas network externalities are presented in process P3 below.

Assumption 9: *High visibility of the electronic purse (system) in an area leads to its increased use by customers (retailers).*

Image: Adopting and using an electronic purse can be perceived as an attribute of social status or fashion. Thus, a “good image” of the product can accelerate or slow down its adoption.

Assumption 10: *A good image of the electronic purse (system) leads to its increased use by customers (retailers).*

Socio-Economic Factors (P2)

The socio-economic factors considered are gender, age, income, and occupation for customers, along with gender, age, education, and location and type of outlet for retailers. The 10 variables described above (along with the socio-economic variables) form exogenous factors that influence the adoption and use of the electronic purse as a new means of payment. However, this process seems to be influenced by an endogenous phenomenon related to the critical mass necessary to ensure the widespread use of a product.

Network Externalities (P3)

The electronic purse is an economic good with positive network externalities because the benefit to a given user from adopting it depends on how many other people are using the same good. By adopting Moneo and thus extending the network, every user also increases the benefits to other customers and retailers. However, with electronic purses, the customer and the retailer are almost never the same person, and a participant is always positioned on only one side of the market. Hence, demand interdependence is determined by the overall number of market participants and by the relative number of customers and retailers. Note that we consider both network externalities as an indirect intra-categorical effect *and as a direct* inter-categorical effect between customers and retailers. In this case, the benefit to the customer depends directly on the number of retailers accepting the means of payment, and the benefit to the retailer depends directly on the number of customers using the electronic purse.

Assumption 11: *Widespread use of the electronic purse by customers (retailers) leads to its increased use by customers (retailers).*

A survey was used in 2004 in the south of France on 200 respondents to test the relevance of our assumptions in explaining adoption and use of Moneo by customers and retailers.

EMPIRICAL RESULTS

Moneo was introduced in the Aix-Marseilles-La-Ciotat area as a trial project before extension to the whole Bouches-du-Rhône region. Data was gathered using a self-administrated questionnaire on four groups: Moneo adopting retailers, Moneo non-adopting retailers, Moneo cardholders, and Moneo non-cardholders. In the following, we briefly explain the method used and provide descriptive statistics on data, then we explore the variables explaining the adoption decision by customers and by retailers, and finally we analyze the use of Moneo by cardholders.

Data and Methods

The study lasted one month, during which 50 people from each category were questioned. Respondents were carefully selected to ensure representativeness of the whole population of the pilot area. A small-scale pilot survey helped to clarify wording and to calibrate the final questionnaire, which used two principal types of questions. First, assertions were proposed to the respondents, with possible answers corresponding to ordinal levels using Likert-style scales (e.g., *Strongly Agree*, *Agree*, *Disagree*, *Strongly Disagree*, or *Very Often*, *Often*, *Seldom*, *Never*). Second, interrogative sentences were proposed with possible answers of: Yes, No, Don't Know. The answers to these questions are then used to create the factors of individual use (P1) and network externalities (P3). Finally, some questions were asked on the status of the respondent and stand for the socio-economic factors (P2).

Two variables will be used successively as dependent variables in the analysis: the decision to adopt the electronic purse (ADOPT) and the monthly frequency of use in case of adoption

(USE). The first is directly collected through the questionnaire, while the second is constructed for cardholders from the weekly number of use of Moneo. Regression analyses will test how assumptions 1-10 predict frequency of use. Tables 2 and 3 present the statistics respectively for customers and merchants.

Socio-demographic characteristics show that 54% of the sample are men; 5% are under 24, 55% are between 24 and 49, and 40% are over 49; the monthly household income is €3,904. Concerning professional status, 25% are not employed, 23% are independent professionals, 35% are white collar workers, and 13% are senior executives. Ninety-five percent of the customers declare familiarity with the Moneo card; they possess on average one payment card besides Moneo that they use on average 288.6 times a year for a total of €3,877—that is an average € 13.4 per use.

Sixty-three percent of the sample is composed of men; 6% are under 24, 78% are between 24 and 49, and 16% are over 49; 33% have primary-level education, 38% have senior high school education, and the remaining 29% have university-level education. They are located in Marseilles (68%), Aix-en-Provence (19%), and La Ciotat (13%). The type of outlets represented are bread and pastry (23%), tobacco (29%), catering (14%), and others (34%). Ninety-eight percent of the retailers declare familiarity with the Moneo system; they possess on average 1.21 payment systems besides the Moneo system which they use on average 5,625 times a year (11 missing values)—that is an average of 20 uses per working day.

Table 2. Descriptive statistics for customers (n=100)

Variables	*Miss.*	**Mean**	**Std. Dev.**
Dependent Variables			
Respondent has a Moneo payment card (ADOPT=1)	0	0.50	0.5025
Average monthly Moneo use (USE)	50	18.32	13.25
Independent Variables			
Respondent declares familiarity with Moneo (=1)	0	0.95	0.2190
Number of payment cards respondent holds (besides Moneo)	0	1.01	0.6741
Annual frequency of use of payment cards	0	288.6	241.92
Annual amount spent with payment cards (thousand EUR)	9	3.88	1.6464
Gender (Male=1)	0	0.54	0.5009
Respondent's age < 24 (=1)	0	0.05	0.2190
Respondent's age > 24 and < 49 (=1)	0	0.55	0.5000
Respondent's age > 49 (=1)	0	0.40	0.4924
Monthly household income (thousand EUR)	5	3.90	2.8935
Not employed (=1)	0	0.25	0.4907
Independent professional (=1)	0	0.23	0.4230
White collar worker (=1)	0	0.35	0.4794
Senior executive (=1)	0	0.13	0.3380
Other (=1)	0	0.04	0.1969

Factors Determining the Decision to Adopt

The factors determining the decision to adopt are explored for customers and retailers, and the reasons given by non-adopters to justify their decisions are then briefly analyzed. The decision on whether or not to adopt the Moneo payment card is modeled by Maximum Likelihood (ML) using a standard Logit model. The dependent variable is ADOPT (ADOPT=1 if the respondent adopts Moneo, and 0 otherwise). The best model for customers (retailers) is given in Table 4 (Table 5) with some measures of fit.

The overall quality of the customers' model is satisfactory, the two measures of fit are high, and the model correctly predicts the adoption in 89 out of 95 cases (93.68%), a highly satisfactory result. Two variables appear as highly significant: age and income. Indeed, being over 49 years tends to significantly increase the probability of adoption, and the higher the household income, the higher the probability of adopting the Moneo card. Hence, all other things being equal, the marginal effect

Table 3. Descriptive statistics for retailers (n=100)

Variable	Missing	Mean	Std. Dev.
Dependent Variables			
Respondent offers a Moneo payment terminal (ADOPT=1)	0	0.50	0.5025
Average monthly Moneo payment terminal use (USE)	51	50.14	70.95
Independent Variables			
Respondent declares familiarity with Moneo (=1)	0	0.98	0.1407
Number of payment systems respondent holds (besides Moneo)	0	1.21	0.7148
Annual frequency of payment system use	11	5,624	6,289.3
Gender (Male=1)	0	0.63	0.4852
Respondent's age < 24 (=1)	1	0.06	0.2398
Respondent's age > 24 and < 49 (=1)	1	0.78	0.4179
Respondent's age > 49 (=1)	1	0.16	0.3700
Primary-level education (=1)	1	0.33	0.4738
Senior high school-level education (=1)	1	0.38	0.4863
University-level education (=1)	1	0.29	0.4574
Respondent lives in Marseilles (=1)	0	0.68	0.4688
Respondent lives in Aix-en-Provence (=1)	0	0.19	0.3943
Respondent lives in La Ciotat (=1)	0	0.13	0.3380
Respondent has a bread and pastry shop (=1)	17	0.2289	0.4227
Respondent has a tobacco shop (=1)	17	0.2892	0.4561
Respondent has a catering outlet (=1)	17	0.1446	0.3538
Respondent has another type of outlet (=1)	17	0.3373	0.4757

of being older than 49 increases the probability of adoption by 35%, and increasing the monthly household income of €1000 increases the probability of adoption by 6.9%.

The overall quality of the retailers' model is not as good as previously, the two measures of fit are poor, and the model correctly predicts adoption in 56 out of 82 cases (68.29%), a barely satisfactory result. Two variables appear as significant at the 5% significance level: age and living in Aix-en-Provence. Indeed, being between 24 and 49 and living in Aix-en-Provence tend to significantly decrease the probability of adoption. The marginal effect of being between 24 and 49 decreases the probability of adoption by 28.7%, and living in Aix-en-Provence decreases the probability of adoption by 24.3%, all other things being equal.

Reasons Given for Non-Adoption

The main reasons why retailers do not adopt the Moneo system are: "Not a useful product" (65%), "Over-expensive service" (45%), "Other reasons" (25%), and "Lack of information" (5%). Customers also answer "Not a useful product"

Table 4. Estimation of the probability of adoption of Moneo among customers (n=95)

Parameter	*Estimate*	Std. Err.	*Student t*	Pr > |t|	*Marginal Effect*
Intercept	-8.2612	3.3189	2.49	0.0128	-
Not employed	1.9046	2.48050	0.77	0.4426	0.095
Independent professional	-1.0620	1.8895	0.56	0.5741	-0.053
White collar worker	-0.0462	1.6027	0.03	0.9770	-0.002
Age >49	7.0594	1.8755	3.76	0.0002	0.35
Male	1.1072	1.3573	0.82	0.4147	0.055
Income (in '000 EUR)	1.3972	0.0507	2.76	0.0058	0.069
Log-likelihood: -16.39 LR test of nullity: 98.82 p-value < 0.0001					
McFadden LRI: 0.7509 Maddala Pseudo R²: 0.8625 % of correct predictions: 93.68					

Table 5. Estimation of the probability of adoption of the Moneo system among retailers (n=82)

Parameter	*Estimate*	*Std. Err.*	*Student t*	*Pr > |t|*	*Marginal Effect*
Intercept	2.1655	0.7119	3.04	0.0024	-
Age > 24 and < 49	-1.3590	0.6521	2.08	0.0371	-0.287
Bread & pastry shop	-0.7450	0.6106	1.40	0.2225	-0.157
Senior high school education	-0.7355	0.5237	1.22	0.1602	-0.155
Lives in Aix	-1.1485	0.5740	2.22	0.0454	-0.243
Log-likelihood: -50.08 LR test of nullity: 10.37 p-value < 0.0001					
McFadden LRI: 0.094 Maddala Pseudo R²: 0.1605 % of correct predictions: 68.29					

(45%), "Over-expensive service" (23%), "Other reasons" (20%), and "Lack of information" (5%), but "Not practical" is also chosen by a noticeable 35% and "Lack of confidentiality" by 5%. Note that "Lack of security" is never mentioned, either by customers or by retailers. In fact, Moneo seems to be over-expensive for both sides. Retailers must bear the installation cost of the hardware as well as the transaction costs each time the system is used. Banks are currently charging 0.3% to 0.9% for each transaction. Cardholders pay a €6 to €10 annual fee, whereas this system is free in most European countries (Austria, Belgium, The Netherlands, Norway, Spain, Switzerland). Yet, for retailers, Moneo wastes more time than a cash payment when the reader is not directly connected to the cash-box, since the retailer must type out the price twice. Moreover, 60% of non-cardholders and 85% of non-adopting retailers answer "I am not going to adopt Moneo (at least in the short run)"; respectively 40% and 15% of them are undecided, and none declares that they intend to adopt Moneo.

Determinants of the Frequency of Use by Cardholders

We focus now on the sub-sample of adopters among customers. Retailers are not analyzed since they are dependent on customers' decisions: once a retailer decides to adopt the Moneo system, the intensity of use of the system will largely be exogenous and will depend on whether it is used by the clientele. Data collected in questionnaires allow us to construct the factors entailed in the P1, P2, and P3 processes. Each factor is composed of one or several questions, either dichotomous or ordinal (with score between 1 and 5, a neutral response corresponding to a score of 3).

Technological Factors

Customers consider the level of security offered by Moneo good (it scores 4.44, significantly higher than 3), and 16% of cardholders use Moneo for security reasons. The frequency of payment failures (safety) is below one per cardholder. The three questions composing the easy factor show that cardholders find the use of Moneo clear and comprehensible (scores of 4.86 and 4.76 are very significantly higher than the neutral response). Seventy-four percent of cardholders declare that they chose Moneo for its ease of use. Most of the respondents declare that the use of Moneo is compatible with their small purchases (score of 4.46, very significantly higher than the neutral response).

Economic Factors

Seventy percent of cardholders know the cost of Moneo, and those who know find it rather expensive (although the score does not differ significantly from "not too expensive"). Twelve percent of respondents choose Moneo to save money. The *relative advantage* factor is composed of the scores for seven questions. The first two questions indicate that cardholders declare that they significantly benefit from the use of Moneo (3.58 and 3.66). The next three questions (interrogative sentences) also show that cardholders find that the use of Moneo has significant advantages for everyday purchases. The last two questions show that cardholders declare that they use Moneo to save time (14%) and for practical considerations (64%).

Social Factors

Cardholders widely believe that Moneo allows them to preserve their anonymity (score of 4.4, very significantly higher than 3), and 8% declare that they use Moneo for confidentiality. The product is seldom seen (visibility) by the public or by the trade (the three scores are significantly lower than 3), which suggests that the degree of influence is weak. Respondents are highly satisfied with the use of Moneo (satisfaction) for low value purchases (score of 4.6, very significantly higher than 3). The image of Moneo seems to be non-significantly different from a neutral vision (score of 3.16).

Network Externalities

Customers significantly think that widespread adoption of Moneo depends on the effects of network externalities (directly, score of 4.66, and indirectly, score of 4.48).

We now look for the factors that best predict the monthly number of use of Moneo among cardholders. A Poisson model is estimated due to the count nature of the explanatory variable. The results are given in Table 6 and will determine which assumptions are confirmed by our data.

First of all, the very significantly different from 0 LR test of joint nullity and the high value of the adjusted R^{2d} (84.83%) indicate that this model performs well in assessing the number of uses of Moneo. Note that two overdispersion tests have been performed and both do not reject the null hypothesis of equality between mean and variance. Table 6 shows that four factors—advantage, security, cost, and visibility—appear very significant, all with the desired (positive) sign. This supports Assumptions 1, 5, 6, and 9. The better a customer perceives relative advantage, security, cost, and visibility, the more frequent his use will be. Moreover, three socio-economic variables—gender, income, and professional occupation—are significant in explaining the number of use and have effects conforming to intuition. First, male respondents have a significantly higher frequency of use than others. Second, the higher the household income is, the more Moneo is used. Third, respondents not employed have a significantly lower number of uses than other professions.

Network Externalities and Social Influence

Networks externalities could be expected to greatly influence the widespread adoption of Moneo as an innovation. Therefore, a minimum rate of adoption among retailers and customers—the critical mass—would have to be reached before there was a takeoff or a massive adoption of Moneo. Indeed, as the electronic purse is an interactive good, its adoption depends simultaneously

Table 6. Estimation of the frequency of use of Moneo among customers (n=46)

Parameter	*Estimate*	Std. Err.	*Student t*	Pr > |t|
Intercept	-4.3256	1.2266	3.53	.0004
Advantage	0.0379	0.0093	4.08	<.0001
Cost	0.3912	0.0472	8.29	<.0001
Visibility	0.094	0.0132	7.12	<.0001
Security	0.3111	0.0535	5.81	<.0001
Male	0.4235	0.0869	4.87	<.0001
Ln (income)	0.2605	0.1173	2.22	0.0264
Not employed	-0.2381	0.1097	2.17	0.0300
Log-likelihood: -131.86 LR test of nullity: 276.33 p-value = <.0001				
G^2= 49.42 R^{2d}: 0.9275				

on customers and retailers. We hence face a two-sided market where the problem of achieving the critical mass can be described as a "Chicken and Egg" problem. This is confirmed by the responses to questions dealing with externalities. Ninety percent of customers think that the diffusion of Moneo depends on its use by other customers and 92 % by its diffusion among retailers. Seventy-two percent of retailers think that the diffusion of Moneo depends on its diffusion among other retailers and 76 % by its use by other customers. Both categories are very aware of the importance of network externalities as a determinant of Moneo diffusion, and the innovation adoption process for such a good is connected with social network contributions.

Social interactions cover three broad types. The first type assumes that adoption is driven by information from a source external to the social system (Bass, 1969). It underlines the influence of retailers' actions on customers' thinking. The second type of interaction assumes that adoption is driven by communication within a specific social system (Bass, 1969). It illustrates the social interactions between the adopters of the innovation and the non-adopters—that is, the adopters can influence the non-adopters towards innovation use. The third type covers spatial interaction—that is, the fact that successful adoption of an electronic purse in a particular area can affect other areas (Steyer & Zimmermann, 1998). The underlying idea is that the electronic purse has a ticketing function in some areas, which constitutes a strategic or catalyst application improving the adoption of the product. Therefore, a perceived successful electronic purse adoption in one area can influence the decision to adopt in other areas.

In the case of Moneo, it appears that the lack of social interaction is sorely felt and may help to explain the current failure of Moneo. Indeed, only 30% of customers and 14% of retailers think that the use of Moneo is widespread, while respectively 62 % and 50% think the opposite (the remaining answer "Don't know"). The visibility factors give the same picture, since 74% (58%) of customers declare that they have seldom or never seen other customers (retailers) using Moneo in their area, and 78% of retailers declare that they have seldom or never seen other retailers using Moneo. Moreover, retailers appear to find the use of Moneo expensive and without any clear benefit to them (in terms of image, relative advantage, or advantage over competitors). Thus, it is unlikely that they will incite customers to adopt and use Moneo and other retailers to install the system, even if current adopters are satisfied with their use of Moneo. Overall, it can be considered that the dynamic adoption generally observed on innovation products is unable to take off and allow the critical mass to be reached.

CONCLUSION

The results of this analysis revealed two essential points related respectively to the exogenous and endogenous processes. On the one hand, according to the estimated results, the security (technological factor), cost and relative advantage (economic factors), and visibility as well as satisfaction (social factors) influence more significantly the process of adoption of Moneo for merchants. Therefore, the links between the various factors are strong. This view joined Lindley's works (1997), which consider the smart card industry as a socio-technical system that requires the support of technological infrastructure, organizational (including economic) infrastructure, and social acceptance. In other words, if we incorporate the technical, organizational, and social considerations as influencing smart card innovation, then the process of innovation can be viewed from within the socio-technical framework. On the other hand, network externalities, even if it was difficult to draw a definitive conclusion, seem to have an important effect on Moneo adoption

To sum up, Moneo is currently cumbersome, expensive, mono-functional, and requires large investment to overcome inertia and reach the critical mass, just as the credit card did. Moreover, psychological factors including individual factors (such as the handling of a transaction, costs, attitude to risk) and group factors (social trends and social interactivity) negatively influence the card adoption process (see Stroborn et al., 2004, on this subject). Hence, what should be done to avoid ongoing convergence towards a failure? We think that aggressive marketing by the various players and the targeting of potential adopting retailers are the first steps towards reaching the critical mass.

First, the main obstacle to the proliferation of the electronic purse and its commercial viability is *mass acceptance*. To ensure or speed up widespread acceptance of this payment technology, a catalyst application may be required as an impetus to use (a transport application, or the adoption by a mass market retailer, for instance) to provide an existing customer and/or retailer user base. Moreover, the electronic purse must be multifunctional, combining systems that can be used in both the real and electronic worlds (Spencer, 2001).

Second, the *suppliers of the product* must enhance their system technologically. They could learn from existing successful electronic purses in other countries, for example the Octopus electronic purse in Honk Kong. The attraction of the Octopus card lies in its simplicity. It does not require contact to be read. The card contains an electronic purse and ticketing application. At rush hour, women can be seen passing entire handbags over scanners, and men do not need to remove the card from their wallet. The contactless system takes only 0.3 seconds to register a payment, compared with one or two seconds for a contact card, not counting insertion and extraction time. This could be an important ergonomic aspect that can influence adoption of the system mainly for merchants.

Third, *strategic development* needs to be reviewed. Although retailers indicate that they would be willing to adopt the electronic purse system only if it provided them with benefits, it seems that there is a gap between expectations and reality. Most analysts think that the electronic purse allows retailers to increase the security of their operations by lowering the amount of cash they have to handle, and is cost-saving by greatly reducing leakage and errors in counting (Srivastava & Mansell, 1998). In practice, interviewed retailers point out that the perceived advantage of a decrease in cash-handling varies according to the size and market presence of the retailer. For smaller retailers, the cash flow at the end of the day makes up a large part of their business incentive: they prefer cash for reasons of accounting and fiscal flexibility. However, for larger retailers, cash-handling is simply costly and cumbersome. Thus, larger distribution networks and chains are more able than independent and small retailers to bear fees and costs, and consequently to adopt the Moneo system.

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ENDNOTES

1. In October 1999, one out of every four calls was paid for by using a Proton card (Van Hove, 2000).
2. Note that the French General Inspection of Finances criticized the lack of security of Moneo. Although this was not the concern of the project promoters, customers or retailers must be given all the information necessary to judge how secure the system is.

Chapter VI
Engineering Banking Applications:
A Service-Oriented Agent-Based Approach

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ABSTRACT

The banking industry has undergone a major change in recent years. Global competition has forced the industry to be more agile and customer focused in all its services. Banks can no longer function in isolation, but have to operate cutting across physical boundaries. Interoperability, scalability, maintainability, and security are the upcoming challenges for the banking industry. This has enthused software architects to develop suitable software development paradigms that can seamlessly integrate business functions across organizational boundaries. This chapter envisages a hybrid approach that uses the service-oriented paradigm along with the software agent technology as a possible solution to the growing issues of inter-and intra-bank operations.

INTRODUCTION

Evolution in information and communication technology (ICT) has radically influenced the business world—how transactions are being carried out, how information is being exchanged, and how business collaborations are being handled. The banking sector is no exception as it plays a vital role in facilitating all kinds of business-related financial transactions. Thus, there is a growing need for the banking sector to keep pace with the emerging requirements of the business sector by adopting appropriate technology for its effectiveness. The emphasis today is on providing banking services anywhere, anytime, to anybody, with the sole objective of enhancing customer outreach and flexibility in transactions. Towards this end, the adoption of Internet banking, mobile banking, core banking, and a range of financial services through different delivery channels holds great promises to bring about a paradigm shift in the banking industry. However, the success of electronic banking system initiatives will largely depend on their effective deployment, interoperability, and automated transaction management. Besides these technical issues, certain basic business needs such as lowering costs, reducing cycle times, integration across banks, greater return on investment, creating an adaptive, and a responsive business model are of paramount importance. The fundamental problem is the lack of a consistent architectural framework within which applications can be rapidly developed, integrated, and reused. Thus, there is a need for a well thought of architectural framework that can facilitate the assembly of components and services for rapid and dynamic delivery of complex services. This should not only cater to the present requirements but must scale up to the needs of next-generation banking systems.

This chapter proposes a hybrid model for engineering banking applications, which are essentially large scale, distributed, and heterogeneous in nature. The model is an integration of service-oriented architectural concepts and the software agent technology. Both the components address two important aspects of building large-scale open systems. The notion of *service* provides a higher level of abstraction for organizing applications in large-scale, open environments. This view of service orientation can provide the basic conceptual building blocks for integrating heterogeneous applications. On the other hand, software agent technology addresses the requirements of autonomy, and reactive and proactive behavior of applications, which are key ingredients of an agile application environment.

BACKGROUND

In order to maintain global competitiveness, the banks today keep introducing innovative financial services for their customers in the form of basic banking services, asset management, investment banking, and a range of online services. Such financial services are accessible through a variety of channels and software applications. Branch office automation, automated teller machines (ATMs), call centers, Internet, e-mail, fax, and mobile devices are some of the means through which it is possible to access any banking service, at any time, in the most convenient manner. But the key challenge here is to develop each application independently and still be able to integrate them whenever necessary. This aspect of banking application development can be appropriately addressed by adopting the service-oriented architecture (Shan, 2004).

Service-Oriented Architecture (SOA)

For a long time, systems were built following monolithic architectures that are highly fragile, customer specific, with non-reusable applications that are tightly coupled. But today there is a shift in the paradigm wherein software systems are built around a loosely coupled principle. There is an evolution in the software design paradigm where software systems are viewed as a collection of interacting service components (Kruger & Mathew, 2004). A service, in this context, refers to a set of functions provided by a software system that is accessible by an application program. In the rest of the text, the word *function* is used to refer to low-level operations, whereas the word *service* has been used as a higher-level concept. Service-oriented computing (SOC) is a computing paradigm that utilizes services as fundamental elements for developing applications (Papazoglou, 2003). The SOC paradigm allows the software-as-a-service concept to handle the delivery of complex business processes and transactions as a service. Further, it enables services to be reused everywhere and by anybody. These features of the service-oriented paradigm can greatly influence the development of banking applications. Services such as core banking, shared use of ATMs among federation of banks, and inter-bank fund transfers require a great deal of interoperability among various banking applications within and across the banks. Moreover, these applications are developed by different vendors and are accessible only through the interfaces provided by the application, as the design details are kept hidden. A service-oriented approach can provide a higher level of abstraction to conceptualize, model, and implement banking applications, and can facilitate flexible interoperation.

SOA allows designing software systems that provide services to other applications through published and discoverable interfaces (Schmidt, 2003). The framework has the ability to accommodate new requirements, and at the same time can integrate different banking applications such as Internet banking, ATM, core banking, and mobile banking. Further, the framework can provide a foundation upon which banks can continue to use their existing applications and, at the same time, build innovative applications like clearance of e-checks, e-bank drafts, and so forth. The benefits of using a service-oriented framework are manifold:

- **Leveraging existing components:** New business services can be constructed as an aggregation of existing software components, simply by referring to the interface without any concern of internals of a service as well as the complexities of service composition.
- **Ease of development and deployment:** Applications can be developed and deployed in a consistent manner across heterogeneous applications and implementation platforms.
- **Faster time-to-market:** Use of standard service libraries can dramatically reduce the time-to-market. This is because the use of service components can reduce design, development, testing, and deployment time and effort.
- **Reduced cost:** Evolving business demands may require enhancement of existing services and even creation of new services. In such cases use of service-oriented framework and the service library can substantially reduce the cost.
- **Risk mitigation:** Reusing existing service components can reduce the risk of new failures while enhancing or creating new business services.
- **Continuous business process improvements:** As the service-oriented framework clearly represents the process flows, it is easy to monitor business operations and workflows such that improvements can be made by the experience gained over a period of time.

Software Agent Technology

The concept of software agents has attracted many software architects to build systems with software components that can exhibit certain pragmatic attributes such as reactive and goal-directed behavior, autonomy, and communication ability. Though there is no universal agreement on what an agent is, there are several commonalities in the definitions, namely, autonomy, social ability, reactivity, and pro-activity (Wooldridge, 1995; Jennings, 1998). Software agents possess knowledge about their environment, namely, the presence of other similar agents with their roles and services that those can offer. Agents adopt reactive behavior in response to events that are realized through message communication and that trigger the execution of appropriate internal processing.

At the same time, agents also exhibit proactive behavior by taking initiatives as and when the situation demands, and they send messages to other agents. Such characteristics of agents make them suitable for applications where human-like flexible behavior is desired in coordinating and controlling organizational processes (Blake & Gomaa, 2005).

Agent-oriented system development methods have been successfully applied to a number of applications. In Fox, Barbuceanu, and Teigen (2000), agents with different functionality—namely, order acquisition agents, logistics agents, transportation agents, scheduling agents, and so forth—are used to manage dynamic supply chains. Agents have also been applied to manufacturing processes (Huang, Gou, Liu, Li, & Xie, 2002). Agent-based infrastructure has been envisioned in Matos (2004) to provide specialized healthcare services to elderly people. In Li, Shen, and Ghenniwa (2004), an agent-based solution has been provided to integrate distributed and heterogeneous product data across enterprise boundaries. In Shen (2004), software agents have been used for information and knowledge sharing among customers, suppliers, and business partners in manufacturing enterprise networks. In Singh and Huhns (1999), agents have been used in the management of business workflows. An agent-based information infrastructure has been proposed in Patra and Moore (2000) to facilitate information access for manufacturers intending to collaborate on joint manufacturing projects. Huhns (2002) advocates agents as the enabling technology for realizing Web services.

With the success story of agent technology for varieties of application areas, it is quite natural to extend the agent-oriented thinking to the development of banking applications. The distributed nature of banking applications and the need for a greater degree of automatic processing capabilities can be supported by the agent technology. Software agents as a technology have a major strength over regular software objects, especially when connectivity across organizations is required. Usually, objects are accessible only inside a computer program, but agents can be implemented as distributed services that communicate through a public protocol such as RMI (Sun Microsystems, 2003), CORBA (Orfali, Harkey, & Edwards, 1997), SOAP (W3C, 2003), ebXML (2003), or Jini (Oaks, 2000). All of these protocols make agents accessible through the Internet. With the proliferation of internetworking, the software agent paradigm is gaining popularity among the developers of large, distributed, real-time systems. This emerging field can support conceptual and programmatic encapsulation of autonomous, goal-driven behavior for a wide variety of banking applications. Software agents can assist in making decisions autonomously during real-time operations such as raising an alert message in the event of an illegal operation by a customer. Agents can encapsulate certain business/application logic and can offer multiple services that can be processed concurrently. These are some of the features that can go a long way to support the emerging trends of banking applications such as electronic payment systems, real-time gross settlements, disaster monitoring and the automatic execution of business process continuity plans, and the management of financial messaging systems. Further, software agents can be deployed at strategic locations in a bank's computing infrastructure to gather relevant data during transaction processing. Such data sources can be analyzed through data mining techniques to extract useful information for tracking malicious activities, and also for strategic financial decision making.

Integration of SOA and Software Agents

The integration of service-oriented technology and software agents can bring about immediate benefits of connecting application domains such that service components can invoke agent services and vice versa. The central theme of this chapter is to identify the means for connecting software agents and service-oriented technology. To the consumers of different services, agents can be a powerful means of indirection, by masking the service-provisioning internals for purposes of redirection, aggregation, integration, and/or administration. Here, we would like to bring a distinction between the words *consumer* and *customer* as used in the text. The word *customer* has been used in the context of a bank customer from the business point of view. Thus, the word *customer* would always refer to a human being. On the other hand, the use of the word *consumer* is more generic, in that it refers to an entity (human and/or software application) that makes use of a service provided by another entity. For example, a computer program (*consumer*) can use the data (service) provided by a database server. *Redirection* describes situations where a service may no longer be available for some reason, or the service needs to be temporarily redirected to another service-provisioning unit without affecting the consumer of the service. *Aggregation* allows several services to be composed into logically interconnected clusters providing abstractions of behavior that can be invoked through a single service interface. *Integration* describes the means of provisioning services to the consumers already using or planning to use certain services. Finally, *administration* deals with aspects of automated service management where software agents autonomously administer one or more services with no/limited intervention from humans.

The chapter draws motivation from closely observing the evolving needs of the banking industry and the customers at large. The aim of the chapter is to provide a pragmatic framework around which banking applications can be engineered while addressing the issues and challenges of the present time and the future banking industry. The current trend has been to simplify customer accessibility to different banking services irrespective of location and nature of the service being accessed. Moreover, the banks would like to have the flexibility of updating their services or introducing new services with minimum surprise to the existing customers so that customers can continue to access the services almost in the same manner as in an old system. This is even more important while integrating new applications to legacy systems. The concept of service would enable one to consider a legacy system as a service component and it can be invoked by other service components. There is also need for scalability of applications wherein one has to deal with the ever-growing volume of customer transactions. In the backdrop of such requirements, one must work out an appropriate strategy to engineer applications.

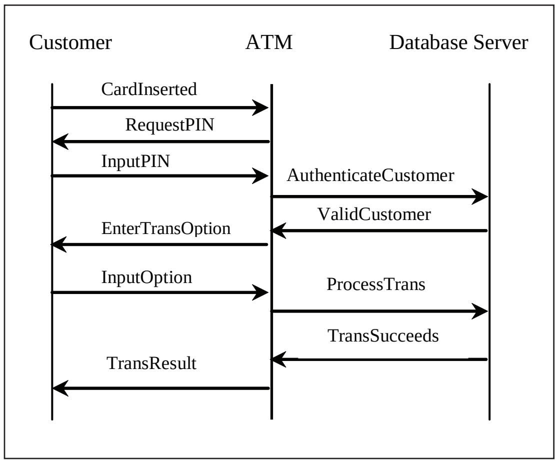
ENGINEERING BANKING APPLICATIONS USING SOAg

Banking applications can be engineered using the service-oriented agent (SOAg) paradigm where basic banking services can be deployed as software agents. The very nature of SOA can help one to describe services as self-describing, platform-agnostic computational elements that can support rapid, low-cost composition of distributed banking applications such as the electronic fund transfer (EFT). Using the notion of services, banks can expose their services programmatically over the Inter/intranet using standard (XML-based) languages and protocols.

SERVICE-ORIENTED METHODOLOGY

The focus of service-oriented methodology is to identify basic services from an application domain and map them into agent functions. Services are externally observable behavior of a software/hardware component which possibly hides the internal processing details that are required for

Figure 1. Internal operations behind the interface



the realization of a requested service, and are accessible only through a set of well-defined interfaces. Thus, a *service* can be viewed as an abstraction of a set of well-defined functions that are available to its user. The functions are realized through certain internal processing that may not be visible to the user of the service. The processing can involve the execution of certain components either in isolation or in unison with the execution of other components through a process of orchestration. We refer to them as *service provisioning components* that encapsulate necessary operations to deliver the basic service for which it is designed. Thus, in simple terms, one can view a *service* as the outcome of certain processing. For example, a bank can provide certain basic services to its customers such as opening/closing an account, balance enquiry, deposit/withdrawal of amount, and so forth. Each of these services requires certain internal processing that is not visible to the customer. For instance, consider a customer transaction at a bank's ATM where the customer only responds to certain display prompts on the ATM screen, which serves as an interface. Actually, the customer neither has the knowledge nor any control of the internal processing that takes place in response to each of his or her inputs. A simplified picture of an ATM operation is portrayed in Figure 1 as a sequence diagram. The arrows to the left of the line titled "ATM" represent the activities at the interface that are visible to the customer, whereas the arrows on the right represent the internal activities taking place behind the interface that are not visible to the customer.

Service Granularity

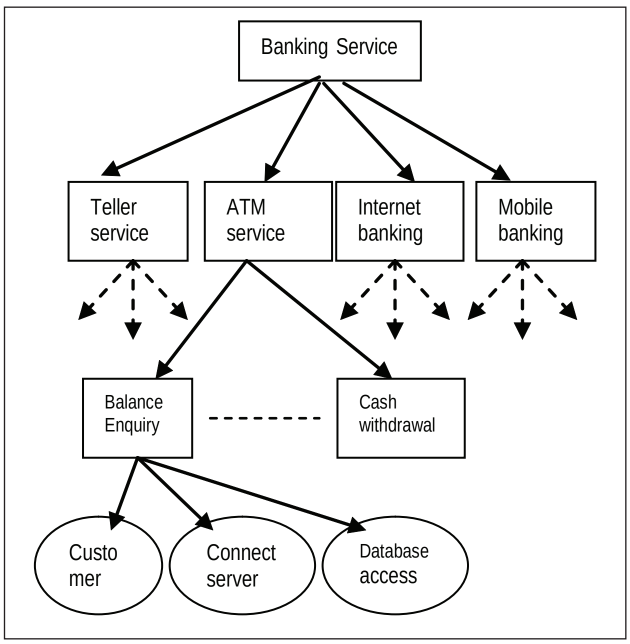
One of the interesting aspects of using the term *service* is to decide whether such a terminology can be used in a given context. Let us consider *banking* as a service. This in turn offers several services such as teller, ATM, Internet banking, mobile banking, and so forth. Each of these services can further be broken down into a set of lower-level services. For instance, an ATM service can provide a set of lower-level services, such as *balance enquiry*, *cash withdrawal,* and *payment for utilities.*

This can go on further to lower-level services, possibly leading towards a recursive definition of service. This may complicate the scenario for conceptualization. In order to avoid such a recursive definition of service, we consider the problem as a matter of granularity and leave it to the designer to use his or her judgment while using the term *service* in a given context. However, we would prefer to use the term *function* if it involves execution of certain primitive operations that help in the realization of a service that the user wants. As a rule of thumb, the ones directly accessible to the user can be termed as *service*. For instance, we would consider *balance enquiry* as a service because it is directly accessible to the customer. Now the operations that are necessary to make the service available would be referred as *functions.* In order to facilitate a *balance enquiry* service, one would need functions like customer authentication, connection to database server, and access to customer records in the database. It is evident from the illustration that the functions are not directly accessible to the customer when he or she requests a *balance enquiry* service. Thus, service is considered a coarse-grained concept that can be decomposed into finer-grained concepts, which can still be termed as services, but beyond a particular level one would prefer to call those functions instead of services. In a broader sense, one can view a service as a logical component and the functions as the technical components that represent software parts that are to be executed in order to implement a service. This basically prompts one to think of a service hierarchy with a coarse-grained service at the root level, and finer-grained services at the subsequent levels up to a leaf level that consists of only functions. A hierarchical arrangement of services in a banking scenario at a different level of granularity is depicted in Figure 2.

Service Point

We introduce the notion of *service point*, which refers to a physical or logical unit where users' requests for services can be processed. Essentially, a service point provides a set of well-defined services, which can be invoked by interested users through appropriate service requests. A service point publishes certain high-level services (represented at the root level of a service hierarchy)

Figure 2. Service hierarchy



through its interface, which is made available to users. This notion helps one to model a loosely coupled distributed application environment as consisting of a set of service points. For instance, an ATM can be considered as a service point as it facilitates high-level services like *balance enquiry, cash withdrawal, payment for utility,* and so forth.

Service Composition

Upon receiving a service request, a service point does the necessary internal processing to deliver the requested service, if it is capable. The service point realizes the service by invoking one or more fine-grained services and/or low-level functions. The process of enabling a service with the help of a set of fine-grained services is referred to as *service composition* or *service orchestration*. Thus, upon receiving a service request, a service point tries to facilitate the required service by using the services that are already available with it. This involves selecting the services and determining the order in which those are to be orchestrated for realizing the service under consideration. How a service request for cash withdrawal has been orchestrated with the help of two finer-grained services, namely "User Authentication" and "Balance Check," is shown in Figure 3.

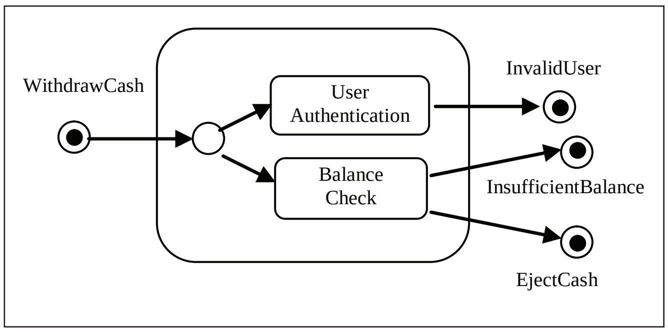
Service Collaboration

There may be occasions when a service point receives a service request that cannot be composed with the help of the finer-grained services and/or primitive functions available with the service point. However, it may be possible on the part of the service point to collaborate with other service points that it is aware of (along with their service capabilities) and try to facilitate the requested service. Such a collaborative effort to realize a service is termed *service collaboration* or *service choreography*. Consider the example of an electronic fund transfer that involves two different banks, for instance the payer has an account in bank A, and the payee has an account in bank B. When the payer invokes an EFT service through an Internet banking facility extended by his or her banker, the request cannot be handled immediately because it also has to contact the database server of the payee through the appropriate payment gateway. Thus, such a service requires choreography of certain external services extended by other service points.

Service Enactment

The above description helps us to categorize the services into three distinct service types, de-

Figure 3. Service orchestration



pending on the nature of the processing required at a service point for responding to a service request.

1. **Readily available services:** These are services that do not require complex processing. For instance, a customer wants to know about the deposit schemes, loan facilities, and interest rates in a bank. Such a request basically requires certain static information, which can be made available by directing the request to a relevant Web page. A low-level function can handle such a request.
2. **Composable services:** These services are not readily available, but require further processing, possibly invoking a set of fine-grained services and/or low-level functions available at a service point. For example, a service like *payment for utilities*, in which a customer can pay for the electricity bill through an ATM, in turn would invoke certain basic services like *balance enquiry* (which checks whether the customer has the required amount in his account) or *fund transfer* (which transfers the specified amount from the customer's account to the indicated account).
3. **Collaborative services:** These are services which are neither available readily nor can be composed using the fine-grained services/functions available at a service point. In such a case, a service point needs to explore whether the requested service can be choreographed using the services of other service points. For instance, in a supermarket, a customer would like to pay via credit card (i.e., avail *payment through credit card* service). The EDC machine at the supermarket would request for a *check balance* service, a *debit amount* service at the issuing bank server, a *credit amount* service at the acquirer bank server, and so on.

Irrespective of the way a service is realized, the relevant service provisioning components (i.e., low-level functions and fine-grained services) and the remote services are to be explicitly invoked. We refer the act of initiating and carrying out all necessary processing for the realization of a requested as *service enactment*. A service-oriented agent deployed at a service point can initiate and monitor the execution of the entire service enactment process. Whenever the service point receives a request for service, the SOAg creates a service instance and monitors it until the final delivery of the service. Thereafter, the service instance is destroyed after maintaining relevant information regarding the final outcome of the service enactment process for future reference.

A CASE STUDY ON ELECTRONIC CHECK PAYMENT SYSTEM

A bank (the issuing bank) issues e-checks to its customers, and a customer (the *payer*) can use such checks while making payment to a party (the *payee*). Upon receiving an e-check, the payee produces it to its own bank (the *receiving bank*). The receiving bank then forwards it to a *central clearinghouse*, after verifying the authenticity of the payee. Next, the central clearinghouse verifies the authenticity of the bank sending the e-check and contacts the issuing bank to validate the e-check with respect to the payer's identity and balance. If the validation process succeeds, the payer's account is debited and the receiving bank is instructed to credit the same amount to the payee's account. The central clearinghouse periodically sends bank-wise consolidated information to a *settlement center* where the inter-bank fund transfers are maintained. While forwarding an e-check, at every stage of the entire e-payment process, a sender has to put its digital signature on the e-check for the purpose of sender-verification. This aspect is not handled in this chapter, with the assumption that a public key infrastructure is in place to deal with it. Further, appropriate acknowledgment/error messages are generated and conveyed to the relevant entities during the execution of an electronic payment transaction.

In a real-life scenario, human beings would monitor the entire process at the relevant processing stages. But as we envisage a completely automated system, monitoring of all activities are to be executed by appropriate software components running at the respective servers—namely, issuing bank server, receiving bank server, and central clearinghouse server. This requires the deployment of appropriate technology that can possibly do the same thing as a human being would have done under similar situations. In keeping with the current trend, we feel the suitability of service-oriented agents to be a possible solution to the problem. In the following section, we depict a multi-agent environment where software agents take the role of human counterparts in executing an entire cycle of electronic payment transaction activities.

Agent Environment and the Enactment of Roles

Here, we provide the description of an agent environment that is populated by agents enacting the roles of *payer, payee, receiving bank, issuing bank,* and *central clearinghouse.* We designate the agents as *PayerAg, PayeeAg, RBankAg, IBankAg,* and *CCAg* respectively. When a payer intends to make a payment through an e-check, it uses an appropriate interface of the e-payment system

Table 1. Possible message types and their semantics for use

Message Code	Message Type	Message Description
M0	Ack	Acknowledgment message
M1	Party_Unknown	The sender of the message is unknown to the receiver
PrM2	Submit_Check	PayerAg submits check
PyM3	Deposit_Check	PayeeAg deposits check with RbankAg
RM4	Solicit_Clearance	RbankAg sends check to CCAg for clearance
CM5	Solicit_Debit	CCAg sends check to IBankAg for debit
ICRM6	Invalid_Payer	Payer is verified to be invalid
ICRM7	Inadequate_amt	IBankAg informs CCAg about inadequate amount
ICM8	Debit_mesg	IBankAg informs CCAg that amount has been debited to payer’s account
CM9	Pl_Credit	CCAg instructs RbankAg to credit the amount
RM10	Credit_mesg	RBankAg informs PayeeAg that amount has been credited to payee’s account
PyM11	Ack_payment	PayeeAg acknowledges to PayerAg about receipt of payment

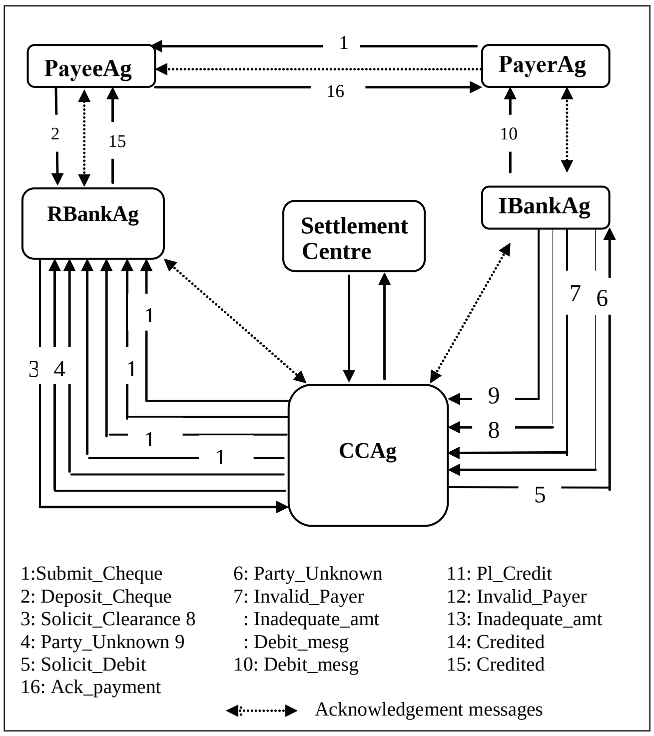
whereby a PayerAg is instantiated. The human payer fills in the required particulars and sends it to the payee. The payee, upon receiving the e-check, submits it to its bank, which is gathered by the RBankAg deployed at the receiving bank server. The RBankAg then verifies the authenticity of the depositor, and depending on the outcome, it either informs the depositor with an "invalid customer" message or passes the e-check for further processing at the CCAg, deployed at the central clearinghouse server. The CCAg, in turn, verifies the authenticity of the RbankAg, presenting the e-check for settling the payment. If the e-check authentication process succeeds, then CCAg contacts the IBankAg, deployed at the issuing bank server to verify the payer's identity and balance; otherwise, messages of the type "invalid payer" and/or "invalid check" are sent back to the RBankAg for further transmission to the payee. If the e-check is valid, then CCAg sends a message of the type "debit payer account" to IBankAg and a message of the type "credit payee account" to the RBankAg.

Inter-Agent Communication Model

The agents communicate with each other by using messages that are derived from a domain-dependent ontology. The use of ontology-based message communication actually drives the behavior of agents, instead of hard-wired implementation. This enables agents to flexibly adopt appropriate action while enacting their roles in the e-payment system. Table 1 lists the ontology of possible message types along with their semantics for use by the agents when they drive the entire e-payment process. Agents drive the e-payment process by communicating messages at the appropriate time and to the appropriate agent by sending an appropriate message in structured format.

A flow diagram of the overall inter-agent interaction model is depicted in Figure 4.

Figure 4. Agent interaction model



Each agent carries a workflow model of the activities that it has to execute while assuming a specific role. This model ensures that an agent performs appropriate actions as depicted in the workflow. The workflow model available with a RBankAg is depicted in Figure 5.

SERVICE-ORIENTED AGENT ARCHITECTURE

A software agent is composed of a set of well-defined functional components that execute instructions to exhibit appropriate agent behavior. The block diagram in Figure 6 depicts the functional components of an agent that inter-operate in a concerted manner to process the events (arrival of messages) and take appropriate action(s) by triggering internal processing and/or external actions by sending messages. The *communication manager* receives incoming messages at the agent's external interface and passes them on to the *agent control* for interpretation. It also sends messages to other agents as a result of some internal processing. The *agent control* interprets incoming messages and instructs other modules for appropriate action. It also performs certain actions proactively when needed, while executing a workflow. For example, upon receiving an e-check clearance request, the *verification* module is invoked to verify the identity of the customer by consulting a customer database. When a message is to be sent, the *message template manager* is delegated with the task to do what is needed by selecting the appropriate message type. The most important module is the *workflow manager,* which monitors the execution of the part of the workflow with which the agent is entrusted in a given role. The workflow specifications can be made available to the agent through an XML document.

BENEFITS OF THE PROPOSED TECHNOLOGY

The proposed technology is a low-cost alternative for application integration. This is important for the banking industry, as individual banks develop their applications either in-house or through third-party vendors. As a result there is no uniformity in the applications. Service-oriented technology can support interoperability among such heterogeneous applications through a publish/subscribe interface such that most of the implementation details of an application are kept hidden and the functionalities are only exposed through certain

Figure 5. Workflow for the receiving bank

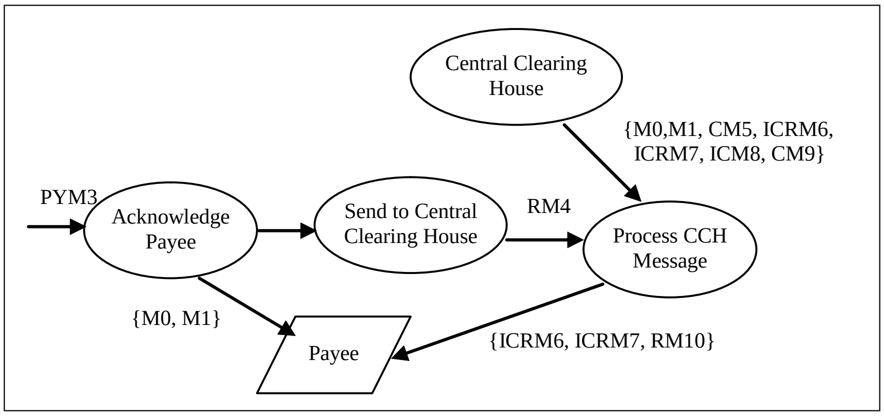
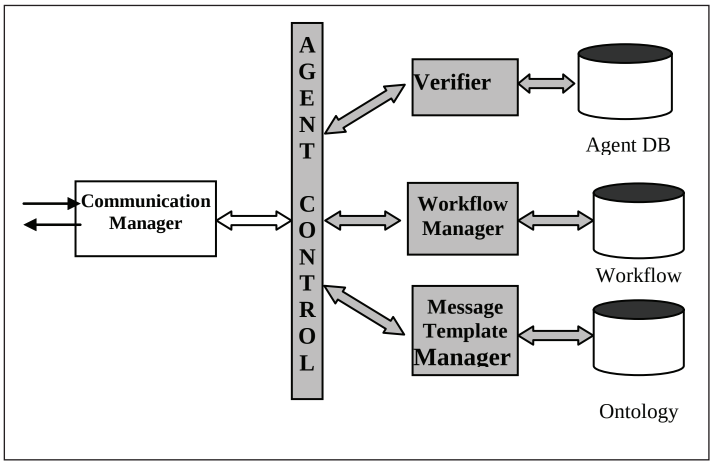


Figure 6. Agent architecture



published services. The use of business process execution language for web services (BPEL4WS, 2002) in the orchestration of services during inter-bank operations can considerably reduce the implementation cost due to the use of open standards. Further, service-orientated technology can facilitate reuse and portability of service components. A service written in BPEL4WS is independent of any software vendor, and thus can be imported and reused as many times as necessary. From the viewpoint of business benefits, then, the investment made in building the software component as a service can be reused in several applications, justifying the ROI. Moreover, the service-oriented paradigm will enable the banks to continue using their legacy applications without overhauling all existing systems. This is possible by building wrappers on top of the legacy applications, which can hide the internal details but allow the functions to be visible as services. However, one can go for a complete changeover in a phased manner for efficiency reasons.

CONCLUSION AND CHALLENGES

This chapter presents a conceptual framework to build banking applications, which are inherently distributed, large scale, and dynamic in nature. The growing need for interoperability among banking applications is highlighted through different application scenarios. The real challenge lies in the selection of a suitable system development paradigm. The chapter shows how the service-oriented agent-based paradigm can be used in conceptualizing and implementing banking applications. Though the service-oriented agent-based approach provides the necessary abstraction for conceptualizing applications, much still needs to be done in standardizing the use of the supporting technology, be it XML, SOAP, or WSDL. The service-oriented approach enables one to develop banking applications as service components, which can be seamlessly invoked while executing complex distributed transactions across banks. Besides this, the agent-based approach can automate many of the activities that would otherwise require a lot of human intervention. This is an essential requirement, especially when one has to process a large volume of transactions efficiently and in a timely manner. In short, the proposed hybrid approach based on the two emerging technologies—service-oriented technology and agent technology—has the potential to provide a pragmatic solution to many of the upcoming applications of the next-generation banking industry.

Though the proposed paradigm holds great promises, there are a number of challenges for its successful adaptation in the banking sector. An insight into a number of challenges and research efforts can be found in Janssen, Gortmaker, and Wagnenaar (2006). One of the major challenges is to ensure that the processes, which implement inter-bank operations, are reliable, otherwise a failure in one subsystem could disrupt the entire process. The second challenge is to provide information integrity and security, because data is accessed from a number of heterogeneous systems under different administrative controls. Yet another issue relates to the performance, because once interoperation is permissible, some of the service components can be heavily loaded and therefore would require proper load balancing. Finally, the use of this rather emerging paradigm would require standardization at different levels for wider adaptation.

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Chapter VII
Smart Cards in the Banking Industry:
Challenges, Competition, and Collaboration in the 2000's

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ABSTRACT

This chapter is concerned with the challenges of smart cards as a system innovation in the banking industry. System innovation is the innovation that cannot be adequately introduced by a single entity and is likely to fail unless two or more parties collectively accept the innovation. The study aims to understand the network system nature of smart cards. The comparative study of previous bank card innovations (ATM/cash cards, credit cards, EFTPOS/debit cards) suggests a collaborative approach to reduce the risk of competitive innovation in the case of smart cards. However, the current situation reflects the competition among the powerful players. Unless innovators in the smart card industry see the benefits of collaboration, the diffusion of smart cards may not happen. Innovators may use an empirical analysis in this chapter to define a strategic approach for their plan to compete in the smart card industry.

INTRODUCTION

This chapter is concerned with the challenges of smart cards as a system innovation in the banking industry. System innovation is the innovation that cannot be adequately introduced by a single entity and is likely to fail unless two or more parties collectively accept the innovation. The objective of this study is to understand the network system nature of smart cards. The smart card industry involves the network collaboration whereby the launch of multi-functional financial smart cards needs linkages between players in the industry for the successful delivery and commercialization. However, the smart card industry at present reflects the situation where Visa, MasterCard/Mondex, Proton World, Microsoft, and Sun Microsystems compete to establish their operating system technology as standard (Visa—the Open Platform, MasterCard/Mondex—Multos, Proton World—Proton, Microsoft—Windows for Smart Card, Sun Microsystems—Java for Smart Cards). In order to better understand the development of smart cards, the analysis of the previous innovation development of ATM/cash cards, credit cards, and EFTPOS/debit cards is undertaken. The comparative study of the innovation in the cases of ATM/cash cards, credit cards, and EFTPOS/debit cards shows that innovators enter into collaboration to work on the complexities/difficulties of innovation and to maximize the benefits in terms of extended scope of card-based services. The analysis in this chapter provides important insights into the complexities/difficulties of smart cards, the challenges, competition, and collaboration. The competitors launching the smart card innovation may use an empirical analysis in this chapter to define an strategic approach for their plan to compete in the smart card industry.

The chapter is organized into four sections. Following this introductory section, background information is presented about innovations in the financial service industry, and the distinction between the bank cards using mag-stripe technology and smart cards using chip technology. Smart cards with are overviewed with regard to the costs and their advantages and disadvantages. The concepts of innovation system approach, standards, and network externalities effects are also reviewed to lay a background for the discussions of the smart cards electronic payment system. The next section discusses the complexities/difficulties of multi-functional financial smart cards in comparison with those of ATM/cash cards, credit cards, and EFTPOS/debit cards. The analysis of the complexities/difficulties along the process of innovation provides the reasons why innovators in the smart card industry should adopt the collaborative strategy. Studying the development of ATM/cash cards, credit cards, and EFTPOS/debit cards compared with smart cards helps us understand the challenges, future trends, and directions, as well as gives us a foresight on what should be the best way forward in exploiting the smart card innovation. The final section concludes the chapter with a summary of the main findings.

BACKGROUND

Innovations in the Financial Service Industry

The term innovation deals with both product and process innovation. Product innovation involves a change in the way products are produced in the market, and process innovation involves a change in the technology and process of supply or distribution of a product (Barras, 1986; Tidd, Bessant, & Pavitt, 1997). In the banking industry, the technological innovation designed to cut branch overhead costs or to improve the delivery of a given service is called process innovation, whereas innovation of a new financial product or service is called a product innovation (Smith & Wield, 1988). Often product and process innovation are interactive—as changes of process can lead to changes of product and vice versa. As a result, delivery of production and the generation of consumption often take place conterminously (Miles, 1993; Gallouj & Weinstein, 1997). For example, the development of automatic teller machine (ATM) for cash dispensing provides a new financial service channel because it allows banks (or potential competitors) to own a new relationship between consumers and their banking service providers. The benefits of ATMs are therefore not simply a matter of cheap costs, but the beneficial value of the incremental businesses sustained by the existence of ATMs.

The service sector is described as the tertiary sector, with raw materials the primary sector and manufacturing the secondary; it may encompass the transformation of material goods, people, or information (Miles, 1993). Service is also defined by Gallouj and Weinstein (1997) as an act or process of operations where the characteristic (provision) is intangible. Service sectors are the dominant users of information technology, specifically in financial services sector where banking is at the forefront of innovations in the use (not the creation) of information and communication technologies (ICTs) (Barras, 1990; Miles, 1993, 1994; Srivastava & Mansell, 1998). The technological change in commercial banking is radically transformed by ICTs (e.g., marketing financial innovations through electronic transfers) (Greenspan, 1994; Consoli, 2005).

There are factors that have effects on the progression of innovations. The concepts of factors determining the progress of innovation development include technology push (Schumpeter, 1939), demand pull (Schmookler, 1962); or their interaction (Freeman, 1982). The Schumpeterian hypotheses of dynamic competition stress the role of competition in innovation, down-playing the role of collaboration. This may be because collaboration is not a sustainable way to innovation. Dodgson (1992, 1993) and Macdonald (1992) argue that collaboration slows innovation because it may end up in direct competition between collaborating firms or in dispute over ownership of the outcomes. Rothwell (1991) argued that innovation arises out of the interaction of a network of companies, and in his fifth-generation model (Table 1), he has stated that innovation is becoming faster as a result of collaboration (Rothwell, 1992a, 1992b).

What is the Smart Card Innovation?

Smart cards are plastic cards that can, like the magnetic stripe, store data, albeit megabytes rather than bytes, but they differ in that smart cards contain a microprocessor, a miniature computer that can manipulate and update the data, control access to data, perform calculations, and support digital interfaces such as wired and wireless telecom computer networks. They also have the capability of interchanging data with external communicators—ATMs, telephones, or readers. The capacity of the chip is large enough to support multiple applications and house a variety of identification and security tools, such as digital certificates for safeguarding Internet transactions and biometric identification (Wonglimpiyarat, 2005). Table 2 shows the difference between magnetic stripe technology and smart card technology.

Table 1. Rothwell's (1992b) five generations of innovation models

Generation	Key Features
First	Technology push: simple linear sequential process
Second	Need pull: simple linear sequential process
Third	Coupling model: recognizing interaction between different elements and feedback loops between them
Fourth	Integrated model: integration within the firm, upstream with key suppliers and downstream with demanding and active customers, emphasis on linkages and alliances
Fifth	Systems integration and extensive networking model: flexible and customized response, continuous innovation

Table 2. Comparison of magnetic stripe card technology and smart card technology (Adapted from Bright, 1988; Brown & Brown, 1987; Gandy, 1999; Kaplan, 1995; Wonglimpiyarat, 2005)

	Magnetic Stripe Technology	Smart Card Technology
Functionality	• Mono-functionality	• Multi-functionality
Memory capacity	• 140 character	• 8-bit, 16-bit, 32-bit microprocessor
	• Limited storage capacity and hence can only be used with single application	• Increased storage capacity to support multiple applications on one card
Infrastructure and processing	• Very high network and central processor costs for online real-time verification	• Off-line readers with information about transactions downloadable after the transaction at lower cost
	• Require transactions clearing and settlement for the users	• No requirement of a third party to settle and clear transactions
Programmability	• Cannot be programmable	• Can be programmable to support complex, memory-intensive products
	• Does not allow for reloadable value	• Allows for reloadable value
Security	• Visual inspection of signature, PIN verification, online verification	• Digital signatures, encryption, digitized photographs, retina scans, fingerprints, etc.
	• Less secure, open to fraud	• More secure, lower fraud loss

The smart card innovation is an enhancement of existing bank card services and/or the addition of new services that a financial institution delivers to its customers via a chip card. The advantages of smart cards are that they are more versatile and powerful than magnetic stripe cards. The greater memory capacity of smart cards enables the card to perform multiple functionalities. Smart cards also offer greater security than magnetic-stripe cards. However, the disadvantages of smart cards are the cost of the cards and the cost of installing new devices or adapting existing terminals to read the cards. The typical cost of a smart card is £3. The contactless smart card cost ranges from £7 to £14, depending on the size of the memory. In order to deliver smart cards for financial applications, EFTPOS terminals need to be equipped with smart card reader slots and ATMs need to be upgraded to be capable of accepting both existing magnetic stripe cards and smart cards. For the upgrades, this requires capital expenditures of up to £1,300 for an ATM terminal and up to £600 for an EFTPOS terminal in order to cope with smart card technology. The high costs have raised serious questions concerning who should pay for the infrastructure (upgrading terminals and installing new software) to support the smart card innovation (Wonglimpiyarat, 2005).

System Innovation

The concept of system innovation in this study is based on the theoretical foundations of the sectoral systems of innovation (Malerba, 2002) and the national innovation systems (Cooke, Uranga, & Etxebarria, 1997; Freeman, 1987; Lundvall, 1992, 1993, 1998, 1999, 2003; Lundvall, Johnson, Andersen, & Dalum, 2002; Nelson, 1988, 1993; Edquist, 1997). An innovation system can be viewed at different levels: national, regional, sectoral, or technological. All these levels involve the generation, diffusion, and use of technology (Carlsson & Stankiewicz, 1995; Carlsson, Jacobsson, Holmén, & Rickne, 2002). The sectoral system is about links and interdependencies and sectoral boundaries. The boundaries of sectors include linkages among related industries and services. The dynamic interaction of activities in the boundaries then triggers growth and innovation. The national innovation system is the interactive system of institutions, private and public firms, universities, and government agencies aiming at the production, diffusion, and exploitation of knowledge within national borders. This concept is quite broad as it includes industries, firms, and other organizations.

In this study, the level of analysis is an innovation level. Based on the theoretical foundations, the term 'system innovation' is defined as an innovation where the benefits increase disproportionately with the use and diffusion of the innovation among users. Most of the benefits are external to any potential innovator of the product or process and accrue to a wide range of users and uses. To put it another way, system innovation can be viewed as an innovation that cannot be adequately introduced by a single entity and is likely to fail unless two or more parties collectively accept the innovation (Wonglimpiyarat, 2006). The characteristics of system innovation are:

- Inter-operability among third parties.
- Investment in assets specific to the system by more than one party.
- Use of extensive software (protocols, procedures) as well as hardware.

According to Shy (2000), the banking industry is a network structure and has the following characteristics:

- Complementarity, compatibility, and standards.
- Consumption externalities.
- Switching costs and lock-in.
- Significant economies of scale in production.

These characteristics deal with the smart card industry as well as the smart card-based service industry since they affect the potential consumers to adopt the smart card technology. The smart card industry can be seen as a system based on a technological infrastructure of which the process of innovation is associated to technical, organizational, and social considerations (Lindley, 1997). On the technical side, the issue of standards is important to support the diffusion of smart cards. The creation of industry standard helps attract more use of the innovation from its capability in compatibility and interoperability (Rogers, 1995; Hawkins, Mansell, & Skea, 1995; Shy, 2000). In the case of smart cards, it may be difficult to see the diffusion of innovation without the industry standards. This is because the economic function to reduce transaction costs may not occur without a common platform for utilization.

Standards have potential adoption effects. The adoption of technology depends, to a certain extent, on the network externalities effect, the degree of compatibility of new technologies with old technology, and the technology growth rate and consumer population size (Shy, 1996; Gandal & Shy, 2001). In the network externalities literature, collaboration is often seen as a means to ensure adoption. Firms with large existing networks (particularly specific purpose networks) tend to be against collaboration and innovation and vice versa. In other words, when firms enjoy large market shares with existing proprietary procedures and routes to customers, they tend to resist innovations that provide shared or open procedures (Katz & Shapiro, 1985, 1986). Smart cards for financial applications (smart cards for debits/credits, e-cash, or multi-application smart cards that have the banking application interacting with non-banking applications) have the complexities/difficulties that require the capabilities beyond those of any single firm to provide. The complexities/difficulties of multi-functional financial smart cards (Table 3) then suggest the use of collaboration to realize the full potential of the innovation.

The analysis of the case study of multi-functional financial smart cards would indicate the need for collaboration (interworking of the industry) to extend the scope of service. The case of Sony FeliCa chip and NTT DoCoMo e-wallet implementation provides a good example of cross-industry collaboration to support the smart card implementation. FeliCa is a wireless smart card chip developed by Sony Corporation and Royal Philips Electronics for use in a mobile wallet. The collaboration among the mobile telephony, travel, and banking industries enables the development of the mobile wallet in financial services. The cellular handset can then be used as an electronic wallet for commuter passing, making e-purchases, and wireless shopping. It can be seen that, without collaboration, the diffusion of smart cards may fail to achieve the potential that the innovation could command. The next section will show the benefits of collaboration where innovators could extend the scope of service beyond the limited scope of their own without having to involve the high cost of investment. The extended scope of card usage (as a result of network externalities effect) can be regarded as a great benefit to customers whose accessibility to banking services would be highly improved.

SMART CARDS ELECTRONIC PAYMENT SYSTEM

The analysis of the complexities/difficulties in the development, delivery, and marketing of bank card innovations and the use of collaboration in the cases of ATM/cash cards, credit cards, and EFTPOS/debit cards compared with multi-functional financial smart cards is shown in Table 3.
Figure 1 shows the progress of bank card innovations from competition (proprietary networks) towards collaboration (collaborative network). From the analysis of the complexities/difficulties along the process of innovation (Table 3), it can be seen that innovators in the bank card industry entered into collaboration (joined the larger networks) to maximize the benefits to them. In the case of ATM/cash cards, innovators linked up their proprietary ATM networks to form interconnected networks—international networks of Visa Plus and MasterCard Cirrus, which allow the cards of one institution to be used at ATMs worldwide. The use of collaboration then progressed the innovation into an open system—Visa and MasterCard in the case of credit cards, and Switch and Visa Debit in the case of EFTPOS/debit cards.

The analysis (Table 3) has shown that a collaborative approach is preferred by innovators because:

1. It reduces the absolute size of risks and capital involved.
2. It reduces the risk of competitive innovation.
3. It provides innovation with opportunities to leverage innovators' resources according to their comparative advantage.

The major lesson learned from Figure 1 is that all the previous bank card innovations begin with competition and progress into collaboration. ATM/cash cards, credit cards, and EFTPOS/debit cards have reached a level of wide adoption from the link up of proprietary networks to form the global networks (the link up to form global ATM/cash cards in the 1980s, credit cards in the 1970s, and EFTPOS/debit cards in the 1990s). Thus, there are challenges regarding a possibility of linking up the competing networks to support the adoption of smart cards. The future of smart cards as a combination of financial and non-financial applications would be difficult unless the players in the smart card industry reduce the degree of competition.

Tables 4 and 5 present the characteristics of system innovations in the bank card industry.

Table 3. Analysis of complexities/difficulties in the development, delivery, and marketing stages of bank card innovations and the use of collaboration

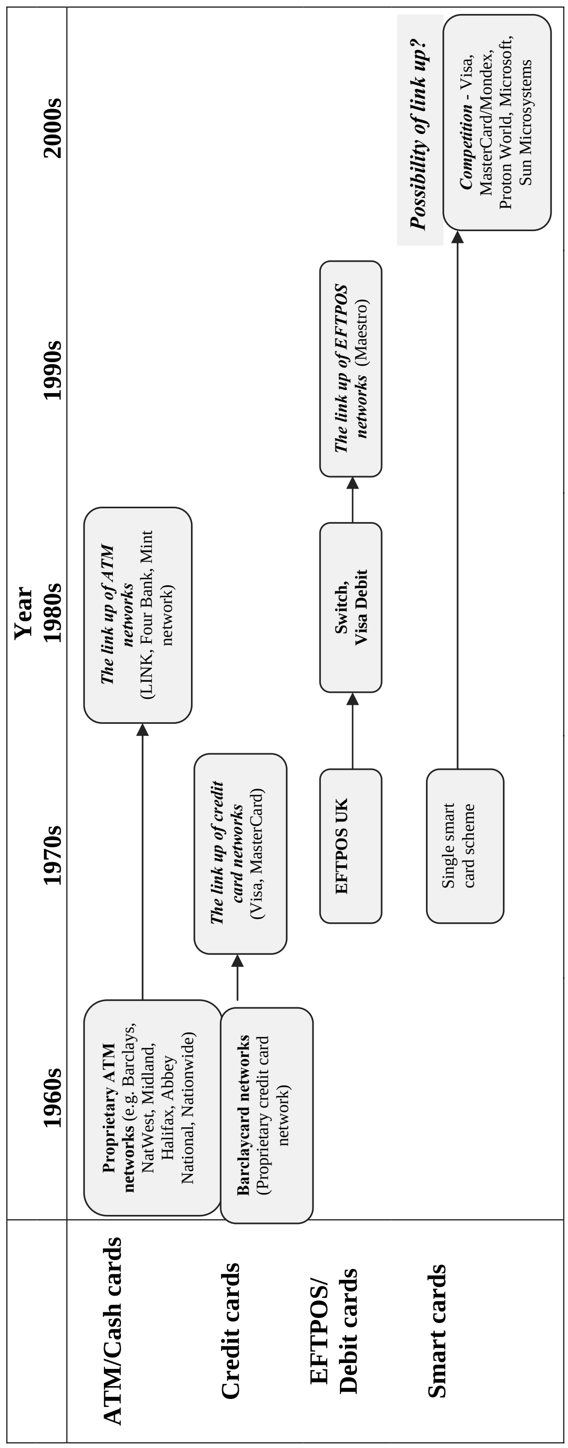
Process of Innovation	ATM/Cash Card Innovation, Credit Card Innovation, EFTPOS/Debit Card Innovation	Multi-Functional Financial Smart Cards
Development stage	For ATM/cash cards, credit cards, and EFTPOS/debit cards, innovators could implement the innovations without entering into collaboration. This is because the technology to assist the implementation of innovation could be purchased in the third-party market. Although there were complexities/difficulties in terms of high capital investment, innovators could manage complexities/difficulties on an individual basis. For example, in the case of ATM/cash cards in the UK, Barclays could purchase ATM technology from the third-party market to establish its Barclaycash service. In other words, Barclays had the capability to connect the computers to the current account system, make the interbranch ATM operational, and solve the mechanical problems without seeking collaboration. In the case of credit cards, there were no technological complexities/difficulties since Barclaycard only adjusted the Bank Americard package to operate in UK banking conditions. Barclaycard, as with any of the other banks, had adequate resources to fund the cost of implementing its credit card service without collaboration. In the case of EFTPOS/debit cards, the development stage of innovation could be carried out on an individual basis. The capital investment on EFTPOS was within the capabilities of any innovators (banks/ building societies) to provide without pursuing a collaborative strategy.	Given that the development of smart cards/financial applications is based on the existing payment network infrastructure, this reduces the complexities/difficulties of building and accessing infrastructure. The major technological complexities/difficulties are in terms of providing security against fraud to expand card usage into Internet payments. Operation of the smart card payment systems incurs the risks of fraud, privacy issues, and credit risks. Dealing with fraud and privacy issues requires improvements in the security framework. Curtailing credit risk requires devising procedures to constrict or moderate credit and reduce float in the market. The operation of smart cards for financial applications requires high investment for the upgrades of ATMs and EFTPOS terminals to be capable of accepting smart cards and presumably a substantial investment in adding smart card technology to mobile computers and telephony. For multipurpose use, the cards require extensive industry backing and high levels of coverage to turn it into a product with wide applications. To achieve card proliferation, the smart card electronic payment system needs an interface between banks and a variety of retailer businesses.
Delivery stage	The major complexities/difficulties lie in the delivery of innovations. In the case of credit cards and EFTPOS/debit cards, the card issuers must rely entirely on retailers to accept the cards. In other words, banks lack the capabilities needed for competitive innovation, so they joined together to share the cost of launching a joint credit card scheme and sign up merchants as the card acceptance location. The complexities/ difficulties in EFTPOS/debit card service provision are that the debit fund transfer could not be carried out without collaboration with the retailer industry. Thus, banks and building societies entered into collaboration with retailers to install the terminals at the retailers' point of sales. To provide EFTPOS on an extended basis, banks and building societies joined the Switch or Visa Debit program to share the cost of point-of-sale (POS) equipment.	There are difficulties in establishing widespread adoption of the smart card innovation among vendors of products and services (and possibly issuers of credits). The cards require an extended network across several industries to allow multipurpose functionalities. In stimulating the diffusion of smart cards, the issue of applications is important to access network externalities. The potential of the smart card take-up depends on the information and communication protocol. In other words, standards are important to achieve technical and data content compatibility for multipurpose application. Standards are pivotal to the delivery of value-added services since standards allow the running of various applications on the same card.

continued on following page

Table 3. continued

Marketing stage	In marketing the ATM service, the banks and building societies saw collaboration as an opportunity to extend the service coverage. In other words, a collaborative approach was considered by the banks and building societies as the cheapest route to provide customers with an exhaustive geographic network. Collaboration was involved in terms of the cooperative price setting over switch and interchange fee for using each other's ATM networks. In the case of credit cards, the large size of the credit card market meant innovators faced difficulties in expanding an exclusive network of retail outlets by themselves. Therefore, they chose to link in larger networks to extend the scope of credit card usage. For example, in the UK, Barclays' link up with the Visa network meant Barclaycard complying with Visa rules for interoperability of card operation. In the case of EFTPOS/debit cards, there was not much difficulty in marketing the EFTPOS service since banks and building societies could launch their card schemes and sign up enough retailers to establish a critical density in particular areas on an individual basis. However, by joining the Visa Debit and Switch card schemes, the geographical scope of debit card service could be extended. In marketing the bank card innovations, innovators generally could manage the complexities/difficulties without entering into collaboration. Nevertheless, innovators consider the use of collaborative strategy to extend the scope of card-based services.	The complexities/difficulties of multi-functional financial smart cards arise from e-cash application. If customers still prefer cash, or because of incomplete adoption of e-payment still require cash for significant amounts of expenses, this reflects the difficulty to change their behavior, and it becomes a case of 'technology push' rather than 'market pull'. Currently, there is competition among many alternative operating systems technology, for example, Visa's Open Platform, MasterCard/Mondex's Multos, Proton World's Proton, Microsoft's Windows for Smart Card, and Sun Microsystems' Java for Smart Cards. Bank and non-bank players compete to launch smart cards with financial applications. There are competitive threats coming from new, virtual, as well as longstanding competitors (Bossone, 2001). The multipurpose smart cards have additional complexities/difficulties concerning price. The cost of chip cards is higher than the magnetic stripe cards, thus being the main constraint for the potential use of smart cards in the financial service industry. A high cost is also seen among innovators themselves as a deterrent against customers' acceptance.

Figure 1. The progress of innovations from competition (proprietary networks) towards collaboration (collaborative network)



Taking into account the complexities/difficulties of smart cards compared with those of ATM/cash cards, credit cards, and EFTPOS/debit Cards (Table 3), multi-functional financial smart cards are complex relative to the capabilities of any innovator since the card functionality needs substantial investment in ATMs and EFTPOS terminal upgrades. The cards require substantive industry backing for multi-application purposes. It is highly unlikely that any innovator would have all competencies to launch the cards on a stand-alone basis. In respect of the network-dependent nature, multi-functional financial smart cards need linkages between players in the industry for the successful delivery and commercialization. However, whether innovators have an interest in linking up their smart card systems to facilitate rapid adoption or not, this needs an empirical observation in the long run.

The analysis of the system innovation characteristics (Tables 4 and 5) and the complexities/difficulties of smart cards (Table 3) has shown that the smart card innovation needs collaboration across industries to support multi-functionalities. Nevertheless, the smart card-based electronic payment systems at present are stunted by the lack of a widely accepted and secure means of transferring money online. The global smart card schemes are still struggling from lack of interoperability. The competition in the smart card industry reflects the situation where Visa, MasterCard/Mondex, Proton World, Microsoft, and Sun Microsystems compete to establish their operating system technology as standard (Visa–the Open Platform, MasterCard/Mondex–Multos, Proton World–Proton, Microsoft–Windows for Smart Card, Sun Microsystems–Java for Smart Cards). Although there are recent efforts to create interoperability among various European purse systems (EMV[1] and CEPS[2]), these standards are not so closely integrated to provide a basis for multi-functional financial smart cards. Unless the competing innovators in the smart card industry see the benefits in terms of increasing their access to markets, they are unwilling to collaborate and the diffusion of smart cards may not happen.

CONCLUSION

This chapter is concerned with the challenges of smart cards as a system innovation in the banking industry. System innovation is the innovation which cannot be adequately introduced by a single entity and is likely to fail unless two or more parties collectively accept the innovation. The

Table 4. Characteristics of system innovations

	Characteristics of System Innovations	ATM/Cash Cards	Credit Cards	EFTPOS/Debit Cards	Multi-Functional Financial Smart Cards
1	Inter-operability among third parties required		X	X	X
2	Necessary investment in assets specific to the system by more than one party	X	X	X	X
3	Comprises extensive software (protocols, procedures) as well as hardware		X		X

Table 5. Description of the characteristics of system innovations in the bank card industry

	Characteristics	ATM/Cash Cards	Credit Cards	EFTPOS/Debit Cards	Multi-Functional Financial Smart Cards
1	Inter-operability among third parties required		• Credit card transaction processing requires interoperability among the merchant or outlet, the merchant acquirer, and the issuer • Electronic funds transfer networks among the cards scheme involving large numbers of banks • Inter-system standardization—technical standards for the cards (design and contents of the magnetic stripe tracks)	• Standard payment message for routing payment details from the cardholder's account to the retailer's account and automated clearinghouse • Encryption (coding) standards for electronic transmission of financial data	• 3G standard and GSM standard for mobile application • Transport network if use in various types of transport journey
2	Necessary investment in assets specific to the system by more than one party	• ATM or cash machine • Data network systems and ISDN data communication lines	• Credit authorization system and terminal • Imprinter	• Point-of-sale terminal (for data processing, verification) • Bank card reader (swipe card reader)	• Investment in GSM operator's network that is compatible for mobile phone use across the world

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Table 5. continued

3	Comprises extensive software (protocols, procedures) as well as hardware Comprises extensive software (protocols, procedures) as well as hardware		• Automated online authorization system for credit-worthiness verification • Extensive transaction authorizing and processing network/extensive system and software for credit process validation • Procedures in guaranteeing and facilitating the payment of the members' bills • Integrated services digital network (ISDN) to link the credit card payment system		• The Value Transfer Protocol for checking the authenticity of cardholders and controlling the movement of the value between cards • Open trading protocols (OTPs) for Internet commerce • Integrated services digital network (ISDN) for network communication • Public Key Infrastructure (PKI) system for information security • Using Asymmetric Digital Subscriber Line technology (ADSL) to connect end users to the local telephone exchange for data transmission • The interconnections between GSM/Internet networks and the WAP (Wireless Application Protocol) protocol for Internet access

smart card electronic payment system is of the network system nature. The smart card industry involves the network collaboration whereby the launch of multi-functional financial smart cards needs linkages between players in the industry for successful delivery and commercialization. From the analysis, innovators enter into collaboration to overcome the complexities/difficulties and to extend the scope of card-based services. Whereas ATM/cash cards, credit cards, and EFTPOS/debit cards have reached a level of wide adoption from the use of collaboration, the smart card innovation has not yet reached a level of diffusion. The current situation in the smart card industry reflects the competition among the powerful players (Visa–the Open Platform, MasterCard/Mondex–Multos, Proton World–Proton, Microsoft–Windows for Smart Card, Sun Microsystems–Java for Smart Cards). Taking into account the smart card electronic payment system, there needs to be sufficient collaboration among organizations competing to launch smart cards. Otherwise, it would be hard for innovators to push smart cards to achieve a level of diffusion.

Multi-functional financial smart cards offer almost limitless opportunity for banks to enhance customer relationships and open up whole new markets. But to get there requires a massive investment in the global payment infrastructure. Without industry standards, the welding of different payment users into different networks and different systems would be difficult. The analysis has shown that smart cards are the system innovation that needs collaboration to achieve the commercialization of innovations. In other words, the links between technological competencies and markets (network relationship with customers) are important for the diffusion of innovation. Innovators in the smart card industry need to make a collective effort to solve complexity problems and create linkages among the parties. Otherwise, it would be hard for multi-functional financial smart cards to be successful if innovators maintain their current competitive approach. Although the industry is in the direction of working together (as can be seen from the agreement to set EMV, CEPS standards for smart card e-cash and SET standard[3] for smart card payment over the Internet), the collaboration is not strong enough. The major players have shown themselves reluctant to make a commitment on a collaborative platform (global standard development and infrastructure investment).

The analysis in this chapter provides insights into the complexities/difficulties of smart cards—the challenges, competition, and collaboration. The challenges of adopting the smart card technology are:

- Why don't innovators in the smart card industry reduce a degree of competition?
- Why do innovators waste financial resources in competition where they may finally enter into collaboration in the future (as happened in the cases of ATM/cash cards, credit cards, and EFTPOS/debit cards)?

The competitors launching the smart card innovation use an empirical analysis in this chapter to define a strategic approach for their plan to compete in the smart card industry.

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ENDNOTES

1 EMV (Europay, MasterCard, Visa consortium) is a specification for integrated circuit cards which fixes the dimensions and communications protocols of the cards so that all cards and card readers produced can work together. EMV is the global standard for chip-based debit and credit transactions.

2 Common Electronic Purse Specifications (CEPS) standard was created in 1999 to govern e-purse programs. The standard is planned for use in the application of e-cash.

3 For e-commerce, SET (Secure Electronic Transaction) was developed as a standard for secure payment over the Internet.

Chapter VIII
Electronic Banking and Information Assurance Issues: Survey and Synthesis

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ABSTRACT

Information assurance is a key component in e-banking services. This article investigates the information assurance issues and tenets of e-banking security that would be needed for design, development, and assessment of an adequate electronic security infrastructure. The technology terminology and frameworks presented in the article are with the view to equip the reader with a glimpse of the state-of-art technologies that may help toward learning and better decisions regarding electronic security.

INTRODUCTION

The Internet has emerged as the dominant medium in enabling banking transactions. Adoption of e-banking has witnessed an unprecedented increase over the last few years. Twenty percent of Internet users now access online banking services, a total that will reach 33% by 2006, according to the Online Banking Report. By 2010, more than 55 million U.S. households will use online banking and e-payments services, which are tipped as "growth areas." The popularity of online banking is projected to grow from 22 million households in 2002 to 34 million in 2005, according to Financial Insite, publisher of the Online Banking Report[1] newsletter.

Electronic banking uses computer and electronic technology as a substitute for checks and other paper transactions. E-banking is initiated through devices such as cards or codes to gain access to an account. Many financial institutions use an automated teller machine (ATM) card and a personal identification number (PIN) for this purpose. Others use home banking, which involves installing a thick client on a home PC and using a secure dial-up network to access account information; others allow banking via the Internet. This article will discuss the information assurance issues (Maconachy, Schou, & Ragsdale, 2002) that are associated with e-banking infrastructure. We hope that this chapter will allow information technology (IT) managers to understand information assurance issues in e-banking in a holistic manner, and that it will help them make recommendations and take actions to ensure security of e-banking components.

INTERNET/WEB BANKING

A customer links to the Internet from his or her PC. The Internet connection is made through a public Web server. When the customer brings up the desired bank's Web page, the customer goes through the front-end interface to the bank's Web server, which, in turn, interfaces with the legacy systems to pull data out at the customer's request. Pulling legacy data is the most difficult part of Web banking. While connection to a direct dial access (DDA) system is fairly straightforward, doing wire transfer transactions or loan applications requires much more sophisticated functionality. A separate e-mail server may be used for customer service requests and other e-mail correspondence. There are also other middleware products that provide security to ensure that the customer's account information is secured, as well as products that convert information into an HTML format. In addition, many of the Internet banking vendors provide consulting services to assist banks with Web site design and overall architecture. Some systems store financial information and records on client PCs but use the Internet connections to transmit information from the bank to the customer's PC. For example, the Internet version of Intuit's *BankNOW* runs off-line at the client and connects to the bank via the Internet only to transmit account and transaction information (Walsh, 1999).

In this section, we discuss some of the key nodal points in Internet banking. The following points are the foundations and principal aspects of e-banking: Web site and service hosting, possibly through providers; application software that includes middleware; regulations surrounding e-banking and standards that allow different organizations and platforms to communicate over the Internet.

Web Site and Banking Service Hosting

Banks have the option of hosting Web sites in-house or outsourcing either to service bureaus or core processing vendors with expertise in Internet banking. Whether outsourced or packaged, Internet banking architectures generally consist of the following components: Web servers; transaction servers; application servers; and data storage and access servers. Vendors such as *Online Resources*[2] offer a package of Web banking services that includes the design and hosting of a financial institution's Web site and the implementation of a transactional Web site. Online's connection makes use of the bank's underlying ATM network for transactions and real-time bill payment. In addition, optional modules are generally available for bill payment, bill presentment, brokerage, loan application/approval, small business, and credit cards. The fact that multiple options of Web hosting exist also brings with them issues in security and privacy—a topic that will be considered in a later section.

The components that form a typical Internet banking initiative are shown in Figure 1.

- **Internet banking front-end:** The front-end is often the client-side browser access to the bank's Web server. Client-side, thin-client access to the bank's Web server: This model allows the customer to download a thin-client software product from the bank's Web site and may allow storing financial data locally. Client-side, thick-client access to the bank's Web server: This is the model used when supporting personal financial management packages as tools to access account data and execute transactions. It is important to note that these models are not mutually exclusive of each other (Starita, 1999).
- **Internet banking transaction platforms:** The Internet banking transaction platform is the technology component that supports transactional processes and interfaces between the front-end user interface and the back-end core processors for functions like account information retrieval, account update, and so forth. In general, the transactional platform defines two main things: (1) the functional capabilities of the Internet banking offering (i.e., whether it offers bill payment or credit card access); and (2) the method of access or interface between the front-end and back-end legacy processors (Starita, 1999).

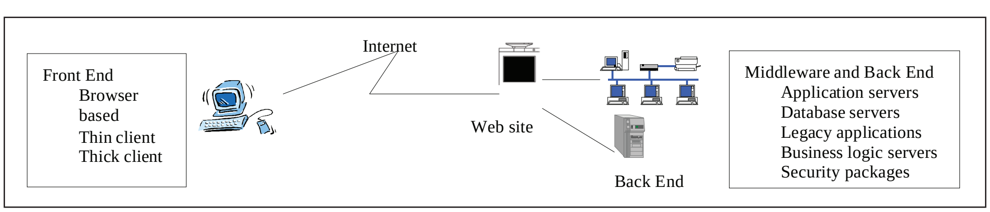
Internet Banking Platforms and Applications

Most of the Internet plumbing to present data onto Web interfaces from data sources is offered by Internet banking application software vendors, who link legacy systems to allow access to account data and transaction execution. Most players position themselves as end-to-end solution providers by including a proprietary front-end software product, integration with other front-end software, or Web design services.

Some of the solutions are middleware platforms with plug-in applications to provide bill payment, bill presentment, brokerage, loan, small business, and/or credit card functionality. Most vendors use open financial exchange standard (OFX) to connect to different delivery channels such as interactive voice response (IVRs), personal finance managers (PFMs), and the Internet. Middleware tools are designed to handle Internet-delivered core banking and bill payment transactions (Walsh, 2002). Middleware platforms provide a link between financial institutions' legacy host systems and customers using browser-based HTML interfaces and OFX-enabled personal financial management software (Walsh, 2002).

Middleware is designed for financial institutions that require a platform that translates messages between collections of separate processing systems that house core processing functions. Core processing systems include bill payment, credit card, brokerage, loans, and insurance. Electronic

Figure 1. Architectural pieces of Internet banking (Starita, 1999)



bill payment and presentment is widely believed to be the compelling application that brings large volumes of customers to the Internet channel to handle their finances. There are two kinds of Web sites: nontransactional and transactional. The nontransactional sites, commonly known as promotional Web sites, publish content with information about bank products and allow customers to investigate targeted areas such as college loans or retirement planning. These sites give basic information on bank products and do not allow any transactions. Banks can collect information to start to develop customer profiles by recording where a customer visits on the Web site and comparing it with demographic information to develop personalized marketing strategies.

Transactional sites link to back-end processing systems and include basic functionality such as the ability to view recent transactions and account histories, download information into PFM software, and transfer funds between existing accounts. As banks become more sophisticated with transactional capabilities, such things as electronic bill payment or moving of funds outside of the bank become possible. Integrating with a third-party processor such as Checkfree or Travelers Express most often does this. Bill presentment is also part of transactional capability; however, it is being done on a limited basis through a small number of pilots. Some banks allow customers to apply for loans, mortgages, and other products online, although much of the back-end process is still done manually. In transactional Web sites, every page must be composed dynamically and must offer continual updates on products and pricing.

Standards Compliance

Standards play a vital role in seamless flow and integration of information across channels and help to reduce risk emanating from diverse platforms and standards. In addition to the challenge of integrating Internet banking products into the bank's own IT environment, many Internet banking functions involve third-party participation. This poses a significant integration question: What is the best way to combine separate technology systems with third parties in a cost-effective way in order to enable each participant to maintain control over its data and maintain autonomy from other participants? The response from the technology marketplace has been to establish Internet banking standards to define interactions and the transfer of information between multiple parties (Bohle, 2001). The premise of a standard is that everyone would use it in the same consistent fashion; unfortunately, that is not the scenario in the current Internet banking environment. One of the problems for the lackluster performance of e-banking arguably is the industry's failure to attend to the payments infrastructure (Orr, 2002). One initiative that does show promise is by the National Institute of Standards and Technology, which has developed a proposed standard—Security Requirements for Cryptographic Modules—that will require role-based authentication and authorization (FIPS, 1992). Some of the standards pervasive in current e-banking models are the ADMS standard, the GOLD standard, and the OFX standard.

INFORMATION ASSURANCE

Web banking sites include financial calculators; e-mail addresses/customer service information; new account applications; transactions such as account balance checks, transfers, and bill payment; bill presentment/payment; cash management; loan applications; small business; credit card; and so forth. The modes by which they can be accessed include online service provider or portal site, direct-dial PC banking program, Internet-bank Web sites, WebTV, and personal financial manager. Depending on the functionality of the Web sites, different information assurance requirements are found.

Some examples of exploitation of information assurance issues in the Web-banking arena include the following:

- Many ATMs of Bank of America were made unavailable in January 2003 by the SQL Slammer worm, which also affected other financial services like Washington Mutual[3,4].
- Barclays suffered an embarrassing incident when it was discovered that after logging out of its online service, an account immediately could be re-accessed using the *back* button on a Web browser. If a customer accessed their Barclays account on a public terminal, the next user could thereby view banking details of the previous customer. According to the bank, when customers join the online banking service, they are given a booklet that tells them to clear the cache to prevent this from happening. However, this procedure shifts the responsibility for security to the end user[5].

Security and Privacy Issues

In their annual joint study in April 2002, the FBI and the Computer Security Institute noted that the combined financial losses for 223 of 503 companies that responded to their survey (Computer Crime and Security Survey) was $455 million for year 2002 (Junnarkar, 2002). Security and integrity of online transactions are the most important technical issues that a bank offering Web services will need to tackle. The Internet bank Web sites handle security in different ways. They can choose either public or private networks. The Integrion consortium, for example, uses the private IBM/AT&T Global Network for all Internet network traffic (Walsh, 1999). Server security is another important issue, usually accomplished by server certificates and SSL authentication. Banks must look at three kinds of security (Walsh, 1999): communications security; systems security, from the applications/authorization server; and information security.

From a user's perspective, security must accomplish privacy, integrity authentication, access control, and non-repudiation. Security becomes an even more important issue when dealing with international banks, since only up to 128K encryption is licensed for export. Currently, most Internet bank Web sites use a combination of encryption, firewalls, and communications lines to ensure security. The basic level of security starts with an SSL-compliant browser. The SSL protocol provides data security between a Web browser

Table 1. Standards in e-banking models

- **The GOLD Standard:** The GOLD standard is an electronic banking standard developed and supported by Integrion to facilitate the exchange of information between participants in electronic banking transactions. Integrion is a PC direct-dial and Internet banking vendor developed as a consortium with 16 member banks, IBM, and Visa Interactive (through acquisition) in an equal equity partnership. IBM is the technology provider for the Integrion consortium.
- **The OFX Standard:** Open Financial Exchange (OFX) is a standard developed cooperatively by Microsoft, Intuit, and Checkfree. Recently, Microsoft launched its OFX version 2.0 without the involvement of its partners, Checkfree and Intuit. OFX v.2.0 is developed with XML to enable OFX to be used for bill presentment. Though OFX can be considered a much better solution for interoperability needs of banks, it imposes problems of incompatibility between older OFX versions.
- **The IFX Standard:** Interactive Financial Exchange (IFX) initiative was launched in early 1998 by BITS (the Banking Industry Technology Secretariat) in order to ensure convergence between OFX and another proposed specification, GOLD, propounded by Integrion Financial Network. According to the IFX forum, IFX specification provides a robust and scalable framework for the exchange of financial data and instructions independent of a particular network technology or computing platform.
- **XML as standard:** XML language is often perceived as a solution to the problem of standards incompatibility. XML appears as an ideal tool for multi-banking, multi-service Internet banking applications.

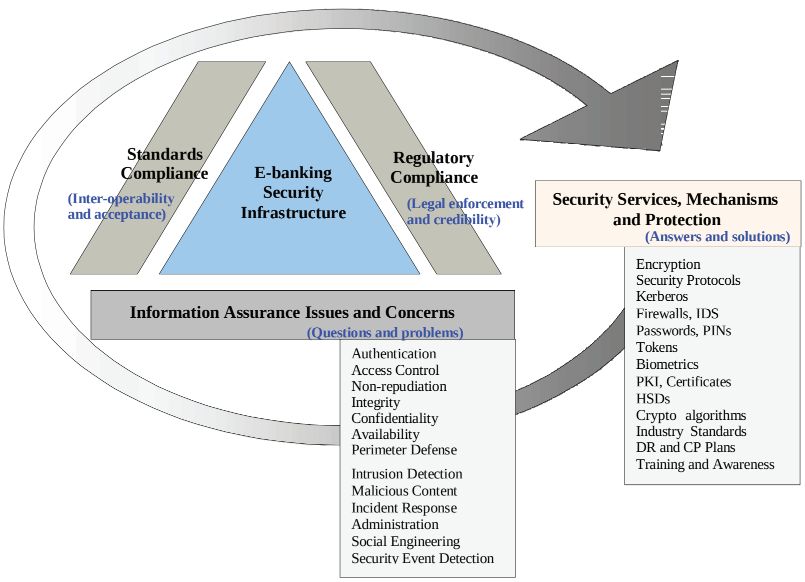
and the Web server, and is based on public key cryptography licensed from security systems. Security has been one of the biggest roadblocks that have kept consumers from fully embracing Internet banking. Even after the advent of highly secure sites with the aid of 128K encryption, a virtually invulnerable encryption technology, the perception among some consumers is that Internet banking is unsafe. They apprehend privacy violations, as the bank keeps track of all transactions, and they are unsure of who has access to privileged data about their personal net worth. The basic security concerns that face financial institutions offering banking services and products through the Internet are summarized in Figure 2 and are discussed next.

Authentication

Authentication relates to assurance of identity of person or originator of data. Reliable customer authentication is imperative for financial institutions engaging in any form of electronic banking or commerce. Strong customer authentication practices are necessary to enforce anti-money laundering measures and help financial institutions detect and reduce identity theft. Customer interaction with financial institutions is migrating from physical recognition and paper-based documentation to remote electronic access and transaction initiation. The risks of doing business with unauthorized or masquerading individuals in an electronic banking environment could be devastating, which can result in financial loss and intangible losses like reputation damage, disclosure of confidential information, corruption of data, or unenforceable agreements.

There is a gamut of authentication tools and methodologies that financial institutions use to authenticate customers. These include the use of passwords and personal identification numbers (PINs), digital certificates using a public key infrastructure (PKI), physical devices such as smart cards or other types of tokens, database comparisons, and biometric identifiers. The level of risk protection afforded by each of these tools varies and is evolving as technology changes. Multi-factor authentication methods are more difficult to compromise than single factor systems. Properly designed and implemented multifactor

Figure 2. E-banking security infrastructure



authentication methods are more reliable indicators of authentication and stronger fraud deterrents. Broadly, the authentication methodologies can be classified, based on what a user knows (passwords, PINs), what a user has (smart card, magnetic card), and what a user is (fingerprint, retina, voiceprint, signature).

The issues that face banks using the Internet as a channel are the risks and risk management controls of a number of existing and emerging authentication tools necessary to initially verify the identity of new customers and authenticate existing customers that access electronic banking services. Besides, effective authentication framework and implementation provides banks with a foundation to enforce electronic transactions and agreements.

- **Account origination and customer verification:** With the growth in electronic banking and commerce, financial institutions need to deploy reliable methods of originating new customer accounts online. Customer identity verification during account origination is important in reducing the risk of identity theft, fraudulent account applications, and unenforceable account agreements or transactions. There are significant risks when financial institutions accept new customers through the Internet or other electronic channels because of the absence of the tangible cues that banks traditionally use to identify individuals (FDIC, 2001).
- **Monitoring and reporting:** Monitoring systems play a vital role in detecting unauthorized access to computer systems and customer accounts. A sound authentication system should include audit features that can assist in the detection of fraud, unusual activities (e.g., money laundering), compromised passwords, or other unauthorized activities (FDIC, 2001. In addition, financial institutions are required to report suspicious activities to appropriate regulatory and law enforcement agencies as required by 31 CFR 103.18.

Access Control

Access control refers to the regulating of access to critical business assets. Access control provides a policy-based control of who can access specific systems, what they can do within them, and when and from where they are allowed access. One of the primary modes of access control is based on roles. A role can be thought of as a set of transactions that a user or set of users can perform within the context of an organization. For example, the roles in a bank include teller, loan officer, and accountant, each of whom can perform different functions. Role-based access control (RBAC) policy bases access control decisions on the functions that a user is allowed to perform within an organization. In many applications, RBAC is concerned more with access to functions and information than strictly with access to information.

The applicability of RBAC to commercial systems is apparent from its widespread use. Nash and Poland (1990) discuss the application of role-based access control to cryptographic authentication devices commonly used in the banking industry. Even the Federal Information Processing Standard (FIPS) has provisions for support for role-based access and administration.

Non-Repudiation

Non-repudiation refers to the need for each party involved in a transaction to not go back on their word; that is, not break the electronic contract (Pfleeger, 1997). Authentication forms the basis for non-repudiation. It requires strong and substantial evidence of the identity of the signer of a message and of message integrity sufficient to prevent a party from successfully denying the origin, submission, or delivery of the message and the integrity of its contents. This is important for an e-banking environment where, in all electronic transactions, including ATMs (cash machines), all parties to a transaction must be confident that the transaction is secure; that the parties are who they say they are (authentication), and that the transaction is verified as final. Essentially, banks must have mechanisms that ensure that a party cannot subsequently repudiate (reject) a transaction. There are several ways to ensure non-repudiation, which include digital signatures, which not only validate the sender but also "time stamps" the transaction, so it cannot be claimed subsequently that the transaction was not authorized or not valid.

Integrity

Ensuring integrity means maintaining data consistency and protecting from unauthorized data alteration (Pfleeger, 1997). Integrity is very critical for Internet banking applications, as transactions have information that is consumer and business sensitive. To achieve integrity, data integrity mechanisms can be used. These typically involve the use of secret-keyor public-key-based algorithms that allow the recipient a piece of protected data to verify that the data have not been modified in transit. The mechanisms are presented further in a later section.

Confidentiality and Privacy

Privacy and security concerns are not unique to banking systems. Privacy and confidentiality are related but are distinct concepts. Protection of personally identifiable information like banking records must be ensured for consumers. Information Privacy (NIIAC, 1995) is the ability of an individual to control the use and dissemination of information that relates to him or her. Confidentiality (NIIAC, 1995) is a tool for protecting privacy. Sensitive information is accorded a confidential status that mandates specific controls, including strict limitations on access and disclosure. Those handling the information must adhere to these controls. Information confidentiality refers to ensuring that customer information is secured and hidden as it is transported through the Internet environment. Information not only must be protected wherever it is stored (e.g., on computer disks, backup tape, and printed form), but also in transit through the Internet.

Availability

Availability in this context means that legitimate users have access when they need it. With Internet banking, one of the strongest selling propositions is 24/7 availability; therefore, it becomes even more critical for e-banks. Availability applies both to data and to services. Expectations of availability include presence of a service in usable form, capacity to meet service needs, timeliness of service, fair allocation, fault tolerance, controlled concurrency, and deadlock management. One example where availability is compromised is the denial of service attack. On the Internet, a denial of service (DoS) attack is an incident in which a user or organization is deprived of the services of a resource they would normally expect to have. When there are enormous transactions on the Internet bank's Web site, the losses that may arise owing to unavailability are severe in terms of financial losses and reputation losses. Typically, the loss of service is the inability of a particular network service, such as email, to be available or the temporary loss of all network connectivity and services. It becomes imperative and crucial for IT managers in the Internet banking world to better understand the kind of denial of attacks possible. Some of the common and well-known types of denial of service attacks (IESAC, 2003) are the following:

- **SYN attack:** It floods the server with open SYN connections, without completing the TCP handshake. TCP handshake is a three-step process to negotiate connection between two computers. The first step is for initiating the computer to send SYN (for *synchronize*) packet.

- **Teardrop attack:** It exploits the way that the Internet Protocol (IP) requires a packet that is too large for the next router to handle be divided into fragments. Here, the attacker's IP puts a confusing offset value in the second or later fragment of the packet. It can cause the system to crash.
- **Smurf attack:** In this attack, the perpetrator spoofs the source IP address and broadcasts ping requests to a multitude of machines to overwhelm the victim.

Perimeter Defense

Perimeter defense refers to the separation of an organization's computer systems from the outside world (IETF, 2000). This must allow free sharing of certain information with clients, partners, suppliers, and so on, while also protecting critical data from them. A security bulwark around network and information assets of any bank can be achieved to a certain extent by implementing firewalls and correctly performing tuning and configuration of firewalls.

Today, with the kind of traffic generated toward Web-banking sites for all kinds of purposes, from balance enquiries to interbank fund transfers, implementation of screening routers to ensure incoming and outgoing traffic would add another layer of security. In this age of systems being hijacked for cyber-attacks, it is also important that screen routers detect and prevent outgoing traffic that attempts to gain entry to systems like spoofing IP addresses. Further, the periphery of the corporate computer infrastructure can be bolstered by implementing VPN solutions to ensure privacy of data flowing through the firewall into the public domain.

Probes and scans often are used techniques that are exploited to learn about exposures and vulnerabilities on the network systems. A probe is characterized by unusual attempts to gain access to a system or to discover information about the system. Probes are sometimes followed by a more serious security event, but often they are the result of curiosity or confusion. A scan is simply a large number of probes done using an automated tool. Scans can sometimes be the result of a misconfiguration or other error, but they are often a prelude to a more directed attack on systems that the intruder has found to be vulnerable.

Intrusion Detection

Intrusion detection refers to the ability to identify an attempt to access systems and networks in a fashion that breaches security policies. The Internet banking scenario, where most of business these days is carried out over public domain Internet and where a banking Web site becomes a single point interface for information as well as transactions, gives hackers enough motivation to intrude into Internet banks' systems. To safeguard from such unwanted activities, organizations need to be able to recognize and distinguish, at a minimum, the following (Gartner, 1999): internal and external intrusion attempts; human versus automated attacks; unauthorized hosts connecting to the network from inside and outside the perimeter; unauthorized software being loaded on systems; and all access points into the corporate network.

Intrusion detection systems (IDS) allow organizations to protect their systems from the threats that come with increasing network connectivity and reliance on information systems. Given the level and nature of modern network security threats, the question for security professionals should not be whether to use intrusion detection, but which intrusion detection features and capabilities to use. IDSs have gained acceptance as a necessary addition to every organization's security infrastructure. IDS products can provide worthwhile indications of malicious activity and spotlight security vulnerabilities, thus providing an additional layer of protection. Without them, network administrators have little chance of knowing about, much less assessing and responding to, malicious and invalid activity. Properly configured, IDSs are especially useful for monitoring the network perimeter for attacks originating from outside and for monitoring host systems for unacceptable insider activity.

Security Event Detection

Security event detection refers to the use of logs and other audit mechanisms to capture information about system and application access, types of access, network events, intrusion attempts, viruses, and so forth. Logging is an important link in the analysis of attack and real-time alerts of any kind of suspicious activity on the Internet bank Web site. For proper tracking of unusual events and attempts of intrusion, the following logs should be collected: basic security logs, network event logging, log authentication failures, log access violations, log attempts to implant viruses and other malicious code, and log abnormal activity. This strongly implies that the technical department that is analyzing logs to identify unusual behavior must be aware of business initiatives. In addition, it has to be ensured that audit logs are retained long enough to satisfy legal requirements. Also, at a minimum, investigation of security breaches should be allowed for up to 14 days after any given attack (IETF, 2000). Today, data mining techniques can interpret millions of items of log data and reveal any unobserved attempts to breach an ebank's Web site. For this, it has to be ensured that logs do not overwrite themselves causing loss of data. For analysis of events at a site, documentation of automated systems that identify what the logs mean should be maintained. Understanding the nature of attempts such as whether an attack was from within the organization or from outside or whether it was just a false alarm is critical to security.

Malicious Content

Malicious content refers to programs of any type that are introduced into a system to cause damage or steal information. Malicious content includes viruses, Trojan horses, hacker tools, and network sniffers. While common in multiple domains, this is as important in the e-banking world, as well. Malicious code brings with it the potential to create serious technical and economic impact by crashing e-mail servers and networks, causing millions of dollars of damage in lost productivity.

Some of the common forms of malicious contents are the following:

- **Virus:** A virus is a computer program that runs on a system without being asked to do so, created to infect other computer programs with copies of itself. Pioneer virus researcher Fred Cohen has defined a virus as "a program that can 'infect' other programs by modifying them to include a, possibly evolved, copy of it."
- **Worm:** A worm has the ability to spread over a network and, thus, can take advantage of the Internet to do its work. Worms reside in memory and duplicate themselves throughout the network without user intervention.
- **Trojan horse:** A Trojan horse is the name applied to a malicious computer program disguised as a seemingly innocent activity such as initiating a screen saver, accessing an e-mail attachment, or downloading executable files from an untrusted Web site. Some of the widely manifested malicious codes are Stoned, Yankee, Michelangelo, Joshi, Lehigh, Jerusalem, MBDF (for Macintosh), Melissa, Concept, LoveBug (ILOVEYOU), ShapeShift, Fusion, Accessiv, Emporer, Sircam, Nimda, and Badtrans.

Protection against malicious codes like viruses, worms, Trojan horses, and so forth could be effectively dealt with by installing security protection software that thwarts and mitigates the effects of codes. However, such software provides only a level of defense and is not by itself sufficient. Recommendations for e-banking IT infrastructure include (Noakes, 2001):

- Install detection and protection solutions for all forms of malicious code, not just an antivirus solution.
- Ensure that all users are aware of and follow safe behavior practices—do not open attachments that have not been scanned, do not visit untrusted Web sites, and so forth.
- Ensure that users are aware of how easy data may be stolen automatically just by visiting a Web site. Install an effective solution. Keep it current with the latest signatures as new forms of malicious code are identified.
- Use anti-spammers, harden operating systems, configure stricter firewall rules, and so forth.

Security Services, Mechanisms, and Security Protection

Security risks are unlike privacy risks; they originate outside the financial service provider (FSP) and change rapidly with advances in technology (DeLotto, 1999). In December 2000, IATF released guidelines that require all covered institutions to secure their clients' personal information against any reasonably foreseeable internal or external threats to their security, confidentiality, and integrity. By July 1, 2001, FSPs were expected to develop customer information security programs that ensured the security and confidentiality of customer information, protected against any anticipated threats or hazards to the security or integrity of customer information, and protected against unauthorized access to or use of customer information that could result in substantial harm or inconvenience to customers.

The services and mechanisms that are prevalent in an e-banking environment are presented below in order to provide an understanding of key issues and terms involved.

Encryption

Encryption is the process of using a key to scramble readable text into unreadable cyphertext. Encryption on the Internet, in general, and e-banking, in particular, have many uses, from the secure transmission of credit card numbers via the Web to protecting the privacy of personal e-mail messages. Authentication also uses encryption by using a key or key pair to verify the integrity of a document and its origin. The data encryption standard (DES) has been endorsed by the National Institute of Standards and Technology (NIST) since 1975 and is the most readily available encryption standard. Rivest, Shamir, and Adleman (RSA) encryption is a public-key encryption system; it is a patented technology in the United States and, thus, is not available without a license. RSA encryption is growing in popularity and is considered quite secure from brute force attacks. Another encryption mechanism is pretty good privacy (PGP), which allows users to encrypt information stored on their system as well as to send and receive encrypted e-mail. Encryption mechanisms rely on keys or passwords. The longer the password, the more difficult the encryption is to break. VPNs employ encryption to provide secure transmissions over public networks such as the Internet.

Security Protocol Services

The Internet is viewed as an insecure place. Many of the protocols used in the Internet do not provide any security. Today's businesses, particularly the banking sector, must integrate security protocols into their e-commerce infrastructure to protect customer information and privacy. Some of the most common protocols are discussed briefly in Appendix A.

Firewalls and Intrusion Detection Systems

A firewall is a collection of hardware and software designed to examine a stream of network traffic and service requests. Its purpose is to eliminate from the stream those packets or requests that fail to meet the security criteria established by the organization. A simple firewall may consist of a filtering router, configured to discard packets that arrive from unauthorized addresses or that represent attempts to connect to unauthorized service ports. Firewalls can filter packets based on their source and destination addresses and port numbers. This is known as address filtering. Firewalls also can filter specific types of network traffic. This is also known as protocol filtering, because the decision to forward or reject traffic is dependent upon the protocol used (e.g., HTTP, ftp, or telnet). Firewalls also can filter traffic by packet attribute or state. But a firewall cannot prevent individual users with modems from dialing into or out of the network, bypassing the firewall altogether (Odyssey, 2001). In this age of systems being hijacked, it is also important that firewalls and screen routers detect and prevent outgoing traffic that attempts to compromise the integrity of the systems. A network intrusion detection system (NIDS) analyzes network traffic for attacks. It examines individual packets within the data stream to identify threats from authorized users, backdoor attacks, and hackers who have thwarted the control systems to exploit network connections and access valuable data. NIDS adds a new level of visibility into the nature and characteristics of the network. They provide information about the use and usage of the network. Host Based IDS/Event Log Viewers are a kind of IDS that monitors event logs from multiple sources for suspicious activity. Host IDS is best placed to detect computer misuse from trusted insiders and those who have infiltrated the network. The technology and logical schemes used by these systems often are based on knowledge-based misuse detection (Allan, 2002). Knowledge-based detection methods use information about known security policy, known vulnerabilities, and known attacks on the systems they monitor. This approach compares network activity or system audit data to a database of known attack signatures or other misuse indicators, and pattern matches produce alarms of various sorts. Behavior-based detection (Allan, 2002) methods use information about repetitive and usual behavior on the systems they monitor. Also called *anomaly detection*, this approach notes events that diverge from expected (based on repetitive and usual) usage patterns. One technique is threshold detection (Allan, 2002) in which certain attributes of user and system behavior are expressed in terms of counts, with some level established as permissible. Another technique is to perform statistical analysis (Allan, 2002) on the information, build statistical models of the environment, and look for patterns of anomalous activity.

Passwords and Personal Identification Numbers (PINs)

The most common authentication method for existing customers requesting access to electronic banking systems is the entry of a user name and a secret string of characters such as a password or PIN. User IDs combined with passwords or PINs are considered a single-factor authentication technique. There are three aspects of passwords that contribute to the security they provide: secrecy, length and composition, and system controls. In the present Internet banking scenario, there are policies, for customers as well as employees, set by banks for passwords to ensure effective authentication, like prohibiting using public e-mail IDs as user IDs, ensuring that there are no user IDs with no password, ensuring that policies exist and can be automatically enforced concerning minimum password length, password format (i.e., which characters make up a valid password), expiration and renewal of passwords, uniqueness of passwords, not allowing the use of real words for passwords, and so forth.

Tokens

The use of a token represents authentication using something the customer possesses. Typically, a token is part of a two-factor authentication process, complemented by a password as the other factor. There are many benefits to the use of tokens. The authentication process cannot be completed unless the device is present. Static passwords or biometric identifiers used to activate the token may be authenticated locally by the device itself. This process avoids the transmission of shared secrets over an open network such as the Internet.

Digital Certificates and Public Key Infrastructure (PKI)

A financial institution may use a PKI system to authenticate customers to their own electronic banking product. Institutions may also use the infrastructure to provide authentication services to customers who wish to transact business over the Internet with other entities or to identify employees and commercial partners seeking access to the business' internal systems. A properly implemented and maintained PKI may provide a strong means of customer identification over open networks such as the Internet. By combining a variety of hardware components, system software, policies, practices, and standards, PKI can provide for authentication, data integrity, and defenses against customer repudiation, and confidentiality (Odyssey, 2001). The Certificate Authority (CA), which may be the financial institution or its service provider, plays a key role by attesting with a digital certificate that a particular public key and the corresponding private key belong to a specific individual or system. It is important when issuing a digital certificate that the registration process for initially verifying the identity of customers is adequately controlled. The CA attests to the individual's identity by signing the digital certificate with its own private key, known as the *root key*. Each time the customer establishes a communication link with the financial institution, a digital signature is transmitted with a digital certificate. These electronic credentials enable the institution to determine that the digital certificate is valid, identify the individual as a customer, and confirm that transactions entered into the institution's computer system were performed by that customer. PKI, as the most reliable model for security and trust on the Internet, offers a comprehensive e-security solution for Internet banking. Unlike the other security models, PKI is a standards compliant, most credible trust framework, highly scalable and modular. PKI comprehensively satisfies the security requirements of e-banking (Odyssey, 2001).

A brief discussion on the processes and mechanisms used in PKI to address common security concerns follows:

- **Authentication:** The customer requests the Registration Authority (RA) for a certificate. The Registration Authority validates the customer's credentials. After valid credentials are ensured, the RA passes the certificate request to the Certification Authority (CA). CA then issues the certificates. A digital certificate can be stored on the browser on the user's computer, on a floppy disk, on a smart card, or on other hardware tokens.
- **Confidentiality:** The customer generates a random session key at his or her end. The session key is sent to the bank, encrypting it with the bank's public key. The bank decrypts the encrypted session key with its private key. The session key is employed for further transactions.
- **Integrity:** The message is passed through a suitable hashing algorithm to obtain a message digest or hash. The hash, encrypted with the sender's private key, is appended to the message. The receiver,

upon receiving the message, passes it through the same hashing algorithm. The digest the receiver obtains is compared with the received and decrypted digest. If the digests are the same, it implies that the data have not been tampered with in transit.

- **Non-Repudiation:** The hash is encrypted with the sender's private key to yield the sender's digital signature. Since the hash is encrypted with the sender's private key (which is accessible only to the sender), it provides an indisputable means of non-repudiation.
- The use of digital signatures and certificates in Internet banking has provided the trust and security needed to carry out banking transactions across open networks like the Internet. PKI, being a universally accepted standards compliant security model, provides for the establishment of a global trust chain. (Odyssey, 2001)

Biometrics

A biometric identifier measures an individual's unique physical characteristic or behavior and compares it to a stored digital template to authenticate that individual. A biometric identifier representing "something the user is" can be created from sources such as a customer's voice, fingerprints, hand or face geometry, the iris or retina in an eye, or the way a customer signs a document or enters keyboard strokes (FDIC, 2001). The success of a biometric identifier rests on the ability of the digitally stored characteristic to relate typically to only one individual in a defined population. Although not yet in widespread use by financial institutions for authenticating existing customers, biometric identifiers are being used in some cases for physical access control.

Banks could use a biometric identifier for a single or multi-factor authentication process. ATMs that implement biometrics like iris-scan technologies are examples of the use of a biometric identifier to authenticate users. The biometric identifier may be used for authentication instead of the PIN. A customer can use a PIN or password to supplement the biometric identifier, making it part of a more secure two-factor authentication process. Financial institutions also may use biometric identifiers for automating existing processes. Another application would be a financial institution that allows customer to reset a password over the telephone with voice-recognition software that authenticates the customer. An authentication process that relies on a single biometric identifier may not work for everyone in a financial institution's customer base. Introducing a biometric method of authentication requires physical contact with each customer to capture initially the physical identifier, which further buttresses the initial customer verification process. But this process may increase the deployment costs.

Hardware Security Devices (HSDs)

This mechanism is an extension to usage of tokens for authentication. Using hardware devices for authentication provides "hacker-resistant" and "snooping-proof" two-factor authentication, which results in easy-to-use, effective user identification (Grand, 2001). To access protected resources, the user simply combines his or her secret PIN (something the user knows) with the code generated by the user's token (something the user has). The result is a unique, one-time-use code that is used to positively identify, or authenticate, the user (Grand, 2001). Some central server validates the code. The goal is to provide acceleration, secure key management.

A hardware security module is a hardware-based security device that generates, stores, and protects cryptographic keys. There are universal criteria for rating these devices. The criteria are documented in a federal information processing standard (FIPS) called FIPS 140-1 to 140-4—Security for Cryptographic Modules. Such hardware devices generate tokens that are dynamic, one-time passwords through the use of a mathematical function. Passwords generated by tokens are different each time the user requests one, so an intercepted password is useless, as it will never be used again. Acceptance and credibility of the devices is reflected in the increasing number of devices in use.

Industry Standards and Frameworks

Industry standards for financial transactions over the Internet are an absolute necessity for ensuring various security aspects of business as well as consumer confidence. There have been a constant search and a development of standards for e-banking infrastructural tenets like authentication, access control, non-repudiation, and so forth. Some of the standards developed and advocated by different industry players and their proponents are briefly discussed in Appendix B, which will provide an overall understanding of the evolution and prevalence of some of the standards.

User and E-Banking Focus on Security Issues

To summarize, Table 2 presents issues over which the user has direct control or with which the user has involvement, and issues that are commonly left for the systems to handle.

CONCLUSION

It should be noted that the discussion of e-banking information assurance (IA) issues also has included several generic IA issues. To illustrate this, Table 3 briefly categorizes e-banking-specific information assurance issues and generic issues separately. Some issues may be more significant than in other areas. We have made an attempt to comprehensively discuss all the areas in the article.

Security for financial transactions is of vital importance to financial institutions providing or planning to provide service delivery to customers over the Internet, as well as to suppliers of products, services, and solutions for Internet-

Table 2. End-user involvement with the security issues

Security issues with direct user focus	User-focused mechanisms that are available	User-transparent mechanisms/technology
Authentication	Passwords, PINs tokens, HSDs, Biometrics	Radius, TACACS, PKI, ISAKMP
Access Control	Roles, User Discretion, Hard-coded systems	
Confidentiality	Training	Encryption
Integrity	Encryption (hashing)	
Malicious Content	Training	Mail/Spam filters, anti-virus
Non-repudiation	Use of PKI, and authentication mechanisms	
Incident Response	Training	
Social Engineering	Training	
Security issues with system-only focus		
Availability	IDSs, Firewall, redundancy, fault-tolerance, application-level security rules	
Security Event, Intrusion Detection	IDSs, probes, firewalls	
Perimeter Defense	Firewalls, IDSs,	
Administration	Depends on the system policies as well as administrators.	

based e-commerce. The actual and perceived threats to Internet-based banking define the need for a set of interrelated security services to provide protection to all parties who can benefit from Web banking in a secure environment. Such services may be specific to counter particular threats or may be pervasive throughout an Internet-based environment to provide the levels of protection needed.

There are also requirements that the entire e-commerce environment be constructed from components that recognize the need for security services and provide means for overall security integration, administration, and management. These services that offer the security from an infrastructure standpoint are found throughout the e-commerce network and computing infrastructure. Financial institutions should carry out, as a matter of corporate security policy, identification of likely targets, which should include all systems that are open to the public network, such as routers, firewalls, Web servers, modem banks' Web sites, and internal unsecured systems such as desktops. They should regularly revise and update their policies on auditing, risk assessment, standards, and key management. Vulnerability assessment and identification of likely targets and the recognition of systems most vulnerable to attack are critical in the e-banking arena. Accurate identification of vulnerable and attractive systems will contribute to prioritization when addressing problem areas.

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Table 3. IA issues

E-banking Specific Issues	Generic Issues (in E-banking)
E-banking related regulations, Banking and E-banking standards and frameworks, banking-specific protocol services.	Authentication, Access Control, Integrity, Availability, Perimeter Defense, Security Event Detection, Malicious Content, Incident Response, Social Engineering, Administration.

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APPENDIX A
Common Security Protocol Services

Protocol	Description
Secure Sockets Layer (SSL)	Originally developed by Netscape, the SSL security protocol provides data encryption, server authentication, message integrity, and optional client authentication for a TCP/IP connection. SSL has been universally accepted on the World Wide Web for authenticated and encrypted communication between clients and servers. However, SSL consumes large amounts of the Web server's processing power due to the massive cryptographic computations that take place when a secure session is initiated. If many secure sessions are initiated simultaneously, then the Web server quickly becomes overburdened. The results are slow response times, dropped connections, and failed transactions.
Secure Shell (SSH)	SSH Secure Shell is the de facto standard for remote logins. It solves an important security problem on the Internet of password hacking. Typical applications include secure use of networked applications, remote system administration, automated file transfers, and access to corporate resources over the Internet.
AS1 and AS2	AS1 provides S/MIME encryption and security over SMTP (Simple Mail Transfer Protocol) through object signature and object encryption technology. AS2 goes a step further than AS1 by supporting S/MIME over HTTP and HTTPS. Both AS1 and AS2 provide data authentication, proving that the sender and receiver are indeed the people or company that they claim to be.
Digital Certificates	Digital certificates are used to authenticate the identity of trading partners, ensuring partners are really who they say they are. In addition to data authentication, digital signatures support non-repudiation, proving that a specific message did come from a known sender at a specific time. A digital signature is a digital code that can be sent with electronically transmitted message and it uniquely identifies the sender. It is based on digital certificates. This prevents partners from claiming that they didn't send or receive a particular message or transaction.
Pretty Good Privacy (PGP)	PGP is a freely available encryption program that uses public key cryptography to ensure privacy over FTP, HTTP and other protocols. PGP is the de-facto standard software for the encryption of e-mail and works on virtually every platform. But PGP suffers from absence of Trust management and it is not standards compliant though it could provide for integrity, authentication, non-repudiation and confidentiality. PGP also provides tools and utilities for creating, certifying, and managing keys.
Secure Multipurpose Internet Mail Extension (S/MIME)	S/MIME addresses security concerns such as privacy, integrity, authentication and non-repudiation, through the use of signed receipts. S/MIME provides a consistent way to send and receive secure MIME data. Based on the MIME standard, S/MIME provides authentication, message integrity, non-repudiation of origin (using digital signatures) and data confidentiality (using encryption) for electronic messaging applications. Since its development by RSA in 1996, S/MIME has been widely recognized and widely used standard for messaging. The technology for S/MIME is primarily built on the Public Key Cryptographic Standard, which provides cryptographic interoperability. Two key features of S/MIME are the digital signature and the digital envelope. Digital signatures ensure that a message has not been tampered with during transit. Digital signatures also provide non-repudiation so senders can't deny that they sent the message.
Secure HTTP (S-HTTP)	S-HTTP is an extension to HTTP, which provides a number of security features, including Client/Server Authentication, Spontaneous Encryption and Request/Response Non-repudiation. S-HTTP allows the secure exchange of files on the World Wide Web. Each S-HTTP file is either encrypted, contains a digital certificate, or both. For a given document, S-HTTP is an alternative to another well-known security protocol, Secure Sockets Layer (SSL). A major difference is that S-HTTP allows the client to send a certificate to authenticate the user whereas, using SSL, only the server can be authenticated. S-HTTP is more likely to be used in situations where the server represents a bank and requires authentication from the user that is more secure than a userid and password.
Simple Key management for Internet Protocols (SKIP)	It is a manifestation of IP-Level Cryptography that secures the network at the IP packet level. Any networked application gains the benefits of encryption, without requiring modification. SKIP is unique in that an Internet host can send an encrypted packet to another host without requiring a prior message exchange to set up a secure channel. SKIP is particularly well suited to IP networks, as both are stateless protocols.
Encapsulating Security Payload (ESP)	ESP is security protocol that provides data confidentiality and protection with optional authentication and replay-detection services. ESP completely encapsulates user data. ESP can be used either by itself or in conjunction with AH. ESP may be implemented with AH, as discussed in next paragraph, in a nested fashion through the use of tunnel mode. Security services can be provided between a pair of communicating hosts, between a pair of communicating security gateways, or between a security gateway and a host, depending on the implementation. ESP may be used to provide the same security services, and it also provides a confidentiality (encryption) service. Specifically, ESP does not protect any IP header fields unless those fields are encapsulated by ESP (tunnel mode).
Authentication Header (AH)	A security protocol that provides authentication and optional replay-detection services. AH is embedded in the data to be protected (a full IP datagram, for example). AH can be used either by itself or with Encryption Service Payload (ESP). The IP Authentication Header is used to provide connectionless integrity and data origin authentication for IP datagrams, and to provide protection against replays. AH provides authentication for as much of the IP header as possible, as well as for upper level protocol data. However, some IP header fields may change in transit and the value of these fields, when the packet arrives at the receiver, may not be predictable by the sender. The values of such fields cannot be protected by AH. Thus the protection provided to the IP header by AH is somewhat piecemeal and not complete.

APPENDIX B
Some Industry Standards and Frameworks in E-Banking

Standard	Description
SET	Secure Electronic Transaction (SET) is a system for ensuring the security of financial transactions on the Internet. It was supported initially by Mastercard, Visa, Microsoft, Netscape, and others. With SET, a user is given an *electronic wallet* (digital certificate) and a transaction is conducted and verified using a combination of digital certificates and digital signatures among the purchaser, a merchant, and the purchaser's bank in a way that ensures privacy and confidentiality. SET makes use of Netscape's Secure Sockets Layer (SSL), Microsoft's Secure Transaction Technology (STT), and Terisa System's Secure Hypertext Transfer Protocol (S-HTTP). SET uses some but not all aspects of a public key infrastructure (PKI). SET provides authentication, integrity, non-repudiation and confidentiality.
HBCI	HBCI is a specification for the communication between intelligent customer systems and the corresponding computing centers for the exchange of home banking transactions. The transmission of data is done by a net data interface, which is based on flexible delimiter syntax.
EMV[1]	Specifications by Europay, MasterCard and Visa that define a set of requirements to ensure interoperability between chip cards and terminals on a global basis, regardless of the manufacturer, the financial institution, or where the card is used.
CEPS	The Common Electronic Purse Specifications (CEPS) define requirements for all components needed by an organization to implement a globally interoperable electronic purse program, while maintaining full accountability and auditability. CEPS, which were made available in March of 1999, outline overall system security, certification and migration. CEPS have paved the way for the creation of an open, de facto, global electronic purse standard (http://www.cepsco.com/).
XMLPay	XMLPay is a standard proposed/developed by Ariba and Verisign. It defines an XML syntax for payment transaction requests, responses and receipts in a payment processing network. The intended users are Internet merchants and merchant aggregators who need to deal with multiple electronic payment mechanisms (credit/debit card, purchase card, electronic cheque and automated clearing house payment). The supported operations include funds authorization and capture, sales and repeat sales, and voiding of transactions.
ECML	The Electronic Commerce Modeling Language ECML is a specification that describes the format for data fields that need to be filled at checkout in an online transaction. The fields defined include shipping information, billing information, recipient information, payment card information and reference fields. Version 2.0 describes these fields in XML syntax.
W3C standard on micropayments	The W3C standard on micropayments has originated from IBM's standardization efforts. It covers the payment function for payment of digital goods. The Micropayment initiative specifies how to provide in a Web page all the information necessary to initialize a micropayment and transfer this information to the wallet for processing. The W3C Ecommerce/Micropayment Activity is now closed.
Passport	Microsoft Passport is an online user-authentication service. Passport's primary service is user authentication, referred to as the Passport single sign-in (SSI) service. Passport also offers two other optional services: Passport express purchase (EP), which lets users store credit card and billing/shipping address information in their optional Passport wallet profiles to expedite checkout at participating e-commerce sites, and Kids Passport (source: Microsoft Passport Technical White Paper).
eWallet project of CEN/ISSS[2]	CEN/ISSS Electronic Commerce Workshop initiated the eWallet project in mid-2001 assuming a need for standardization in the field. CEN/ISSS has chosen a flexible working definition considering an eWallet as "a collection of confidential data of a personal nature or relating to a role carried our by an individual, managed so as to facilitate completion of electronic transactions".
SEMPER	Secure Electronic Market Place for Europe (SEMPER) was produced by an EU supported project under a special program, undertaken by a 20 partner consortium led by IBM. It is a definition of an open and system independent architecture for Electronic Commerce. The project was concluded in 1999. Based on access via a browser, the architecture specifies common functions to be supported by applications which include Exchange of certificates, Exchange of signed offer/order, Fair contract signing, Fair payment for receipt, and Provision of delivery information.
IOTP	The Internet Open Trading Protocol (IOTP) is defined as an interoperable framework for Internet commerce. It is optimized for the case where the buyer and the merchant do not have a prior acquaintance. IOTP is payment system independent. It can encapsulate and support several of leading payment systems.
SEPP	Secure Electronic Payment Process is a protocol developed by MasterCard and Netscape to provide authentication, integrity and payment confidentiality. It uses DES for confidentiality and 512, 768, 1024 or 2048 bit RSA and 128 bit MD5 hashing. RSA encrypts DES key to encrypt hash of account numbers. It uses up to three public keys, one for signing, one for key exchange, one for certificate renewal. Besides, SEPP uses X.509 certificates with CMS at top of hierarchy[26].
STT	Secure Transaction Technology was developed by Visa and Microsoft to provide authentication, integrity and confidentiality to the Internet based transactions. It is based on 64 bit DES or 64 bit RC4 (24-bit salt) for confidentiality and 512, 768, 1024 or 2048 bit RSA for encryption with 160 bit SHA hashing. It uses two public keys, one for signing, one for key exchange. It has credentials similar to certificates but with account details and higher level signatures, though they are not certificates.
JEPI	(Joint Electronic Payment Initiative) CommerceNet and the W3 Consortium are jointly initiating a multi-industry project to develop an Internet payment negotiation protocol. The project explores the technology required to provide negotiation over multiple payment instruments, protocols and transports. Examples of payment instruments include credit cards, debit cards, electronic cash and checks. Payment protocols include STT and SEPP (amongst others). Payment transport encompasses the message transmission mechanism: S-HTTP, SSL, SMTP, and TCP/IP are all categorized as transport technologies that can be used for payment.

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Chapter IX
M-Payment Solutions and M-Commerce Fraud Management

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ABSTRACT

Mobile security and payment are central to m-commerce. The shift from physical to virtual payments has brought enormous benefits to consumers and merchants. For consumers it means ease of use. For mobile operators, mobile payment presents a unique opportunity to consolidate their central role in the m-commerce value chain. Financial organizations view mobile payment and mobile banking as a way of providing added convenience to their customers along with an opportunity to reduce their operating costs. The chapter starts by giving a general introduction to m-payment by providing an overview of the m-payment value chain, lifecycle and characteristics. In the second section, we will review competing mobile payment solutions that are found in the market-place. The third section will review different types of mobile frauds in the m-commerce environment and solutions to prevent such frauds.

INTRODUCTION

Mobile commerce (m-commerce) grows dramatically. The global m-commerce market is expected to be worth a staggering US$200 billion by 2004 (Durlacher Research, n.d.; More Magic Software, 2000). M-commerce can be defined as any electronic transaction or information interaction conducted using a mobile device and mobile networks, for example, wireless or switched public network, which leads to transfer of real or perceived value in exchange for information, services or goods (MobileInfo.com). M-commerce involves m-payment, which is defined as the process of two parties exchanging financial value using a mobile device in return for goods or services. A mobile device is a wireless communication tool, including mobile phones, PDAs, wireless tablets, and mobile computers (Mobile Payment Forum, 2002).

Due to the widespread use of mobile phones today, a number of payment schemes have emerged which allow the payment of services/goods from these mobile devices. In the following sections an overall view of the m-payment value chain, the m-payment life cycle and the m-payment characteristics is given. Also the operational issues are analyzed, which are critical to the adoption level of a payment system. The operational issues or characteristics will help in the unambiguous identification of the payment solutions.

M-PAYMENT VALUE CHAIN

Many different actors can be involved in mobile payment process (McKitterick & Dowling, n.d.; Mobile Payment Forum, 2002). For example, there is a consumer who owns the mobile device and is willing to pay for a service or product. The consumer initializes the mobile purchase, registers with the payment provider and authorizes the payment. A content provider or merchant sells product to the customer. In the mobile payment context, content can range from news to directory services, shopping and ticketing services, entertainment services, and financial services. The provider or merchant forwards the purchase requests to a payment service provider, relays authorization requests back to the customer and is responsible for the delivery of the content. Another actor in the payment procedure is the payment service provider, who is responsible for controlling the flow of transaction between mobile consumers, content providers and trusted third party (TTP) as well as for enabling and routing the payment message initiated from the mobile device to be cleared by the TTP. Payment service provider could be a mobile operator, a bank, a credit card company or an independent payment vendor. Another group of stakeholders is the trusted third party, which might involve network operators, banks and credit card companies. The main role of the TTP is to perform the authentication and the authorization of transaction parties and the payment settlement.

Finally there are mobile operators who are more concerned with the standardization and interoperability issues. They may also operate mobile payment procedure themselves and provide payment services for customers and merchants. One thing that needs to be considered is who receives the customer data. Customers rarely wish to divulge any information, whereas the same customer information might be important for merchants or content providers for their business. Payment procedures need to ensure that none of the players receive the data, for example, when customers use a prepaid payment solution to buy goods but also need to require divulging customer information to any of the players considered.

M-PAYMENT LIFECYCLE

Payment transaction process in a mobile environment is very similar to typical payment card transaction. The only difference is that the transport of payment detail involves wireless service provider. WAP/HTML based browser protocol might be used or payment details might be transported using technologies such as blue tooth and infrared (Mobile Payment Forum, 2002).

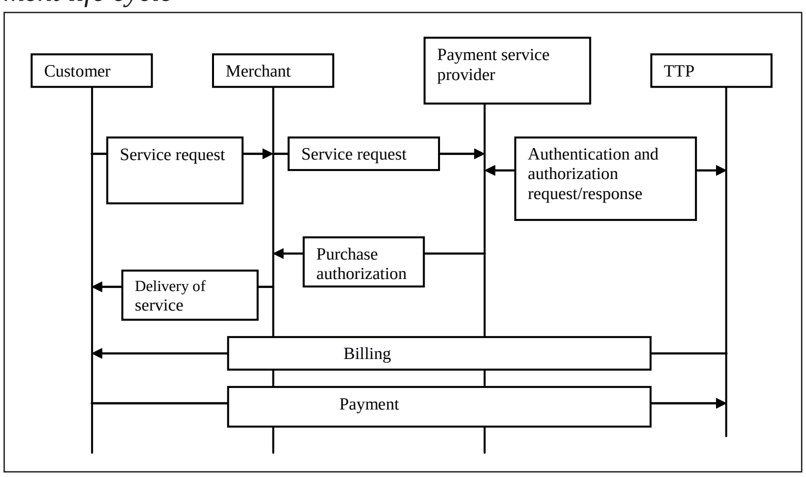
Mobile payment lifecycle shown in Figure 1 includes several main steps (Telecom Media Networks, 2002):

1. **Registration:** Customer opens an account with payment service provider for payment service through a particular payment method.
2. **Transaction:** Four steps are identified in an m-payment transaction.
   a. Customer indicates the desire to purchase a content using a mobile phone button or by sending an SMS (short message service).
   b. Content provider forwards the request to the payment service provider.
   c. Payment service provider then requests the trusted third party for authentication and authorization.
   d. Payment service provider informs content provider about the status of the authentication and authorization. If customer is successfully authenticated and authorized, content provider will deliver the purchased content.
3. **Payment settlement:** Payment settlement can take place during real-time, pre-paid or post-paid mode (Xiaolin & Chen, 2003). A real-time payment method involves the exchange of some form of electronic currency, for example, payment settlement directly through a bank account. In a pre-paid type of settlement customers pay in advance using smart cards or electronic wallets. In the post-pay mode, the payment service provider sends billing information to the trusted third party, which sends the bill to customers, receives the money back, and then sends the revenue to payment service provider.

OPERATIONAL ISSUES IN M-COMMERCE PAYMENT

Payment schemes can be classified as account based and token based. In the account-based scheme, consumers are billed on their account. This scheme is not suitable for small value transactions. In the token-based scheme, a token is a medium of payment transaction representing some monetary value and requires the support of the payment provider or TTP. Customers have to convert the actual currency to tokens. There are three different billing methods. One is real time, in which some form of electronic currency is exchanged during the transaction. The payment settlement can also be pre-paid where customers pay in advance to have a successful transaction. Another method is the post-paid method

Figure 1. M-payment life cycle



in which customers pay after they receive the service/good.

Customers will choose a new payment method only if it allows them to pay in an accustomed method. The different payment settlement methods offered by the provider will hence play a crucial role. Based on payment settlement methods, the payment solutions can also be categorized as smart and prepaid cards solution, electronic cash or digital wallets solution, direct debiting and off-line-procedure solution, and credit cards and payments via the phone bill solution. In the payment using smart card or pre-paid card solution, customers buy a smart card or pre-paid card where the money-value is stored and then pay off for goods or services purchased. Customers can also upload a digital wallet with electronic coins on a prepaid basis. The smart cards, prepaid cards and digital wallets are thus used for pre-paid payment solution. Another form of payment settlement is direct debit from the bank, which is a real-time payment method, since the purchase amount will be deducted as soon as the customer authorizes the payment. Payment method can also be using the phone bill or the credit card, where the customer pays for the good or services purchased at a later time. Payment by phone bill is one of the simplest methods of payment in which a special merchant-specific phone number is called from the mobile phone, which causes a predefined amount to be billed to callers' telephone bill. These types of payment schemes are applicable only to a single payment amount, providing limited security, and requiring users and merchants to share the same mobile operator (Pierce, 2000).

Smart cards can be used for all the three types of payment methods, for example, credit, debit and stored value as well as in authentication, authorization and transaction processing (Shelfer & Procaccino, 2002). A smart card thus enables the storage and communication of personal information such as value of goods and identity. A smart card can be either a memory card or processing enabled card. Memory cards are one type of prepaid cards, which transfer electronic equivalent of cash to the merchant electronic register. Processor cards, on the other hand, can be used as a debit card, credit card or a stored value card. A major drawback is the large costs associated with replacement of the existing infrastructure. In addition, the model lacks technical interoperability among existing smart card architectures.

The adoption of various payment frequencies in payment process is also a critical factor to make m-commerce payment succeed. It can be pay per view where consumers pay for each view, or increment, of the desired content; for example, downloading Mp3 files, video file or ring tones. It can also be pay per unit, where consumers pay once for each unit successfully completed with the content provider. A consumer would spend a certain number of units during each session, which is subsequently billed to the customer; for example, customer participating in an online game. The third type is a flat rate payment where consumers pay a recurring amount to access content on an unlimited basis for a certain period of time; for example, customer being charged to have access to an online magazine (McKitterick & Dowling, n.d.). The success of a payment solution will also depend on whether it can pay for a wide range of products and services. The payment can be a micro-payment, which refers to a payment of approximately $10 or less. In a micropayment system the number of transactions between each payer and the merchant is large as compared to the amount of each individual transaction. As a result transaction-processing cost grows for such systems. This kind of setting is addressed by a subscription scheme where a bulk amount is paid for which the use of a service is bought for a certain period of time. Traditional account based systems are not suitable for these kinds of transactions and hence the need for third-party payment processors arises which accumulate the transactions that can be paid for at a later time.

The payment can also be macro-payments, which refers to larger value payments such as online shopping. It is also important to consider the technical infrastructure required by the customers to participate in a payment system (Krueger, 2001; Mobey Forum Mobile Financial Services Ltd, 2001). Some solutions do not require any changes to the hardware or software, which will then have a tradeoff on the security aspect of payment. Some solutions require a sophisticated technology, which may be very secure but may not have taken the user's convenience into consideration. Most current payment solutions are SMS or WAP (wireless application protocol) based. Some of the solutions use dual chip. In addition to SIM (secure identification module), a second chip, such as WIM (Wireless Identity Module), standard smart cards and memory flash cards, is integrated into mobile device to provide the security functionality. The dual slot technology can also be used for payment services. This technology uses a regular SIM-card to identify the mobile device and also provide a second card slot for a credit or debit card integrated within a mobile phone. Payment solutions relying on an external chip card reader, which is connected to the mobile terminal using bluetooth, infrared technologies or a cable, also come under the dual slot category.

In addition, software based payment solutions have been considered. A software agent based wireless e-commerce environment has been proposed (Maamar et al., 2001), called electronic commerce through wireless devices (E-CWE). The environment associates users with user-agents, embodies user-agents with personalization and mobility mechanisms, and relates providers to provider-agents. Initially a J2ME application has to be downloaded which provides the interface to credit card information, including merchant and payment data. Then credit information is posted via HTTPS connection to the payment service provider. All business logic is fetched from the Web server and usually no new software or hardware is required on the device.

Mobile Payment Systems or Solutions

This section will portray current mobile payment solutions and compare them from user perspective of cost, security and convenience. The Electronic Payment Systems Observatory (ePSO) identified over 30 different mobile payment solutions, each with its own particular set of technologies (ePSO, n.d.). Mobile operators provide many solutions: some by financial players and others involving alliances between operators and financial organizations. Most of the solutions involve a relatively similar process.

Existing mobile solutions are categorized based on the payment settlement methods that are pre-paid (using smart cards or digital wallet), instant paid (direct debiting or off-line payments), and post paid (credit card or telephone bill). The three payment settlement options may vary in their requirements, process of payment and technologies used. The only requirement to a prepaid type of payment solution is a PIN for authorizing a transaction and a smart card value or stored value card for making payment. The technological requirements range between just a mobile phone to a smart card with a dual slot phone and smart card reader. The payment procedure starts with customers selecting a product or service and the mode of payment. Next, customers authorize the transaction using PIN number and then the payment amount is deducted from the stored value card.

Payment solutions based on payment direct from credit or bank accounts require an agreement between customer and payment provider that authorizes the payment provider to divulge the customer information to merchant and charge the customer. Customers have to divulge their credit card information or bank account number to payment service providers. The transaction also requires a PIN or a password. The technologies in use today for this type of solutions are a dual slot phone with a smart reader, dual chip phones (SIM+WIM), and payment provider calling back the customer's mobile phone. In general the solutions in this category follow the same high-level process. Customers select a product or service and the payment mode and authorize the transaction by entering a PIN or password. The payment provider forwards the card/bank information to the merchant. The payment amount is deducted from bank account or credited to customers' account and paid to the merchant.

The solutions based on charging the customer through phone bill require an agreement between customer and payment provider to charge the customer's phone bill. Such solutions require infrared or bluetooth technologies for establishing connection to the point of sale. In some cases a premium rate is enough. If the mobile phone uses a bluetooth/infrared technology, the point of sale contacts the mobile phone using the technology. Customers will then choose the product or service and authorize the payment with a button click on the mobile phone. Subsequently, the amount is charged to the phone bill. If the mobile phone uses just a premium rate to select a product or service, the mobile network calls the point of sale to authorize the sale and subsequently the amount is charged to the phone bill.

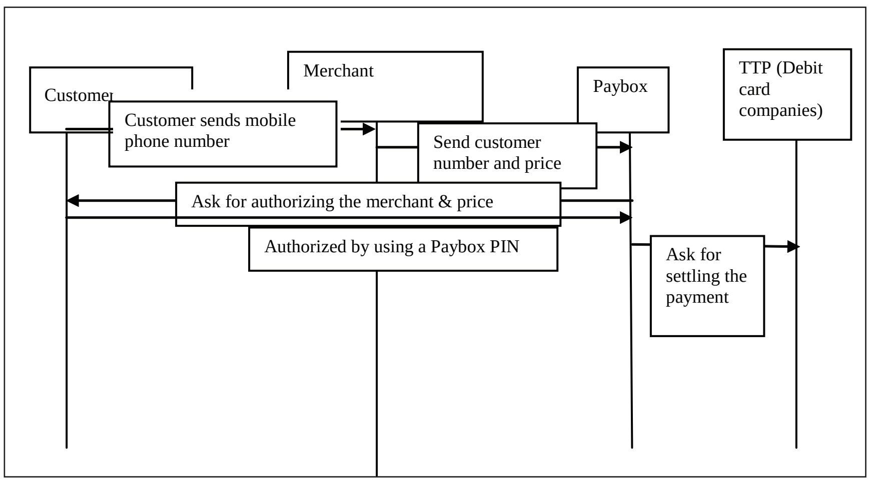
The following section portrays some current payment solutions such as Paybox, iPIN, m-PayBill, m-Pay and Jalda. A general analysis of the payment solutions based on customer requirements of cost, security and convenience is also provided.

PAYMENT SOLUTIONS

Paybox

One of the most widespread mobile phone payment applications is Paybox (Paybox.net, 2002), which was launched in Germany in May 2000. Later it was launched in Austria, Spain, Sweden and the UK. This service enables customers to purchase goods and services and make bank transactions via mobile phone. The value of purchases or credit transfers is debited from customers' bank account. The infrastructures needed to use Paybox are a mobile phone, a bank account and a paybox registration. A typical real-world mobile transaction using Paybox is given in Figure 2. Customers send

Figure 2. Paybox transaction



their phone number to a merchant. The merchant communicates this phone number and the price. The Paybox system calls the customer and asks for payment authorization. Payers authorize by their PIN. Paybox informs the trusted third party to settle the payment.

The Paybox is very simple and easy to use because of the very limited infrastructures needed and only costs a small annual fee for customers. M-payment is independent. For example, it allows services to customers of any bank or mobile operator. A key advantage of the independent payers is that they enable every mobile user to use the service upon registration, regardless of their mobile service provider. This independency of Paybox is also helpful to merchants since teaming up with such a payer is more efficient than teaming up with three or more separate mobile operators. Paybox also promises to provide a fraud protected cost effective system. The disadvantages are that the operation of Paybox is expensive since the system has to make voice calls using integrated voice recognition system (IVR) to the customer, which could range over various durations. In addition, there is no data privacy and customer and merchant have no proof of transaction, which might be a possible cause of fraud. The high latency also restricts it to high value transactions (Fischer, 2002). Most of all the transaction can be done only using a GSM enabled phone.

An annual fee is charged to customers, but there is no transaction fee involved. Paybox can be used with any mobile phone. Hence infrastructure costs are low. Peer to peer transactions come with an extra cost. Customers need to know only the PIN number to participate and the IVR system will then guide them through the rest of the payment process. Processing of transactions is fast. Paybox is suitable for macro as well as small payments. Paybox can also be used for peer-to-peer transactions where customers can send and receive money to other participants. Paybox owns customers' data and does not give the personal data to any other parties involved in the process. However, one drawback is that both customers and merchants do not have any proof of the transaction. Some fraud prevention techniques are promised by Paybox (Paybox.net, 2001), including address checking and correction using fuzzy logic tools, using checksums for credit card numbers and bank account numbers, checks on the demographic data, credit history checks, and address verification by sending the final PIN.

iPIN

iPIN is a privately held corporation based in Belmont, CA (USA) (ePSO, n.d.; Cap, Gemini, Ernst &Young, 2002). iPIN's Enterprise Payment Platform (EPP) is a leading end-to-end electronic and mobile commerce payment technology. It allows virtual point of sale and peer-to-peer payments over fixed as well as wireless networks. Seven software components have been identified in iPIN (Cap, Gemini, Ernst &Young, 2002). The main component of the iPIN payment system is the commerce router, which manages transactions throughout the payment lifecycle. It serves the user-interface pages and manages all end-user customer account activity. The repository is used for managing configurations and merchant information. Billing engine does the transaction fee calculation and facilitates account settlement. The merchant POS controller connects to the merchant's point of sale. The payment gateway connects to financial providers such as banks and credit card companies. The business intelligent module of iPIN keeps track of the success and returns on investments. The usage of the iPIN multiple payment instruments enables a customer to choose pre-paid, debit or credit solution.

A typical transaction using the iPIN payment system is shown in Figure 3. Customers initiate purchase requests to merchant. The merchant sends an authorization request to the issuer's commerce router. Customers are redirected to the commerce router for authenticating themselves after a secure session is established with the commerce router. After successful authentication is complete, the commerce router authorizes the transaction. Then the router establishes a transaction record in the database and sends the authorization response to the merchant. The merchant then sends a clearing message to the commerce router, confirming the transaction.

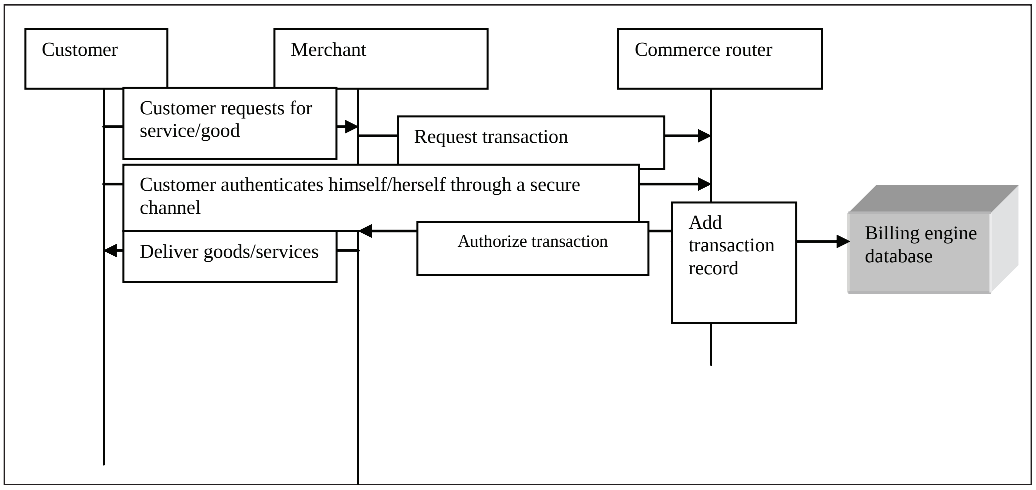
iPIN offers users a secure and efficient way to purchase virtual goods and services with a variety of connected devices including Web, WAP, SMS and IVR. Throughout the purchase process, the enterprise houses the user's personal profile and guarantees payment to merchants without actually transferring customers' private financial information. Fees are based on transactions. There is no setup fee for the customer. The only effort by consumers is to open or activate an account. Users are afforded several payment options including micro payment, and can choose to associate these charges to a prepaid account, monthly bill, and bankcard or loyalty program. Available via a mobile handset, self-care tools let users access detailed transaction histories, set account preferences such as spending limits and preferred account details, and receive answers to frequently asked questions. iPIN provides for interoperability between a group of individual payment networks, allowing merchants from one network to sell to users from other networks, while giving users access to a larger group of merchants and products.

Vodafone m-PayBill

m-PayBill supports virtual POS for micro and small payments (ePSO, n.d.; Vodafone M-Pay bill, n.d.). The bill is charged to customers' phone bill or from the prepaid airtime. The requirements for this payment solution are a WAP phone or a Web browser to settle the payment. Figure 4 shows a typical micro payment transaction using Vodafone. The Vodafone customers register for m-PayBill online by entering their mobile phone number, choosing a username, a password, and a four-digit PIN. When using a WAP phone the user is asked to enter the PIN for identification. Purchase amount is then charged to the phone bill or deducted from prepaid airtime.

m-PayBill membership is free; there are no basic or transaction fees. No extra infrastructure needed to perform the transaction except for a

Figure 3. Transaction in an iPIN payment solution



WAP phone. m-PayBill provides interoperability by having service providers outside of European Union plus Norway, Iceland and Liechtenstein. The personal information is transferred to the service providers in other countries for purchases outside the European Union. The security of the information will then depend on the privacy policy of that country. Payment information is maintained on the server and does not change hands, thus preventing any chances of fraud. The process is basically easy to understand and provides faster transactions. Customers already registered with the Vodafone network operator need not register again to use the procedure. Payment solution, however, is only applicable to micro-payments.

m-Pay

m-Pay is a mobile payment solution developed in corporation between PBS, Orange and Gem plus (PBS ,n.d.). It is a server-based credit/debit card payment solution via mobile phone for goods ordered via telephone sales and on the Internet through the PC or a WAP mobile phone. To use this application the user sends a written application to Orange asking to link the payment data to the GSM data in a payment server. Activating the payment function on the mobile phone requires an individually allocated PIN-code, which is connected to the SIM-card in the mobile phone. A typical transaction using m-Pay is given in Figure 5.

Customers request a service or product from the content provider. This request in the form of an SMS message is sent to payment server, which takes care of authorizing the payment request. Payment server sends the order information to customers for confirmation, which customers do by using a personal identification number presented in the SIM card. The server will then translate the mobile phone number into a valid card number and conduct a debit/credit card transaction. This confirmation is sent to the payment gateway for clearing, after which a receipt is generated by the gateway and sent to the content provider.

Customers must first register with Orange to use m-Pay. The registration is free but a new "Orange" SIM card required and payment confirmation service provided comes with a cost. An advantage with regards to cost is that customers need not buy new handsets to use the solution. None of the sensitive information is put on air. A payment receipt will be sent, whereupon customers receive notification in the form of an SMS message. The payment is carried out by exchange of e-payment certificates. The PBS payment server verifies any transaction from the SIM card, which

Figure 4. Transactions in Vodafone-mPayBill solution

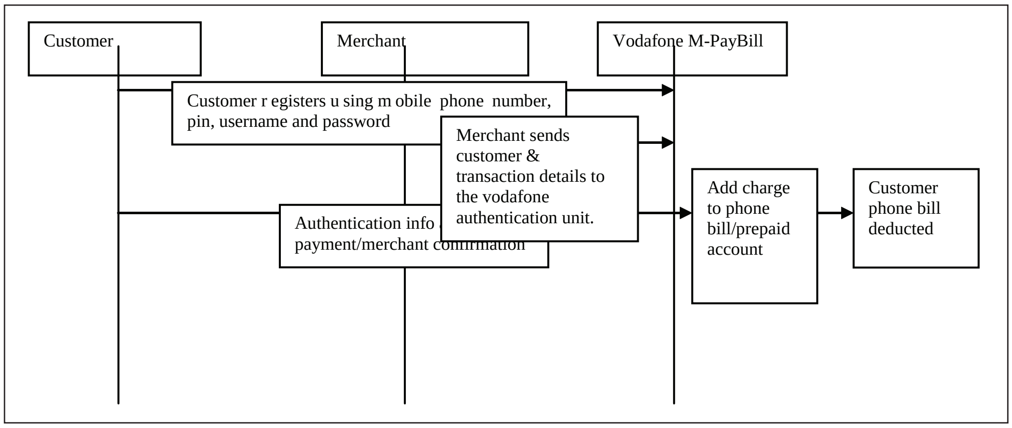
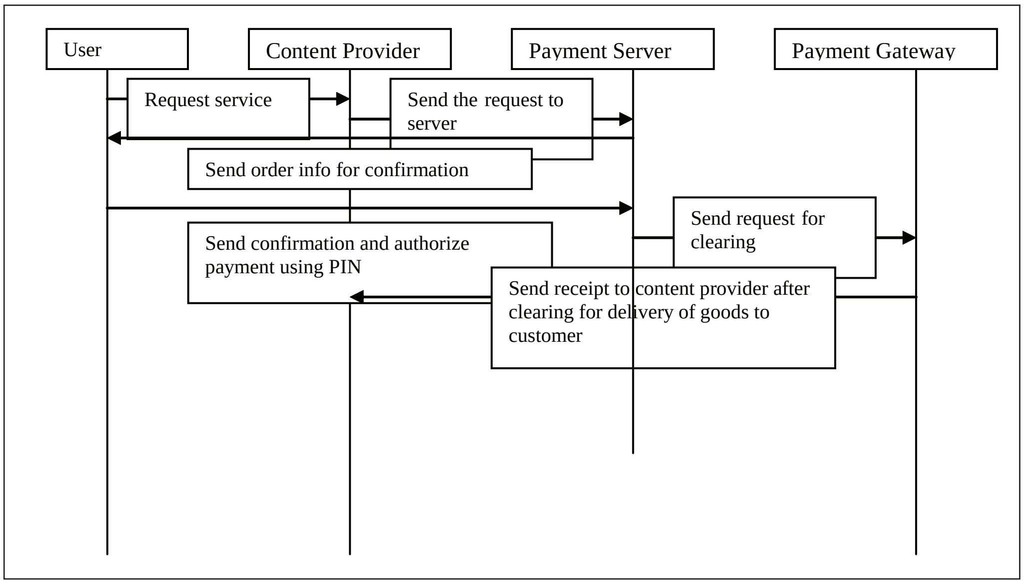


Figure 5. Payment transaction in an m-Pay solution



ensures that the merchant is approved to trade and also that the card has not been reported stolen or stopped from further transactions. To use this payment application, users have to download a script over the air to activate the dormant payment application in their SIM card. The payment transaction will take less than 10 seconds. After the PIN code has been accepted by the SIM application, customers are able to buy airtime and the amount will automatically be drawn from their credit/debit card account.

Jalda

Jalda is an account-based system wherein both consumers and retailers are connected to a special account managed by a payment provider, who usually acts as the Certificate Authority (Dahlström, 2001; ePSO, n.d.). For payments using mobile phones, the certificate is stored centrally with the payment provider. Users authorize a transaction through a PIN-code. It can also be used for Internet transactions, in which case the certificate is stored in the hard drive. Jalda is a session-based Internet payment method that enables payment by the second, item, quantity, mouse click, search, character, page, or practically any other parameters. Jalda consists of two parts: an application program interface (API) and a payment server that administers user data and keeps track of transactions. The Jalda actors are consumers who use Jalda API applications to purchase via the mobile phone and the content provider who uses the Jalda API to charge consumers for service.

The system enables customers to be charged by whatever parameter the content provider desires. The content provider deducts a small transaction fee from the customer phone bills. The infrastructure required is a WAP phone. Security of payments is guaranteed by using strong authentication and non-repudiation protocols. Self-administration interface enables users to control their account. A payment receipt is sent to users, which may be stored in the WAP phone. Jalda is an account-based payment method, enabling both pre-paid and credit-based payments. The accounts are managed and held by the payment provider and the payment provider usually acts as the Certificate Authority. Jalda can also be used for normal payments as well as micro-payments. The Jalda micropayment protocol is based on a concept of a payment session that is initiated by the payer by accepting and electronically signing a session contract with the merchant. The payment provider will then verify the contract for the vendor. After successful verification the vendor can then start keeping track of the service used by sending periodic indications when the consumer is consuming the service.

Jalda supports interoperability but does not enforce it as a global standard. Hence two payment providers need to make an agreement before the respective users can purchase goods from the other payment provider's merchants.

Other Solutions

Nokia launched a dual chip solution called electronic mobile payment services (EMPS). One chip was a usual subscriber identity module (SIM) card and the other was a WAP identity module (WIM) for making mobile payments. Parkit is used in some cities of Finland to pay for parking. In this solution a service number of the parking area is called after which parking is registered and customers end the parking by calling again to a nationwide "ending number". The parking fee will be included on customers' telephone bill, credit card bill or a separate bill.

GENERAL ANALYSIS OF THE PAYMENT SOLUTIONS

Payment solutions can be categorized on the basis of the payment settlement methods, which are instant-paid, post-paid, prepaid or a combination of these. In the prepaid solution, customers buy a smart card where the amount equivalent is stored and then pay of this for goods or services desired. Subscription of services can also be considered as prepaid type of payment. The prepaid type of solutions allows privacy to users since at no point of the process is it required to disclose any personal data. The instant paid solution is that payment settlement is done as soon as users confirm the payment as in direct debiting systems. In the postpaid solution customers pay for goods or services later. Payment by credit card and phone bill is an example. Table 1 shows this categorization for Paybox, iPIN, m-PayBill, m-Pay and Jalda.

The key to the acceptance of a mobile payment procedure is in the hands of customers. The determinants affecting the adoption of a payment solution are cost, security and convenience. Cost includes direct transaction cost, fixed cost of usage and cost for technical infrastructure on the part of the customer. Security is evaluated by confidentiality of data and confirmation of the payment. Convenience means ease, comfort, fast processing and number of accepting merchants and interoperability. Table 2 gives a summary of the payment solutions based on the customer requirements.

FRAUD MANAGEMENT SYSTEMS IN M-COMMERCE

Fraud is defined as access or usage of the network with the intent of not paying for the service accessed. It can be either external or internal to the operator's network, and often involves both. Telecommunication fraud is estimated at 22 billion US dollars (USD) per year and growing annually at 2 billion USD (18 billion to fixed line fraud and 4 billion attributed to cellular). The convergence of voice and data communications, which has been driven by the tremendous uptake of the Internet and mobile phone ownership, has made fraud a high priority item on the agenda of most telecommunication operators. The advent of e-commerce activity further compounds the problem as industry analysts predict phenomenal growth in e-commerce over the next 3 years, with

Table 1. The categorization of payment solutions

Payment Solutions	Instant Paid	Prepaid	Postpaid
Paybox	X		
IPIN	X	X	X
m-PayBill		X	X
m-Pay	X		X
Jalda		X	X

Table 2. Summary of the payment solutions

Payment Model	COST	CONVENIENCE	SECURITY
Paybox	An annual fee is charged to customer, but no transaction fee involved. Peer-to-peer transaction comes with extra cost. Infrastructure costs are low.	Useful for macro, micro and peer-to-peer transactions. Customer required to know only the PIN number to participate.	Customer personal data kept in the Paybox server and not exchanged with other participants. Fraud prevention techniques employed.
iPIN	No setup fee. Fees are based on transactions. Infrastructure costs are low.	Several payment options including micro-payments are offered. Interoperability between groups of individual payment networks is provided.	Enterprise houses users' personal data and guarantees privacy.
Vodafone m-PayBill	Membership free. No basic or transaction fees. Infrastructure cost does not exist except that the customer might require a WAP enabled phone.	Only applicable to micro-payments. Payment process is more customer friendly. Customer registered with Vodafone operator can automatically use the solution.	Interoperability between various countries is provided, but requires transfer of personal information. The privacy of the data will depend on the countries' privacy policy.
m-Pay	Registration is free. A new Orange SIM card is needed, which comes with a cost. Payment confirmation is also provided with a cost.	Customers need to download a script to activate applications on SIM card. Payment transaction is fast.	Payment carried out by exchange of certificates. Customer receives payment confirmation in the form of SMS. Server verifies every transaction from SIM card
Jalda	Content provider charges a small transaction fee from customers' phone bills. The customer might require a WAP enabled phone.	It can be used for normal as well as micro-payments, and supports interoperability but has not been enforced as a global standard.	Usage of strong authentication and non-repudiation protocols guaranteed. Payment receipt sent to user.

40% of all e-commerce transactions expected to occur using mobile devices such as phones and personal assistants.

Many mobile payment solutions failed since they were unable to accumulate critical user mass. Merchants and consumers expressed their distrust in the electronic payment systems (Dahleberg & Tuunainen, 2001). The possible modes of fraud that will be experienced within m-commerce payment activity will encompass frauds related to security breaches in the underlying payment model, as well as in the underlying carrier network. A number of technologies are being used to prevent and detect these kinds of frauds. The frauds that can occur in the m-commerce environment have thus been categorized as mobile phone fraud, mobile network fraud and fraud specific to the m-commerce transaction process.

MOBILE PHONE FRAUD

Criminals and hackers have devoted time and money to develop and refine their techniques, applying them to mobile phones as well. Not only is mobile phone fraud profitable, the stolen handsets have also provided anonymity to callers engaged in criminal activities. The various types of mobile phone fraud may be classified into two categories: subscription fraud and cloning fraud. Subscription fraud occurs from obtaining a subscription to a service, often with false identity details and no intention of paying. Cases of bad debt are also included in this category. In subscription fraud, all the calls for an account are fraudulent so there is no fraud-free period. Rules that are good for one time period may not be relevant for future time periods because calling behavior changes over time.

A signature-based system has been proposed in Cahill, Lambert et al. (2000). This system is event-driven rather than time driven so that fraud can be detected as it is happening and not at fixed intervals of time. It is based on the concept of account signatures, which may describe call durations, times between calls, days of week and times of day, terminating numbers, and payment methods for the particular account. All fraud records for particular kind of fraud are put into a fraud signature. For detecting a possible fraud, the call is scored by comparing its probability under the account signature to its probability under a fraud signature. Calls that are unexpected under the account signature and expected under the fraud signature receive higher scores and will be considered as more suspicious.

Cloning is the complete duplication of a legitimate mobile identification, namely, the MIN/ESN pair. Cloned phones can be identified with a technology called call pattern analysis. When a subscriber's phone deviates from its normal activity, it triggers an alarm at the service provider's fraud management system. It is put into queue where a fraud analyst ascertains whether the customer has been victimized and then remedies the situation by dropping the connection.

Location awareness of the mobile phone can be used to detect clones within a local system and to detect roamer clones (Patel, 1997). The success of these techniques is based on the assumption that the legitimate phones will stay powered up most of the time. Clones, by definition, will exist at a different location from the legitimate mobile phone. Clone detection within a user's current system can be recognized by "too many locations" and "impossible locations". A phone cannot be making a call from one cell site, and sending a registration message from another. In the cases of too many locations, fraud can be detected when getting registration messages from two different locations at almost the same time or getting two registration messages in an interval shorter than the re-registration period. Impossible location or velocity violation occurs when after a registration message at a location, another registration attempts from a location that is impossible to reach in the time elapsed. For the roaming, fraud is detected by monitoring handsets locations at the Home Location Register (HLR) and registration messages from Mobile Switching Center at Visitor Location Register (MSC/VLR) when mobiles enter a new system.

MOBILE NETWORK FRAUD

A mobile wireless network is vulnerable due to its features of open medium, dynamic changing network topology, cooperative algorithms, lack of centralized monitoring and management point, and lack of a clear line of defense. There are many techniques to prevent mobile network intrusion such as secure MAC, secure routing and encryption. Intrusion detection approaches can be broadly classified into two categories based on model of intrusions: misuse and anomaly detection. Misuse detection refers to attempting to recognize the attacks of previously observed intrusions in the form of a pattern or signature, and monitor the occurrence of these patterns; for example, frequent changes of directory or attempts to read a password file. Anomaly detection refers to establishing a historical normal profile for each user, and then using sufficiently large deviation from the profile to indicate possible intrusions.

Anomaly detection is a critical component of the overall intrusion detection and response mechanism. Trace analysis and anomaly detection should be done locally in each node and possibly through cooperation with all nodes in the network. In the anomaly detection model (Zhang & Lee, 2003), the attack model consists of attack on routing protocols wherein attacks behave by acting on routing protocols, or it may be a traffic pattern distortion. The audit data of the model are comprised of the local routing information and position locator of the mobile node. Classifiers are used as intrusion detectors and features are selected from the audit data. There are five steps to detect a possible intrusion in the network: selecting audit data, performing appropriate data transformation, computing classifier using training data, applying the classifier to test data, and post-processing alarms to produce intrusion reports.

A technique called Trace modulation has been used in Nobile, Satyanarayanan, and Nguyen, 1997), where the end-to-end characteristics of a wireless network are recreated. Trace modulation is transparent to applications and accounts for all network traffic sent or received by the system under test. These techniques can be used to detect possible bugs in the mobile network system

M-COMMERCE PAYMENT SPECIFIC FRAUD

Various types of frauds may arise due to security breaches in the payment model. With the mobile Internet, a fraudster can pick sensitive information out of the air. The vulnerabilities may include infection of the mobile device by a virus, use of PINs and passwords, which are easily guessable, possibility of messages getting lost, spoofing on cardholder or the payment provider and message replay. The requirements for protecting m-commerce transactions are similar to those for protecting fixed-line transactions. Sensitive data, for example, must be secured during transmission. The following sections state various frauds that may occur during the payment life cycle and the availability of the prevention and management schemes.

Fraud Prevention During Payment Authentication

Just as with the fixed line Internet, authenticating a user's identity may be the hurdle at which demand for m-commerce services could fall. Authentication is a process of associating a particular individual with an identity. Two different techniques have been used for authorization. One is a knowledge-based approach in which individuals use the "personal knowledge" about something, like a password or a PIN to identify themselves. The other is a token based approach in which the identification is done based on something a person has, like a driver's license number and credit card number. Both these approaches are susceptible to fraud due to lost or stolen tokens and also due to personal identifications that are used by fraudsters (Miller, 1994**).** A distributed scheme that solves the problem of uncovering the PIN has been proposed in Tang, Terziyan, and Veijalainen (2003). The authors suggest that instead of storing the entire PIN digits in the SIM of the mobile device, a part of the PIN is stored in the remote machine in the network. The PIN verification then involves both the mobile device and the remote machine, each verifying their respective parts of the PIN.

The increased use of wireless devices in m-commerce makes the need for identity verification even more important yet difficult to ensure; hence the need of biometrics in this field becomes more important. A biometric identification process for smart cards has been proposed in Jain, Hong, and Pankanti (2000). A biometric system has been defined as a system that makes personal identification based on some physical or behavioral characteristics of the person. In the enrollment phase a characteristic feature of the individual is scanned and converted to a digital representation. This digital form is then processed to a compact but expressive form called a template, which is stored in the smart card. During the recognition phase the biometric reader captures the characteristic and converts it into a digital form. The generated template is compared with the one stored in the smart card to establish the identity of the individual. In voice biometric systems mobile phone speakers are identified and verified based on their voice. The significant difference between a regular biometric system and the voice biometric system is that the regular one processes an image for identification whereas the voice biometric system processes acoustic information. This difference in processing results in a major difference in their acceptance since the regular biometric system requires extra infrastructure like image scanner whereas the voice biometric system can be deployed in the existing telecom systems using specialized applications (Markowitz, 2000). Radio frequency fingerprinting has been used to identify mobile phones. The supervisory audio tones (SAT) tone frequency, SAT tone deviation, maximum deviation, frequency error, supervisory frequency, and supervisory tone deviation are used to fingerprint or individualize a mobile phone (Boucher, 2001).

It is being observed that the mobile phone is vulnerable to malicious software like viruses, which might be capable of creating unauthorized copies of the PIN or password when the user creates an authentication response to the payment provider. Therefore the various possibilities of virus infection in mobile phones should also be addressed. Two kinds of applications infected by virus can be downloaded. One is the signed application, which is authenticated by checking the signature using the public key stored in the mobile phone. The other is an unsigned application, which is basically un-trusted, and is the basic cause of identity fraud. To prevent such a fraud it would be appropriate to limit the access of the application to a sensitive resource on the mobile device by systematic denial or by sending a prompt to the user for validation.

Fraud During Payment Transaction and Settlement

A fraudulent transaction requires the fraudster to be in possession of the customer signature, such as PIN or password, and also to be able to send the response message to the payment provider. A possible way to prevent such a fraud is to send an authentication request number from authentication server to customer together with the authentication request, which should be unique for the transaction and should only be used for the message exchange with the cardholder.

The authentication gateway in a mobile commerce environment injects messages into the mobile network through a Short Message Switching Center for SMS as the transport or Unstructured Supplementary Services Data Center (USSDC) when using USSD as the transport. The messages pass through the Signaling System 7 (SS7) based network associated with the mobile network. This is the signaling network used for control of the mobile network. It is possible that SMS messages can be read or manipulated if the SMS switching center is accessible to the user. The capture of the messages is a source of mass fraud attacks. Hence mobile operators involved in the payment process should be encouraged to review their procedures for protecting all the vulnerable parts of their network, including the BSSs, SS7 networks and the SMSC/USSDC and their interfaces.

To decrease the probability of fraud, pre-paid solutions were introduced which allow users to access specific services for which they pay in advance. In GSM mobile networks the prepaid solutions are intelligent network, which allows automatic call termination when the pre-paid value reaches zero. Fraud prevention during payment settlement generally involves supporting the non-repudiation property of mobile networking. Zhou and Lam proposed an efficient technique for non-repudiation of billing using digital signatures and hashing mechanisms (Zhou & Lam, 1998). In this scheme a mobile user needs to submit a digital signature when requesting a call along with a chained hash value. After this, a series of hashed values are released at predefined intervals, which allows at most the last unit of service in dispute. The problem of uncollectible debt in telecommunication services is addressed by using a goal-directed Bayesian network for classification, which distinguishes customers who are likely to have bad debt (Maamar et al., 2001). Digital data can be copied and a user can spend a valid electronic coin several times. Requiring the vendors to contact the financial institution during every sale, in order to determine whether the dollar spent is still good, can prevent double spending. Double spending can also be prevented using tamper resistant smart cards, which contain a small database of all transactions. Double spending can also be detected, in which case a double spender is identified when the cash is settled in the bank. In another detection mechanism tamper resistant device, "Observer" is used to prevent double spending physically. This allows the owner to spend the coin once in an anonymous manner, but the identity of the owner would be revealed if he or she tries to use it again (Chaum & Pedersen, 1992). The detection schemes thus do not prevent but deter double spending and also do not require any specific hardware.

RESEARCH ISSUES AND CONCLUSION

Research Issues

Without a wide popularity and usage, any given payment solution will not survive, regardless of its different attractive features. The disappearance of some innovative electronic payment procedures like eCash serves as an example of this fact. A mobile payment procedure today should not only consider the option of low to medium macro-payments, but also include at least the potential for further development in the direction of cost-effective micro payments.

Apart from the widespread acceptance of the solution by customers, another issue that remains to be solved is an issue of different mobile payment service providers. Because of their existing customer base, technical expertise and familiarity with billing, mobile telephone operators are natural candidates of the service providers. However, risk management and the need to ensure the cooperation of different providers for interoperability in an efficient m-payment system may complicate the issue. Future payment models may be the bank-dominated models where the mobile phones will provide just another way for customers to access their bank account. The PKI security standard, which is now widespread in the e-commerce scenario, can be applied to the m-commerce scenario as well. Integrating PKI into a single SIM handset needs further study. Finally, EMV, a standard for debit and credit bankcards, deserves consideration.

CONCLUSION

Mobile security and payment are central to m-commerce. Today, a number of competing mobile payment solutions have already found their way into the marketplace. In this chapter we surveyed several payment solutions and listed some fraud management schemes, which are central to a successful payment solution.

An important point which influences the establishment of the mobile payment procedure is the technical infrastructure needed on the customer side. A sophisticated technology may fail if the customer is not able to handle it with ease. On the other hand, simple procedures based on simple message exchange via short messaging services (SMS) may prove profitable. Thus, at present and in the future the important payment solutions will be SMS-based, which can easily be charged to the mobile phone bill of customers. Some other procedures may integrate two or more solutions. An important observation is that m-payments are still in their infancy. The m-payment solutions are still being developed with standards defined on individual business segments, which is a major reason for market fragmentation in this area even though the mobile marketplace is global. Other interesting areas related to m-commerce payment not mentioned in this chapter are issues of standardization and interoperability. These issues will have to be resolved for these solutions to reach their full potential, especially in places like Europe, where there are a large number of mobile operators and users who tend to roam into different areas.

Mobile commerce can only be conducted if all parties believe that there is adequate security. The majority of users of mobile commerce technologies are concerned about security. A sound security policy includes identifying security risks, implementing effective security measures, and educating users on the importance of security procedures. Fraud management systems are becoming increasingly important for wireless carriers. The challenge is to monitor and profile the activity of the users and to be alert to the changing nature of fraud.

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Section II
Business Management

Chapter X
The CRM Process and the Banking Industry:
Insights from the Marketing Literature

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ABSTRACT

This chapter's aim is to synthesize and present insights relevant to CRM process implementation in retail banking drawn from the marketing research literature. The authors first summarize strategic concepts from the marketing discipline that they believe are fundamental to the CRM process, but appear to be frequently forgotten in actual implementations that focus on the enabling technologies. They then describe a comprehensive framework for conceptualizing, operationalizing, and measuring CRM process implementation and its impact on firm performance, and illustrate its use to identify activities that must be performed for successful CRM in the context of a published case study of CRM implementation at a European Bank. Subsequently, the authors summarize research in one area of great importance to CRM managers at banks, namely, customer response to self-service banking technologies. The chapter concludes with some interesting directions for future research drawn from recent work in the marketing research literature.

INTRODUCTION

There has been an explosion of interest in the discipline and practice of customer relationship management (CRM) in the worlds of business and academe over the last decade. According to a projection made by the Aberdeen Group in 2003, worldwide spending in the CRM application area would grow at a compound annual growth rate of 6.7% until 2006, by which time it would cross $17.7 billion in spending, with the U.S. accounting for more than 50% of this expenditure (Barlas, 2003). Other projections from groups such as the Gartner and TowerGroup suggest that about half of total CRM spending in 2006 will be allocated toward analytical CRM software, which includes market-centric applications, and it is expected that financial services firms will be the single largest market for CRM systems, accounting for about a third of the total market (Pastore, 2002; InsightExec, 2006).

Factors Driving Business Interest in CRM

The origins of the great surge of business interest and investments in CRM over the last decade can be traced to powerful empirical research findings demonstrating the benefits of a customer-focused as opposed to product-focused approach to business management which emerged and were publicized in the beginning of the 1990s (e.g., Reichheld & Sasser, 1990; Reichheld & Teal, 1996). These findings focused business executives' attention on, first, caring about customer retention as much as customer acquisition, and, second, examining how customer profitability with retained customers can be grown over time. More specifically, startling observations—such as that by decreasing the customer defection rate by 5%, service companies can boost profits by 25% to 85% (Reichheld & Sasser, 1990), calculated by comparing the net present values of the profit streams over the average customer life at current and 5% lower defection rates—sparked immense business interest in better understanding and exploiting this phenomenon. Subsequent assertions about the positive impact of CRM on customer satisfaction (e.g., highly satisfied customers increase repeat sales and retention, Bolton & Lemon, 1999) and firm performance (e.g., higher firm value is correlated with higher customer satisfaction, Zeithaml, Rust, & Lemon, 2001) continued to stoke this interest.

At the same time, there were significant advances in the data-capture, storage, and analyses technologies and tools enabling more fine-grained "one-to-one" marketing efforts (Peppers & Rogers, 1993). The concomitant advent of the Internet and e-commerce have also enabled producers in many industries, especially services businesses (e.g., airlines, banks, and insurance companies), to bypass middlemen and directly interact with end customers, for example, via online banking and investment programs, direct selling of books, airline tickets, insurance, and so forth. This growing *disintermediation* process has made *relationship marketing*—including *customer co-creation of value*, for example, consumers assuming the responsibilities of direct ordering, personal merchandising, and product use with little help from the producers—more popular (Parvatiyar & Sheth, 2001-2002; Prahlad & Ramawamy, 2000). All of these forces have contributed to the rapid growth and evolution of CRM, especially in financial services such as banks.

CRM's Appeal to Banking

Within the last two decades, the competitive landscape in the banking industry has dramatically changed all around the globe due to forces such as deregulation, globalization, technology advances and commoditization of bank services, and increasingly demanding customers. Deregulation and globalization, beginning in the U.S. in the early '90s (e.g., Berger, Kashyap, & Scalise, 1995; *European Banker,* 2006), have led to industry consolidation, pan-European cross-border mergers (e.g., the Italian UniCredito acquired German HypoVereinsbank in 2005), while the implementation of new technologies (Zineldin, 2005) has opened multiple new channels (or touchpoints) for bank-customer interactions (e.g., bank branches, automated teller machines, self-banking, home banking, call centers, electronic mail, online banking, etc.).

As disintermediation has taken hold, banks are facing increased competition from other banks as well as non-bank providers of traditional banking business products and financial services, for example, brokerage houses, market funds, cooperatives, retailers, and online sources. The intensified competition from diverse formats and the need to coordinate interactions with customers across multiple channels have compelled banking organizations across the globe to change their traditional ways of doing business, become more marketing-oriented—knowing more about clients and prospects than your competitors has become a key to survival—and invest in CRM systems aimed at greater customer retention, cross-selling, and up-selling of a range of financial products and services.

Troubles with CRM

However, despite the growing investments in CRM, there is converging evidence from many sources (e.g., Boulding, Staelin, Ehret, & Johnston, 2005; Reinartz, Krafft, & Hoyer, 2004) that CRM implementation is anything but straightforward and the failure rate of CRM initiatives is high—for example, approximately 70% of CRM projects result in either losses or no bottom-line improvement in company performance (Gartner Group, 2003). Not surprisingly, given the magnitudes of investments in CRM and the yawning gap between its promise and fulfillment, improving understanding of the nature of the CRM process and how to make it work has been a subject of much debate and research in recent years. A search on Google Scholar provides about 261,000 "hits" with respect to articles and books that have CRM in their titles and/or abstracts, while a search on ProQuest (an electronic database) for the term "customer relationship management" yields some 25,000 articles on the topic, many written by technology or systems-focused analysts and consultants, reflecting the early trend of equating CRM technology with CRM. Indeed the term 'CRM' actually emerged in the information technology (IT) vendor community in the mid-1990s and is often used to describe technology-based customer solutions, such as sales force automation (SFA) (Payne & Frow, 2005). However, there is mounting evidence that a key reason for CRM failures at many firms is their *viewing it narrowly as a technology initiative rather than a fundamental change in a firm's business (marketing and customer) strategy enabled by new technology* (Reinartz et al., 2004). Business executives' attention is returning to the CRM concept's roots in marketing, the management discipline most directly concerned with strategies and programs for creating, satisfying, and keeping customers. It is therefore insights for more effective CRM contributed by research in marketing that are the focus of this chapter.

Chapter Objectives and Organization

The objectives of this chapter are four-fold:

1. Provide a marketing perspective on what CRM is and how to improve it in a way that would be helpful to banking CRM management, operations researchers, and technologists.
2. Outline a specific, systematic approach to measuring CRM process implementation in an organization, and illustrate its use to identify activities that must be performed for successful CRM within the context of a previously published case study of CRM implementation at a European Bank.

3. Provide recent research insights into one area of growing importance in banking CRM, namely, consumer adoption of self-service technologies.
4. Identify some interesting future research opportunities for CRM scholars.

The rest of this chapter is organized as follows. In the next section, we summarize strategic concepts from the marketing literature that we believe are fundamental to the CRM process but appear to be frequently forgotten in actual implementations which focus on the enabling technologies. We then describe and illustrate the recent research study (Reinartz et al., 2004) presenting a framework for conceptualizing, operationalizing, and measuring CRM process implementation and its impact on firm performance, followed by the review of research on customer response to self-service technologies. The chapter concludes with suggestions for future research.

BACK TO CRM'S ROOTS: MARKETING PERSPECTIVES ON EFFECTIVE CRM

It is customer relationship *strategy,* not *technology* that should drive CRM. By now this has become a common refrain among analysts (e.g., 2005 World Banking Report from Capgemini, www.capgemini.com), but it is not clear that many firms and CRM executives and technologists fully appreciate what this entails. Thus, it would be appropriate to recall some fundamental strategic concepts from marketing that form the underpinnings of CRM philosophy, but often appear to be forgotten in CRM process implementation.

Hark Back to the Marketing Concept

Philosophically, CRM espouses a customer-focused rather than product-focused view of a firm's business, as well as calls for shifting attention from immediate transactions to development of a customer relationship that is of value to both sides, encompassing all firm-customer touchpoints and channels for exchange. These fundamental notions of CRM are discerned in the basic tenets of the *marketing concept* put forward a half-century ago, well before the dawn of the CRM era, by McKitterick (1957), Borch (1957), Keith (1960), and subsequently expanded upon by Kotler (1967) and Kotler and Levy (1969). The marketing concept evolved as businesses in the West (e.g., the United States, Britain, Germany) found their earlier market philosophies—namely, the *production concept* (i.e., customers favor products that are standardized, widely available, and low in cost, and managers should focus on high production efficiency), the *product concept* (i.e., customers favor products that offer the most quality), and the *selling concept* (i.e., products must be sold at favorable prices and be aggressively pushed, as otherwise customers will not buy if left alone)—less profitable over time. More specifically, as Western societies matured into consumer societies after World War II, and competitive offerings proliferated, the marketing concept evolved, as volume, price, and promotional orientations were found to be less rewarding than an orientation that focused on the needs of particular sets of customers (Webster, 1988).

The marketing concept posits that for a firm to stay in existence, it must *determine and develop products and offerings that meet the needs and wants of its target customers, and deliver the desired satisfactions more effectively and efficiently than its competitors* (e.g., Kotler, 1976, p. 14). That is, firms should focus on identifying and fulfilling customer needs rather than selling products, otherwise they can succumb to *marketing myopia* (Levitt, 1960) when customers find alternative and superior ways to satisfy the same needs, e.g., as with non-bank servers of financial needs. The marketing concept clearly advocates that a firm follow a *customer needs-based strategy* toward developing not just a competitive core product, but its total offering or *"augmented product"* (Levitt, 1969) which includes, for example, the means of distribution and accompanying service, as consumers typically derive value from the total buying experience and not just the core product. The marketing concept also inherently emphasizes the *dual creation of firm and customer value*—that is, a firm creates value for itself (stays profitable) by creating value for the customer, which is of course a major theme of CRM and "the service profit chain" (Heskett, Jones, Loveman, Sasser, & Schlesinger, 1994). To effectively implement the marketing concept, firms must become and remain *market oriented* (Kohli & Jaworski, 1990), that is, establish good, organization-wide marketing information-gathering and intelligence-producing processes and capabilities to understand the needs and wants of their customers as well as the offerings of competitors.

However, while the marketing concept and the idea of market (or customer) orientation are easy to grasp, they are often lost sight of in practice in general (e.g., Webster, 1988) and CRM program execution in particular. For example, one of the basic perils of CRM is assuming that a valuable customer actually needs or wants to have a buying relationship with the firm as much as the firm would like to have this with him or her (Rigby, Reichheld, & Schefter, 2002). The reality is that many do not. For example, writing about banks' attempts to build customer relationships, Spitler and Meleis (2004) note: "It does no good to position 95% of the brands and products as being relationship-based when only 50% of the market is interested in that value proposition." Considering that discount carriers have captured over 25% share of the U.S. commercial passenger air travel market, and that discount U.S. commercial banks increased deposits 50% faster than others between 1998 and 2003, it is evident that not all customers want relationships. A banker Capgemini (*2005 World Banking Report*) interviewed said: "We put in place a relationship approach for all high-value clients, but a significant number do not appreciate the extra attention." Indeed, persisting with a relationship marketing approach with resistant customers can end up losing the customer. Just because technology permits you to contact and cultivate individual customers does not mean you should.

Focus on Needs-Based Customer Segmentation and Positioning

The aggressive, sometimes indiscriminate, pursuit of relationships with high-value customers by services firms such as banks is understandable as they have discovered considerably skewed distributions of profitability across their customer bases with the help of modern accounting practices such as activity-based costing as well as individual customer behavior tracking capabilities. Many services firms found some form of the "80/20" rule—that is, 80% of profit derived from just 20% of customers—applicable to their customer bases. Indeed, in the case of retail banking, the 80/20 rule appears to be optimistic in light of several reports that find even more dramatic profitability skews (Frei & Campbell, 2006). For example, one study finds that retail banks are characterized by a "150/20" rule, namely, 150% of profit contributed by just 20% of customers (Stoneman, 1999), while another by the Council on Financial Competition in 1996 suggests that only 40% of a retail bank's customers are profitable, contributing approximately 300% of value, while the other 60% of customers *destroyed* 200% of value (Frei & Campbell, 2006.) As noted by Frei and Campbell, notwithstanding the variations in the size of the profitability skew, the problem for retail banks is clear: *the contribution of individual customers to bank earnings varies widely, with a small percentage of customers cross-subsidizing the profitability of the bulk of the customer base.*

Additionally, investigations of resource allocations against customer relationship profitability distributions have often revealed that the best customers do not receive their fair share of attention and that some companies overspend on marginal customers. These observations have naturally led many services firms such as retail banks to enthusiastically embrace the process of customer segmentation and prioritization, or 'tiering', by profitability (e.g., Rust, Zeithaml, & Lemon, 2000; Zeithaml et al., 2001), with the aim of maintaining their most profitable relationships, attracting similar customers, reallocating customer service resources away from customers in lower profit tiers to customers in higher profit tiers, and fashioning pricing initiatives, fees, and cross-sell programs aimed at migrating customers from lower to more profitable tiers. For example, specialized service tactics used to retain the more profitable customers include:

- Assigning the most valued customers to appropriate relationship officers.
- Priority problem resolution.
- Priority telephone response and routing telephone calls to specially trained problem solvers.
- Discretionary pricing initiatives, for example, Bank of America offers its most profitable customers a quarter-point discount on mortgage rates and an extra quarter-point interest on certificates of deposit.
- Proactive contacts from the local relationship officer.
- Special mailings and product offers.
- Annual thank you mailing.
- Reward programs, for example, a loyalty bonus point scheme that enables customers to secure discounts on service charges for selected products.

While such steps to build *picket fences* around and service the high-value customers identified in the customer base appear eminently sensible from a tactical viewpoint, many firms' profitability segmentation model-based CRM programs are still characterized by a basic strategic shortcoming: specifically, they neglect the marketing concept dicta that *customer needs must drive firms' augmented offerings* and firms create value for themselves by creating value for their customers. In other words, customers are not intrinsically profitable based on their characteristics, but become profitable based on how satisfactorily firms' augmented offerings satisfy their needs (e.g., Giltner & Ciolli 2000). This implies a customer *needs-based segmentation analysis*—that is, understanding each customer's needs and how the firm can profitably serve those needs is what must ultimately drive CRM programs for optimum results. Segmentation by profitability is a useful starting point, but it is not a given that all or even most customers within a certain profitability tier are necessarily alike in their needs. Consequently, the real payoff from customer profitability segmentation for the firm comes from examining each profitability segment to uncover possible sub-segments of customers whose behavior patterns or other shared characteristics suggest they might have common unmet needs which can be served with a common solution. Or, as Larry Selden, coauthor of *Angel Customers & Demon Customers*, puts it: "So who are all the people you can go at with a common offer that will make you a boatload of money?" (e.g., Dragoon, 2005). We would add "sooner or later" to the Selden quotation, because needs-based segmentation helps to identify opportunities for growing profits from currently high-value as well as low-value customers rather than simply fencing off the former for better service. For example, Dragoon (2005) describes how by following a needs-based segmentation analysis, RBC Royal Bank identified currently low-value medical and dental school students and interns as a group with a high potential to turn into profitable customers. Therefore, in 2004 the bank put together a program to address the unmet financial needs of this group, including help with student loans, loans for medical equipment for new practices, and initial mortgages for their first offices. Within a year, RBC's market share among customers in this sub-segment rose from 2% to 18%, and the revenue per client is now 3.7 times that of the average customer. More generally, RBC's customer needs-based segmentation strategies are seen as an important reason why RBC's overall return on equity is nearly 25%.

Understand the Effective and Efficient Level of Customer Segmentation

RBC Royal Bank's success with the medical students' group was not only because it developed effective products and services to serve their unmet needs, but also because it was *efficient* to do so in that a common offering could be developed and marketed to a sufficiently large, identifiable, potentially profitable, and responsive segment of customers. Unfortunately, many other CRM projects have failed because they were motivated more by the availability of enabling technologies than a strategic appraisal of the effectiveness and efficiency of these projects. More specifically, as indicated in the previous section, the efficiency of CRM depends on the heterogeneity in customer profitability as well as needs across a firm's customer base. From an efficiency viewpoint, the mass market approach using a common message and medium would suffice when there is low variance in both customer needs and values, while the more one-to-one (value proposition and messaging) marketing approach is advantageous when there is high variance in customer needs and values. However, segment-level marketing strategies, intermediate between individual-level (personalized) CRM and a mass market approach, can be optimal when there is high variance in customer values but low variance in customer needs (segment customers by value) or when there is low variance in values but high variance in customer needs (segment customers by value proposition) (e.g., Wayland & Cole, 1997, ch. 4).

Following the marketing concept's emphasis on dual creation of value, firms should also ask themselves *whether the right (profitable) consumers will be responsive* to a CRM program? As already noted, some high-value customers may simply not want a relationship with the firm while others may be very responsive to personalized attention. In the retail banking context, managers should also be aware that quite a few high-value customers are inherently very loyal to their banks and need not be specially targeted by customer relationship managers. Their loyalty might originate from habitual behavior, superior products or service, strong social bonds/social switching barriers, past experience, and so forth. Low-value customers who are also not responsive would not be a priority, while low-value customers who are highly responsive would be problematic and costly to serve by the firm. In other words, the optimal allocation of CRM investment across a firm's portfolio of customers should be guided by both their values and responsiveness to this effort (e.g., Reinartz, Thomas, & Kumar, 2005). As shown in other marketing contexts (e.g., Mantrala, 2002; Mantrala, Sinha, & Zoltners, 1992), improving the allocation of the total CRM investment is likely to impact total returns much more than mere changes in the magnitude of the total CRM investment.

Take Advantage of New Analytical CRM Tools

One of the key components of CRM is a good measurement and analysis process. In recent years, research by marketing scholars has contributed significantly to analytical CRM models and tools (e.g., Kamakura et al., 2005). These include advancing segmentation techniques for supporting targeting decisions in database marketing such as neural networks, CHAID, or CART, and genetic algorithm-based decision trees (e.g., Levin & Zahavi, 2001), as well as latent class/finite mixture model-based techniques (e.g., DeSarbo & Ramaswamy, 1994); methods for customer development—cross-selling and up-selling, for example, Kamakura, Ramaswami, and Srivastava (1991) and Li, Sun, and Wilcox (2005) offer cross-selling models with applications in financial and consumer bank services; the modeling and prediction of customers' retention probabilities and lifetime values, or 'scoring models' (e.g., Malthouse & Blattberg, 2005); and approaches for customer defection or churn management—for example, Neslin, Gupta, Kamakura, Lu, and Mason (2006) investigate the performance of alternative approaches for predicting defectors from the customer base in a churn-modeling tournament and found that logistic regression-based and decision tree approaches offer a relatively good level of predictive ability compared to discriminant analysis-based approaches.

However, recent studies (e.g., Verhoef, Spring, Hoekstra, & Leeflang, 2003) indicate that this growing pool of scientific knowledge and advanced tools are still only limitedly used by managers in CRM practice who continue to rely on intuition and on long-standing methods such as 'recency, frequency, monetary value' (RFM) (e.g., David Shepard Associates, 1990) and cross-tabulation analyses for customer segmentation and predictive modeling. Further, many CRM vendors offer information systems and automated systems, but continue to fall short on analytical support even though it is recognized that analytics makes the difference between average and excellent implementation of CRM (*Computerworld*, 2001).

Current methods that most companies use to decide whether or not to maintain their current customer relationships remain quite crude. For example, as already noted, the most popular framework for assessing customers' expected lifetime values, namely the RFM method, classifies customers in terms of the recency, frequency, and monetary value (revenue, not profitability) of prior transactions. Holding monetary value constant, more recent and frequent purchasers are given higher probabilities of buying in the future and allocated greater promotional resources. However, the use of the RFM approach to score customers can be quite problematic. For example, Reinartz and Kumar (2002) provide some evidence that applying scoring approaches of this kind can lead to a significant overinvestment in lapsed customers (a Type 2 error) and ignoring customers who should be cultivated (a Type 1 error). Further, such misallocation of resources is likely to make it very difficult to practically realize the profit gains from increased loyalty that were originally publicized by Reichheld and Teal (1996) and which fueled the growth of loyalty programs, namely:

1. It costs less to serve loyal customers.
2. Loyal customers spend more.
3. Loyal customers market the company by way of referrals.
4. Loyal customers may tolerate higher prices for the same bundle of goods.

Reinartz and Kumar (2002) report analyses of data from four actual case studies which provide little support for either the general idea that the most profitable customers are the ones who stay longer with the firm or the specific claims that customers who purchase steadily from a company over time are cheaper to serve, less price sensitive, and help to bring in new business. Reinartz and Kumar (2002) conclude that the dimensions of customer loyalty and profitability are not necessarily positively correlated, and the way to strengthen the link between profits and loyalty is to *manage both at the same time.*

To summarize the key takeaways from this section, many services firms' CRM programs appear to have fallen short of their promise due to insufficient attention paid to the strategic marketing concept and basic principles of effective and efficient market segmentation, product positioning, and marketing resource allocation. In particular, customer needs-based segmentation must ultimately drive CRM programs even though a customer profitability segmentation analysis can serve as a good starting point for efficient program development. In a number of instances, firms seem to have launched CRM programs simply because they were enabled by emerging technologies without evaluating the necessity and/or incremental payoff of these programs relative to traditional marketing strategies. Lastly, investments in analytical support services can make more of a difference to the success of CRM projects than investments in IT systems. The marketing research literature to date offers a number of powerful analytical models and methods for predicting customers' lifetime values, customer segmentation analysis, customer development, and customer churn management, which have so far diffused only to a limited extent among the CRM practitioner community. CRM program successes are likely to rise as these analytical methods become more widely disseminated and used in practice.

Having presented some high-level insights from a marketing perspective regarding the recorded gap between the CRM promise and its fulfillment, we now focus on a systematic approach to conceptualization of CRM process implementation and assessing its impact on firm performance.

THE CRM PROCESS: CONCEPTUALIZATION, DEFINITION, AND MEASUREMENT

Reinartz et al. (2004) propose that the proper level for conceptualizing the CRM process in companies is the customer-facing level, encompassing the coordination of information across time and all contact channels, and the distribution of customer intelligence to all customer-facing functions to systematically manage the entire customer relationship. For example, a bank customer who has both a loan product and a savings product might interact with the bank through various channels and different types of interactions (e.g., transaction, information request, complaint), *which may change over time*. A CRM process on the customer-facing level would capture these interactions and, on the basis of the generated intelligence, would result in coordinated and well-defined actions through different functions. Reinartz et al. (2004) further propose that the conceptualization should reflect:

1. The marketing concept.
2. The evolution of customer relationships over time with different phases, for example, relationship initiation or exploration, maintenance or maturity, decline, and termination.
3. The idea that firms should interact with customers and manage relationships differently at each stage, for example, attempt to mature relationships via cross-selling and up-selling products.
4. Recognize that the distribution of relationship value to the firm is not homogeneous.

Accordingly, they offer the following definition of CRM:

CRM is a systematic and proactive process to manage customer relationship initiation, maintenance, and termination across all customer contact points in order to maximize the value of the relationship portfolio.

Based on this definition, Reinartz et al. (2004) propose a comprehensive conceptual model of CRM process implementation which posits that each of the three primary dimensions of the CRM process (relationship initiation, maintenance, and termination) has several distinct sub-dimensions. These are indicated by the survey instrument exhibited in the Appendix. Reinartz et al. (2004) measured and validated the components of this model using multi-item scales to assess the extent to which the dimensions are implemented utilizing survey data from 214 companies distributed across three countries and four industries: Utilities (28), Financial Services (78), IT/Online

Figure 1. Conceptual model of CRM process implementation impact on firm's performance (Reinartz et al., 2004)

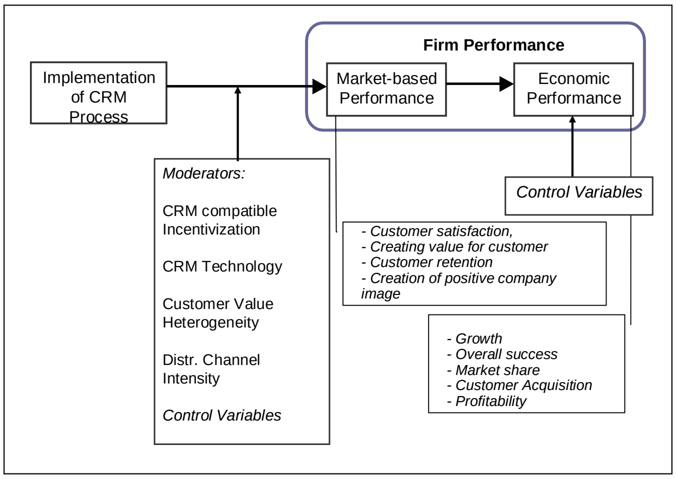
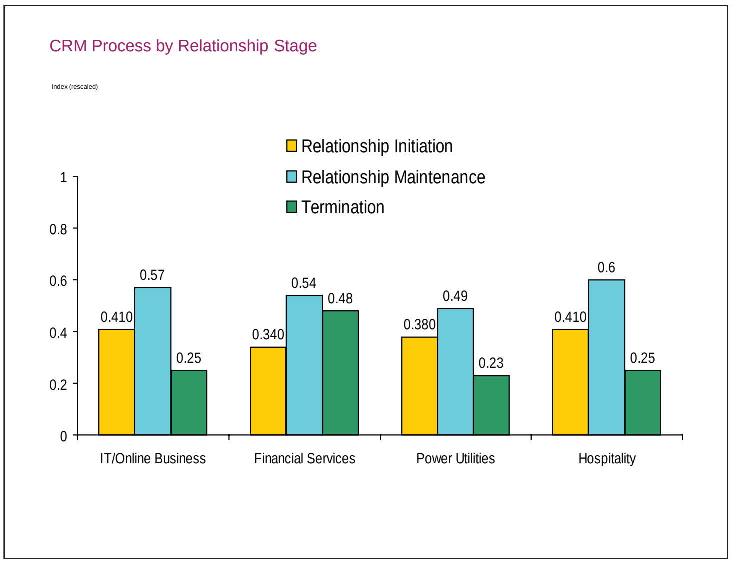


Figure 2.



Sector (64), and Hospitality Industry (41). Based on these measures, aggregate indexes of CRM process implementation at the initiation, maintenance, and termination stages were constructed. Utilizing these indices and collected data on the economic performance of firms, Reinartz et al. (2004) investigated the impact of CRM process implementation on company performance. They also investigated some key moderators of the relationship between CRM processes and performance as shown in their model of the performance outcomes of the CRM process (see Figure 1).

The first set of key findings of the Reinartz et al. (2004) study relating to the variation in CRM process implementation across relationship stages by industry are shown in Figure 2.

It is clear that investments in the relationship maintenance process are higher than those in the relationship initiation and termination processes in all four industries. This reflects the general emphasis on customer retention or loyalty management, encompassing cross-selling, up-selling, and referral management in most CRM programs. However, what is particularly noteworthy is the comparatively high investments and efforts in the financial services industry directed toward the customer termination process relative to investments in the relationship initiation (new customer acquisition) process. Is this a case of CRM myopia in financial services considering that in the other three industries, investments in the relationship initiation process implementation are significantly greater than those directed at termination?

A second set of key findings of the Reinartz et al. (2004) study offering much food for thought is listed below:

1. The good news is that *CRM process implementation is indeed associated with better firm performance in two of the three stages, namely, relationship maintenance, followed by relationship initiation*. The effects for relationship termination were either low or not significant, possibly because companies are either reluctant or not as effective in terminating relationships with customers who are not profitable.
2. *Organizational alignment (via incentives) plays an important enabling role*. Thus, it is not enough for a company simply to implement CRM processes. It must organize itself and install a reward structure to support these processes.
3. Consistent with previous studies, *a large proportion of CRM technology deployments do not perform to expectations*. If firms focus on only this aspect, their efforts are likely to be disappointing, at least in the short run. *In particular, the successful implementation of CRM requires a strong people-related component.*

An important managerial implication of the Reinartz et al. (2004) framework is that it can be used to identify and/or crosscheck the activities that must be implemented for the CRM process to be successful. We illustrate this in the following case study.

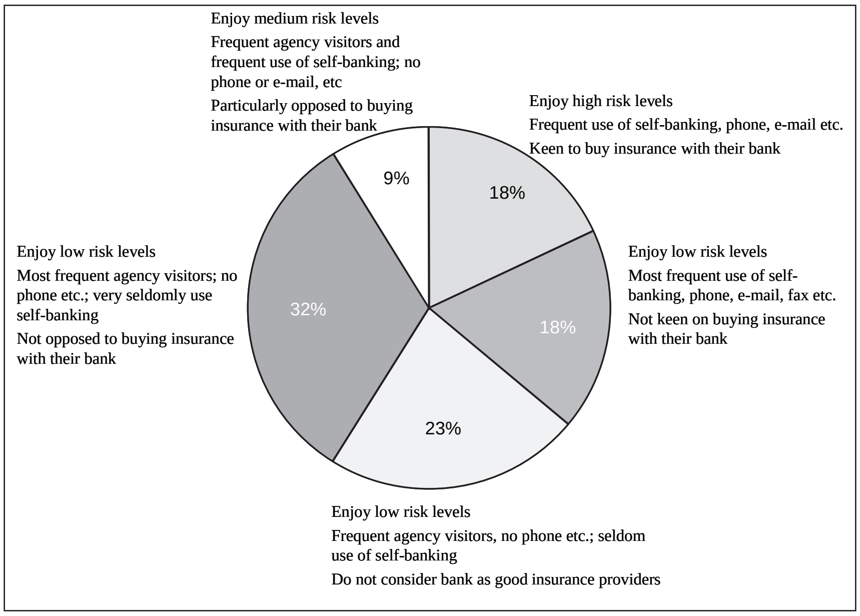
AN ILLUSTRATION OF THE CRM PROCESS MODEL: LINDGREEN AND ANTIOCO'S (2005) FIRST EUROPEAN BANK CASE STUDY

Background

In the late 1990s, First European Bank (FEB), facing fierce competition, extended its product and service offerings to the insurance sector, and began marketing them through multiple channels to individual clients. Realizing the need for a customer-centric approach, in 2001, FEB initiated a major CRM program that was expected to be completed in five years and aimed at achieving the following major goals:

- Concentrate on profitable customers by means of advanced segmentation.
- Better understand "who buys what and how much" (i.e., distinct combinations of clients, products, and volumes).
- As a result of better client information, create demand instead of just experiencing it.
- Design a mix of distribution channels with specialized services (e.g., special relationship managers and problem solvers) for the most profitable customers, and standardized services (e.g., automated e-mail responses) for the least attractive customers.

Figure 3. First European Bank's customer segments (Adapted from Lindgreen & Antioco, 2005, p. 147)



Based on these reported goals, it is clear that FEB's proposed CRM program investments all relate to the "relationship maintenance" process dimension of the comprehensive model of the CRM process proposed by Reinartz et al. (2004) and is consistent with their large-scale survey-based finding that investments in the relationship maintenance process are higher than those in the relationship initiation and termination processes in the financial services industry. Therefore, we assess FEB's relationship maintenance process implementation in terms of the process sub-dimensions identified in the Reinartz, Krafft, Hoyer model, namely, *customer evaluation*, *retention management*, and *up/cross-selling* (see Appendix).

FEB's Relationship Maintenance Process Implementation

Customer Evaluation

With regard to the customer evaluation process of relationship maintenance, Reinartz et al. (2004) identify some of the key sub-processes as:

1. Implementing a formal system for determining which of the bank's current customers are of the highest value.
2. Continuously tracking customer information in order to assess customer value.
3. Actively determining the costs of retaining customers.
4. Tracking the status of the relationship during the entire lifecycle.

As described by Lindgreen and Antioco (2005), FEB's implementation with respect to most of the specified customer evaluation processes was quite thorough.

Specifically, FEB developed a *real-time database* as a means to fully understand which types of clients it was dealing with and their interactions with sales services and client support services through the distribution network, which contains every possible channel to contact the bank, including agencies, call centers, self banking, home banking, client services, and so forth.

Next, FEB invested in developing an effective and efficient *customer segmentation strategy and* *system,* which uses both external (attitudes and needs) and internal customer information (e.g., channel choice, buying behavior, socio-demographics, actual and potential profitability, and behavior in terms of distribution channel use and products; see Figure 3). The identification of the clients' profiles also allows First European Bank, first, to identify profitable and less profitable clients and, second, to direct the less profitable clients to less costly distribution channels (although, the bank did find that the less costly channel, the Internet, is preferred by the more profitable clients for its ease of use and real-time access). Clearly, actively determining the costs of retaining a customer would be necessary to do this (although no explicit information about this is provided in the case study.)

Further, as regards continuous tracking of customer information to establish customer value, FEB implemented *client systems information programs,* primarily used to stock, extract, and analyze data in order to identify a behavior tendency and adapt marketing accordingly. Every time a client contacts the bank through any distribution channel, the data collected are transferred to large central data warehouses where they are classified, treated, and submitted to sophisticated data mining tools, regression, and causal model analyses to predict customers' next actions. "Trigger events" such as terminating an account or a substantial reduction of transactions at FEB initiate marketing activities, for example, direct mail or contact from FEB's outbound call center. Thus, this CRM program helps to forecast customers' future behavior and value to the company.

Lastly, FEB links individual clients' financial behavior with their lifecycle and cash availability. This enables the bank to anticipate and propose "fit-to-situation" products. FEB is also able to identify profiles of profitable customers and uses these profiles to target prospects who promise to be profitable as well. Thus, FEB clearly applies Reinartz et al.'s (2004) customer segmentation differentiated by lifecycle stages. In particular, FEB evaluates prospects, current clients, and even customers at the end of their individual business relationships.

Retention Management

With regard to retention management, the key sub-processes identified by the Reinartz, Krafft, Hoyer model are:

1. Maintaining an interactive two-way communication with current customers.
2. Actively stressing customer loyalty or retention programs.
3. Integrating customer information across the multiple customer contact points.
4. Optimally responding to groups of customers with different values.
5. Systematically attempting to customize products/services based on the value of the customer.
6. Systematically attempting to manage the expectations of high-value customers.
7. Attempting to build long-term relationships with high-value customers.

As described by Lindgren and Antioco (2005), FEB's CRM program included some of these retention program elements such as the *client systems information programs* described previously; interactions between client services and FEB's customers that generate additional important information about clients' needs and preferences (e.g., via customer complaints, feedback, or mail surveys); *channeling integrated data available in different departments and across the different channels, including home banking and self-banking,* to the sales department as input toward their *sales force automation*; distributing intelligence to and creating a steady dialogue between all channels involved, which is truly a complex task given that FEB provides seven different distribution channels, namely agencies, call centers, self-banking, home banking, technical support, communications, and client service departments; developing selection programs and client *loyalty programs*; proactively identifying *"predictive leavers,"* to try and retain them by further focusing on their needs; developing a powerful *artificial intelligence system,* to enable the bank to send out standardized but the right replies to *e-mail communication messages* and requests—otherwise an employee will have to intervene to individualize the response the client requires; and creating a *help service* responsible for handling specific questions or complaints, which will deal with the clients much faster than the actual current response times.

Up-Selling, Cross-Selling, and Referrals

Lindgren and Antioco's (2005) case study is rather silent on these aspects, except for noting that effective segmentation will also enable the bank to find and focus on clients who will be treated as referrals by others. More specifically, FEB uses its customer segmentation to identify customers who are likely to refer or who probably are considered by non-customers as opinion leaders or referrals.

Following the Reinartz, Krafft, Hoyer study, the overall impression one gets from the FEB case study is that the customer relationship maintenance process implementation at FEB was quite comprehensive—with the exception of the up-selling and cross-selling processes about which there is little information.

Finally, some observations regarding *change management* at FEB are pertinent in light of the research of Reinartz et al. (2004). Lindgren and Antioco (2005) report that, recently, the bank has changed its call centers from cost centers to profit centers—FEB's employees are incentivized for selling new products, motivating customers to use less-costly channels, cross-selling, and regaining lost customers. This is very consistent with the importance of employee commitment and the provision of appropriate incentives to employees for the successful implementation of CRM shown in the research by Reinartz et al. (2004). Also, implementation of FEB's CRM program turned out to be complex and tedious. FEB's top management had to be involved in initializing and following-up on the development of the program. A systematic change management was necessary to successfully transform FEB from a mostly product-oriented to a customer-centric organization. Of particular importance was the human resources, and that all employees internalized the company's new strategy. According to Lindgren and Antioco (2005), First European Bank's CRM program reached its breakeven after about three years. The program consumed substantial resources and has to be evaluated steadily to ensure it stays profitable and successful.

To summarize, the FEB case study is a good illustration of the following key points made by Reinartz et al. (2004):

1. CRM programs have the opportunity to improve company performance when there is heterogeneity in customer relationship values to the firm.
2. CRM process implementation can improve company performance when sufficient attention is given to the important role of organizational alignment, and it is recognized that change management of the people-related component, including their incentive systems, is as important as the CRM technology deployment component.

In the next section, we focus on recent marketing contributions to *customer co-creation* aspects of CRM in a domain of particular relevance to banks (e.g., Zineldin, 2005), namely, self-service technologies.

CUSTOMER CO-PRODUCTION AND SELF-SERVICE TECHNOLOGIES IN BANKING

The unique characteristics of services often require customers to participate in co-creating service values, either by serving themselves (such as at an ATM) or by cooperating with service providers (e.g., investment consulting). Dabholkar (1990) defines customer co-production as involving customers into the process of producing and delivering the service. Beyond this view, Vargo and Lusch (2004) posit that marketing is a value co-creation process achieved by firms collaborating with customers. That is, customers are no longer "passive audience," but "active co-producers" with service providers, an activity through which their personal needs are better served and satisfaction enhanced. In this sense, training customers to become "experienced" and "competent" "co-workers" is very critical to the firm. Figure 4 depicts the concept of customer co-production, while Figure 5 summarizes its benefits to both customers and firms.

Three Levels of Customer Co-Production: Application to Banking

Based on the level of customer participation in service production and delivery, Meuter and Bitner (1998) distinguish among three types of service production: *firm production, joint production,* and *customer production* (see Figure 6).

Thus, in banking, if the financial transaction (e.g., opening of new account, balance transfer) is performed mostly by the banking staff, while the customer may only have a physical presence or merely offer basic and necessary input/information, it is classified as *firm production.* For *joint production*, a customer behaves like a partial employee who contributes effort, time, or other resources to undertake some of the delivery functions. For instance, investment consulting requires both the customer and investment consultant to work together. For *customer production*, financial transaction is delivered almost entirely by the customers, for example, using self-service technologies (SSTs). One study performed by Prendergast and Marr (1994) suggested that transaction-based services, for which banks traditionally charged a relatively low fee, are moving away from human tellers (*firm production*) and towards SSTs (*customer production*). This is freeing up time for human tellers, who are now being trained in the giving of advice related to high involvement banking services and cross-selling (*joint production*). Human bank staffs will become banking consultants and salespeople, rather than the mere order takers of the past.

Figure 4. Customer co-production: A paradigm shift of marketing logic

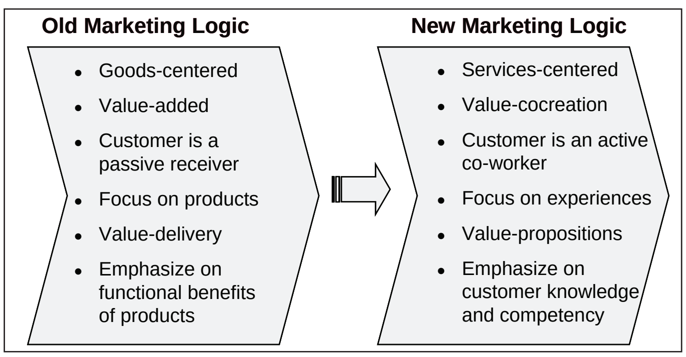


Figure 5. Managerial implications of customer co-production

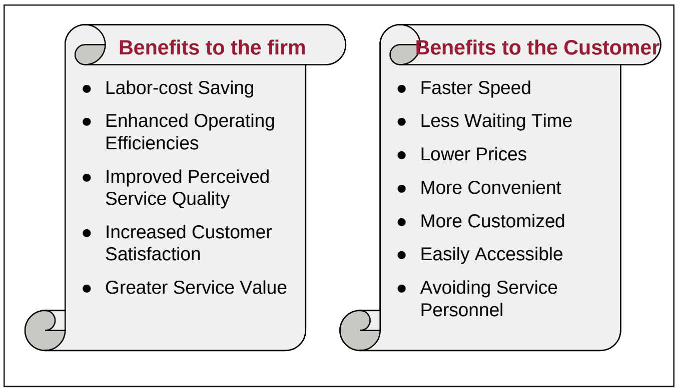
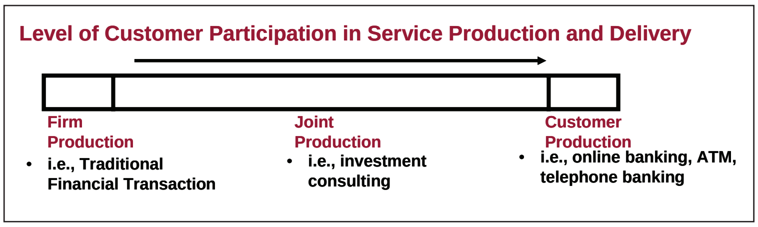


Figure 6. Level of customer participation in service production and delivery (Meuter & Bitner, 1998)



Research Insights into Customer Use of Banking Self-Services Technologies (SSTs)

SST is one important type of customer co-production that is particularly prevalent in the banking industry. SSTs are technological interfaces that enable customers to produce a service independent of direct service employee involvement, for example, online banking and ATMs. Meuter and Bitner (1998) discuss how such technologies introduce a host of complexities in firm-customer-technology interactions. SSTs can benefit the service providers by reducing labor costs and standardizing service delivery. However, as SSTs often require increased involvement or work from the customers, it seems SSTs have mixed successes (e.g., ATMs have been successfully adopted by customers, while the acceptance of online banking and telephone banking is far from being satisfactory). Some of the reasons identified in research by marketing scholars (e.g., Dabholkar, 1994, 1996; Meuter, Ostrom, Roundtree, & Bitner, 2000; Dabholkar & Bagozzi, 2002) for why customers use or do not use SSTs are summarized in Figure 7. With regard to the initial SST trial decision, Meuter, Bitner, Ostrom, and Brown (2005) find that consumer readiness variables (e.g., role clarity, motivation, and ability) are key factors influencing the likelihood of trial. With regard to degree of use of self-service banking technologies, studies based on clustering of customer SST usership profiles (e.g., Durkin, 2004; McPhail & Fogarty, 2004) indicate medium-to-high users of SSTs heavily use credit cards to facilitate their activities, while non-users and low users prefer the customary way of conducting transactions and enjoy the personal interaction with the banking staffs.

Considering the huge benefits and record of mixed successes of SSTs, banking marketers, therefore, are facing an imperative question: how to best design, manage, and promote new SSTs in order to have the best chance of customer acceptance. Some thought-provoking findings and important guidelines are offered by a recent survey study by Curran and Meuter (2005) which examines the effect of four antecedent beliefs on customer adoption of SSTs across three banking technologies—ATMs, telephone banking (TB), and online banking (OB). These three technologies are in different stages of the diffusion process. ATMs have been developed for a long time and are widely accepted, while TB has been available for many years but not widely adopted. OB is relatively new to the market. A total of 628 banking customers in the northeast United States participated in the survey. Among them (see Figure 8), 80% had used ATMs, while only 28% had used TB and 13% had used OB. In terms of customer's knowledge of the availability of these technologies, 95% knew their bank offered ATMs, while only 59% and 49% knew TB and OB were offered. More surprisingly, 11% and 7% indicated that their bank did not offer OB and TB respectively, when in fact, the bank did offer those services. These patterns show that ATMs are widely adopted and used, while the other two are much less frequently used. Great efforts are needed to increase the consumer awareness and possible adoption of the other two SSTs.

The impact of the four antecedent beliefs investigated by Curran and Meuter (2005)—namely, ease of use, usefulness, perceived risk, and need for interaction—varied depending on the technology. *Usefulness of SST* was a significant predictor for ATM and TB. *Ease of use* only significantly predicted ATM, while *perceived risk* was an important determinant only for OB. The effect of *need for interaction* was not found in this study.

As these three technologies represent different stages of diffusion, these findings indicate that the effects of beliefs change during the diffusion process of a new technology. In the initial stage of introducing a new SST like OB, consumers are most concerned with the risk and uncertainty about the technology. Banks should work on overcoming consumer uncertainties by helping them learn how to operate it and appreciate its benefits. After passing the initial stage, there remain other substantial hurdles, such as the problem of ease-of-use being experienced with TB. At this stage, marketers should either improve the interface design or change customers' perceptions of difficulties of the technology. ATMs have made significant progress by demonstrating to consumers that they are easy to use and useful.

Customer Participation in Service Recovery

It is impossible to ensure 100% error-free service, even for service giants like CitiBank. The marketing literature on service recovery (e.g., Fisk, Brown, & Bitner, 1993; Tax, Brown, &

Figure 7. Reasons for customers to adopt or refuse SSTs

Why Adopt SSTs	Why Refuse SSTs
• Usefulness	• Anxiety and Stress with SSTs
• Easy of use	• Perceived Threat of SSTs
• Availability	• Need for Interaction with Personnel
• Convenience	• Inertia to change delivery habits
• Time and cost savings	• Cost of learning new SSTs is too great
• Great control over delivery	
• Fun and enjoyment	

Chandrashekaran, 1998; Zeithaml & Bitner, 2003) has argued that effective recovery can impact customer satisfaction, deflect the spread of damaging word-of-mouth, and improve bottom-line performance. As customers are co-creating values, the service quality will largely depend on customers' competencies. Moreover, many customers refuse to use SSTs due to either their incapability or uncertainty of the technology. Therefore, customer education becomes an important topic for service providers to pursue.

With the benefits of customer co-production being well recognized, the question becomes: what happens when co-produced services (e.g., online banking) fail? More specifically: (1) Will customers be frustrated/discouraged about future co-production? (2) How can customers be involved in the service recovery process? And (3) if the quality of co-produced services largely depends on customers' input, can recovery serve as a learning process to enhance customers' future co-production capability and efficacy?

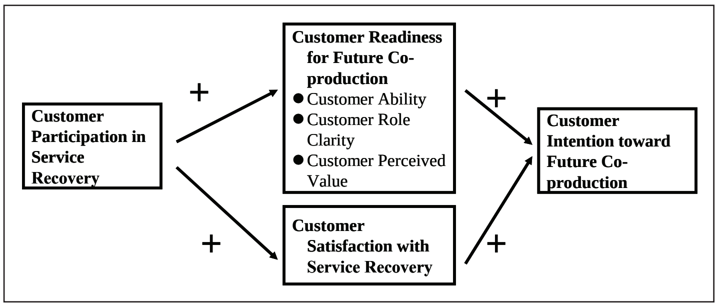
A study currently conducted at University of Missouri–Columbia by Dong, Evans, and Zou (2006) incorporates the idea of customer participation into service recovery by exploring the role that customer participation in service recovery has on the customer's intention to co-produce in the future (see Figure 9).

In the study, customer participation in service recovery is defined as the degree to which a customer is involved in taking actions in response to a service failure. For example, when a customer is using online banking to transfer his balance, as he does not know exactly how to proceed, he messes up. He calls customer service for help. If the representative simply gets all the customer's information and processes the task for him, this is *firm recovery.* As the recovery is mostly delivered by the banking staffs with little contribution from the customer, the customer still does not know how to do it himself. Probably next time he will not bother to use online banking and he will let the banking staff perform the task. If the representative teaches the customer via phone how to do balance transfer online step-by-step, and the customer is guided through the whole process, this is *joint recovery.* If the customer tries to figure out how to fix the problem on his own and eventually solves the problem himself, this is *customer recovery.* The Dong et al. (2006) study yields some surprising findings. Specifically, rather than *firm recovery*, failure in a co-produced service context *is better resolved with co-produced service recovery.* With participation in recovery (i.e., *joint recovery* or *customer recovery*), customers understand their roles and procedures better, and develop skills to function more productively. Their ability and role clarity of future co-production are improved. They perceive greater value of co-production with the successful recovery experiences. They are more satisfied with the service recovery where they participate. Customers tend to have more confidence and efficacy to

Figure 8. Descriptive statistics (Curran & Meuter, 2005: 628 banking customers participated in the survey)

	ATM	Telephone Banking	Online Banking
Current Usage	80%	28%	13%
Know bank offers this SST	95%	59%	49%
Don't know bank offers this SST but bank does offer	2%	7%	11%

Figure 9. Theoretical model of Dong et al. (2006) study



participate in future co-production. Factoring the customer out of the recovery equation (firm-only recovery) damages the fundamental premise of the exchange context.

FUTURE RESEARCH OPPORTUNITIES IDENTIFIED IN THE MARKETING LITERATURE

The field of CRM has matured considerably over the last decade (Boulding et al., 2005). What CRM stands for and what it entails has become clearer as the results of much research have become available. The question now is: where does CRM research go from here? A few general suggestions for research that would be relevant to industries like banking are given below.

First, much of the CRM research that has been conducted thus far appears to have concentrated on organizations for which CRM was a new initiative. Hence, future work investigating CRM should seek to examine its effects during the later stages of CRM adoption, directly following CRM adoption (Jayachandran, Sharma, Kaufman, & Raman, 2005) or in more mature markets (Srinivasan & Moorman, 2005). In such research, the relevance of longitudinal data for assessing causality issues in CRM research seems clear, as does the possible use of Bayesian methods to account for customer heterogeneity (Boulding et al., 2005; Gustafsson, Johnson, & Roos, 2005).

Second, CRM research should also seek to identify differences in CRM requirements between business-to-consumer and business-to-business markets faced, for example by banks (Mithas, Krishnan, & Fornell, 2005; Ryals, 2005). How about differences across low- vs. high-involvement goods and services? And how much do we already know about CRM for (core) products vs. services and across industries?

Third, research needs to be done to improve customer targeting and selection processes—that is, how to distinguish and select the profitable prospects from the not-so-profitable ones, a common question faced at banks (e.g., Cao & Gruca, 2005; Ryals, 2005), as well as the "real options" of abandoning unprofitable customers (e.g., Haenlein, Kaplan, & Schoder, 2006; see also Rajagopal & Sanchez Romulo, 2005).

Fourth, more detailed research into how changes in marketing policy, as a result of CRM, affect future customer behavior and their value is needed (e.g., Lewis, 2005). That is, customer behavior and values are not static but will change as marketing policies towards them change. What is then the long-term impact on customer value? For example, Ryals (2005) discusses how a straightforward, relatively simple analysis of its personal loan borrowers' lifetime value—lifetime revenue (loan interest) less acquisition and retention costs—led to dramatic changes in the bank's customer targeting, acquisition, and retention strategies (e.g., raising the loan prices for unprofitable customers and offering new products to the larger and more profitable customers), resulting in the department achieving profits 270% ahead of target for the year. However, what then will be the long-term effects as customers learn and adapt their behavior to the product policy changes and the corresponding optimal marketing policies? This line of research would no doubt call for the development and deployment of more sophisticated methods of dynamic optimization and control (e.g., Raman & Angur, 2000). However, many CRM processes are characterized by non-linear and dynamic phenomena for which classical optimization methods are extremely difficult to implement. In such cases, new approaches based on innovative techniques such as fuzzy control, neuro-fuzzy control, and neural networks (e.g., Raman & Angur, 2002) need to be pursued.

CONCLUSION

The purpose of this chapter was to synthesize and draw out important insights useful to CRM process implementation—including customer self-service technologies—in retail banking from a wide, deep, and growing body of academic research in marketing, beginning with the need to hark back to and imbue CRM initiatives with the fundamental marketing concept, which stresses that customer needs—not enabling technologies—must drive these efforts. To implement this philosophy successfully, a deeper understanding is needed of what specifically constitutes CRM processes. This chapter reviews a comprehensive, validated marketing conceptualization of the multi-faceted CRM process construct, which encompasses the three key stages of customer relationship initiation, maintenance, and termination. This conceptualization helps to identify activities that must be performed at each stage for successful CRM, as illustrated in the case of one bank's CRM implementation effort. The activities themselves need to be supported by the application of more sophisticated analytical tools to the available customer-level data to better understand customers' unmet needs and motivations driving their behaviors. As noted earlier in this chapter, there have been many important advances made with respect to such analytical models and tools in the marketing research literature which have been disseminated and adopted in practice only to a limited extent. Greater investments and use of these tools within the overarching framework of the CRM process implementation described in this chapter have the potential to greatly improve the payoff from CRM initiatives while building a more satisfied customer base. We hope this chapter stimulates bank CRM managers to investigate the rich knowledge base in the marketing literature in more depth, as well as triggers more marketing-oriented research on effective CRM in the banking industry.

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APPENDIX

Description of Reinartz, Krafft, and Hoyer (2004) measures of the CRM Process

CRM Initiation (INITIATE)

Measurement at initiating stage (IMEASURE) *

With regard to your strategic business unit, to what extent do you agree to the following statements?

- We have a formal system for identifying *potential* customers.
- We have a formal system for identifying which of the *potential* customers are more *valuable*.
- We use data from external sources for identifying potential high-value customers.
- We have a formal system in place that facilitates the continuous evaluation of prospects.
- We have a system in place to determine the cost of re-establishing a relationship with a lost customer.
- We have a systematic process for assessing the value of past customers with whom we no longer have a relationship.
- We have a system for determining the costs of re-establishing a relationship with inactive customers.

Activities to acquire customers (ACQUISIT) *

With regard to your strategic business unit, to what extent do you agree to the following statements?

- We made attempts to attract prospects in order to coordinate messages across media channels.
- We have a formal system in place that differentiates targeting of our communications based on the prospects' value.
- We systematically present different offers to prospects based on the prospects' economic value.
- We differentiate our acquisition investments based on customer value.

Activities to regain customers (REGAIN) *

With regard to your strategic business unit, to what extent do you agree to the following statements?

- We have a systematic process/approach to re-establish relationships with valuable customers who have been lost to competitors.
- We have a system in place to be able to interact with lost customers.
- We have a systematic process for re-establishing a relationship with valued inactive customers.
- We develop a system for interacting with inactive customers.

CRM Maintenance (MAINTAIN)

Measurement at maintaining stage (MMEASURE) *

With regard to your strategic business unit, to what extent do you agree to the following statements?

- We have a formal system for determining which of our *current* customers are of the highest value.
- We continuously track customer information in order to assess customer value.

- We actively attempt to determine the costs of retaining customers.
- We track the status of the relationship during the entire customer lifecycle (relationship maturity).

Activities to retain customers (RETAIN) *
With regard to your strategic business unit, to what extent do you agree to the following statements?

- We maintain an interactive two-way communication with our customers.
- We actively stress customer loyalty or retention programs.
- We integrate customer information across customer contact points (e.g., mail, telephone, Web, fax, face-to-face).
- We are structured to optimally respond to groups of customers with different values.
- We systematically attempt to customize products/services based on the value of the customer.
- We systematically attempt to manage the expectations of high-value customers.
- We attempt to build long-term relationships with our high-value customers.

Activities to manage up- and cross-selling (CROSS_UP) *
With regard to your strategic business unit, to what extent do you agree to the following statements?

- We have formalized procedures for *cross*-selling to valuable customers.
- We have formalized procedures for *up*-selling to valuable customers.
- We try to systematically extend our “share of customer” with high-value customers.
- We have systematic approaches to mature relationships with high-value customers in order to be able to cross-sell or up-sell earlier.
- We provide individualized incentives for valuable customers if they intensify their business with us.

Activities to manage customer referrals (REFERRAL) *
With regard to your strategic business unit, to what extent do you agree to the following statements?

- We systematically track referrals.
- We try to actively manage the customer referral process.
- We provide current customers with incentives for acquiring new potential customers.
- We offer different incentives for referral generation based on the value of acquired customers.

CRM Termination (TERMINATE)
Measurement at termination stage (TMEASURE) *
With regard to your strategic business unit, to what extent do you agree to the following statement?

- We have a formal system for identifying non-profitable or lower value customers.

Activities to actively de-market customers (EXIT) *
With regard to your strategic business unit, to what extent do you agree to the following statements?

- We have a formal policy or procedure for actively discontinuing relationships with low-value or problem customers (e.g., canceling customer accounts).
- We try to passively discontinue relationships with low-value or problem customers (e.g., raising basic service fees).
- We offer disincentives to low-value customers for terminating their relationships (e.g., offering poorer service).

** These scales were rated on a seven-point Likert format anchored 1 = strongly disagree, 7 = strongly agree.*

The following indices were computed based on the construct formation as described above:
INITIATE = .389*IMEASURE + .379*ACQUISIT + .375*REGAIN
MAINTAIN = .283*MMEASURE + .340*RETAIN + .388*CROSS_UP + .267*REFERRAL
TERMINATE = .367*TMEASURE + .759*EXIT

Chapter XI
Technology and Customer Value Dynamics in the Banking Industry:
Measuring Symbiotic Influence in Growth and Performance

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ABSTRACT

This chapter attempts to critically examine the available literature on the subject, discuss a model that provides a framework for analyzing the variables associated with customer value, and to identify potential research areas. The chapter argues through a set of linear equations that maximizing customer value, which is an interdependent factor for technology adoption and profit optimization in the banks, needs to be backed with appropriate economic parameters for attaining competitive efficiency and optimizing profit. The framework of the construct is laid on the theory of competitive advantage and customer lifetime value, so as to maximize the potential of the organization and all its subsystems to create and sustain satisfied customers. The chapter draws theoretical impetus from new technologies in banking services such as mobile banking in the North American region and discusses the technology-led marketing process towards optimizing profit. The discussion in the chapter also analyzes the main criteria for successful Internet-banking strategy and brings out benefits of e-banking from the point of view of banks, their technology, and customer values, and tentatively concludes that there is increasing returns to scale in bank services in relation to banking products, new technology, and customer value.

INTRODUCTION

The new information technology is becoming an important factor in the future development of the financial **services** industry, and especially the **banking** industry. The developments in information and communication technology have significantly contributed to the exponential growth and profits of financial institutions worldwide. This evolution had transformed the way banks deliver their services, using technologies such as automated teller machines, phones, the Internet, credit cards, and electronic cash. However, banks face a number of important questions on strategies for deriving full advantage of new technology opportunities and tracking electronic development changes affecting interactions with the customers.

In general terms, increasing convenience is a way of raising consumers' surplus, provided new technology is adopted by the banks in order to offer convenience to the customers through an electronic transaction as a substitute for a trip to the branch. The technology-based services imply different combinations of accessibility attributes (time, distance, and search costs), ease of use, and price. Another factor in determining the magnitude of the surplus that the bank can seize is the relative importance of cross-selling. The bundle of services provided electronically is usually not the same as the one available at a branch. For this reason new technology-based banking services with high customer value may offer better service conditions to harmonize the flow of information and services across the spatial and temporal dimensions.

The following sections of the chapter will critically examine the available recent literature on this subject and present an analytical framework to measure the intrinsic contribution of various attributes related to technology and customer value in banking services. The construct of the measure is described through linear equations for technology, customer value, and their symbiotic relationship, followed by the general discussion on the sub-models. The focus of the model has been placed on the subsets of technology adoption in reference to common services and customer value as a profit driver in the banking industry. The common services generated by those services which can be linked and enhanced through new technology include: (1) brokerage and asset management services, (2) personal banking services, (3) checking accounts, and (4) services bills collections, which are standardized and homogenized across branches of the banks.

REVIEW OF LITERATURE

Electronic Banking vs. Conventional Wisdom

The maxims of technology spread in the operations of financial institutes may have relational effect with the size and volume of operations of the organization. Whenever the innovation is initially introduced, large banks have an advantage to adopt it first and enjoy further growth of size. Over time, as the innovation diffuses into smaller banks, the aggregate bank size distribution increases stochastically towards a new steady state. Applying the theory to a panel study of Internet banking diffusion across 50 U.S. states, it has been observed that technological, economic, and institutional factors largely govern the transaction process supported with technology. The empirical findings disentangle the interrelationship between Internet banking adoption and growth of average bank size, and explain the variation of diffusion rates across geographic regions (Sullivan & Wang, 2005). Technology in banking industry also has cost implications that lead to a slow down in the adoption process in many countries. The effect of technical change on the costs of banking firms operating in Central and Eastern European countries has been studied using Fourier, a flexible cost function specification, for the period 1995-2002. A common cost frontier with country-specific variables is employed in order to take into account the macro-economic and regulatory conditions that vary over country and time. The findings of the study reveal that the rate of reduction in costs resulting from technical change increased during the sample period. Banks operating in Hungary, the Czech Republic, and Poland benefited more from technical change than their counterparts. In terms of cost reduction, large banks benefited more from technical progress, which underpins that large banks are more able to change their optimal input mix in response to changes in technology (Adnan & Saadet, 2006).

The recent dot.com boom/bust cycle, as equilibrium industry dynamics triggered by technology innovation, has been analyzed in various studies. When a major technology innovation arrives, a wave of new firms enters the market implementing the innovation for profits. However, if the innovation complements existing technology, some new entrants will later be forced out as more and more incumbent firms succeed in adopting the innovation. Such a situation has revealed that the diffusion of Internet technology among traditional brick-and-mortar firms is indeed the driving force behind the rise and fall of dot.coms as well as the sustained growth of e-commerce (Wang, 2005). However in reference to banking reforms in India, technology has been found to be the major input in driving competition, which has been evidenced in a study revealing a positive relationship between the level of competition and banking efficiency. However, a negative relationship between the presence of foreign banks and banking efficiency is found, which attributes to a short-term increase in costs due to the introduction of new banking technology by foreign banks (Ali & Hang, 2006).

Many financial institutions have built Web sites to inform and attract customers. Financial aggregation presents an opportunity by which they can build stronger relationships with customers. Information technology affects banking in two main ways. First, it may reduce costs by replacing paper-based, labor-intensive methods with automated processes. Second, it may modify the ways in which consumers have access to banks' services and products, and hence may enhance the contestability of markets, especially in retail banking. Due to deregulation and technological advances, new opportunities become available, but the skill needed to exploit them effectively may be unknown. Early entry of financial institutions into the technology-expanding activities may have learning benefits that are manifested in discovery of the skill needed to operate effectively. E-banking products and services are getting more and more advanced and increasing in variety by providing information at the early stage to providing transactional activities. The average e-banking penetration for developing countries by the end of 1999 was close to 5%. In Brazil, the number of e-banking users reached 8 million in 2000, while in Mexico the number of e-banking users reached 1.25 million in 2000 (Chinn & Fairlie, 2006). It has been established that increasing the role of technology in a service organization can serve to reduce costs and often improve service reliability. It remains the case however that there is an important role for personalized relationships in the delivery of any service proposition (Durkin & O'Donnell, 2005).

The e-banking services include e-remittances, e-payments, e-trades, and e-credit. However, many e-banking businesses have been forced out of the market due to the low customer perception such as e-procurements supporting the banking transactions of large work tenders. Internet-based transactions require their own security measures for which private solutions may not be sufficient. For example, government actions are needed to set up a framework for digital signatures and to designate agencies or processes to authenticate public keys associated with transactions. Consequently, Internet-only banks have been substantially less profitable. They generate lower business volumes, and any savings generated by lower physical overheads appear to be offset by other types of non-interest expenditures, notably marketing to attract new customers (de Young, 2001). Among the e-banking products, electronic money transactions have become more popular since early in this decade due to an increase in Internet users and IT-enabled banking services networks in developing countries, including

Asia and Latin America. E-money products and transactional values in the selected developing countries are exhibited in Table 1.

However, e-banking develops an automated credit authorization system by developing an appropriate credit scoring system and a cash-flow scoring system to reduce operating costs, improve asset quality, and increase client profitability. One of the major benefits of a credit scoring system is that lenders can make credit decisions without necessarily obtaining financial statements, credit reports, or other time-consuming and hard-to-get information.

There has been a string of research studies exploring the economic and relational issues on Internet and advanced technology diffusion in the banking industry. The model developed for estimating Internet banking adoption at the early stages when there is considerable uncertainty about consumers' demand argues that relative bank size and demographic information prediction of future demand positively influence the process of Internet banking adaptation (Courchane, David, & Richard, 2002). Similarly, the Logit model estimates the determinants of Internet banking adoption, which reveals that larger banks are more likely to adapt to Internet banking when they are younger, better performing, located in urban areas, and members of a bank holding company (Furst, William, & Daniel, 2001). However, other studies analyze the reverse effect of technology on bank performance but obtain mixed results in reference to characteristics, including costs and profitability, of early adopters of Internet banking and find little difference from non-adopters (Sullivan, 2000), though many banks enjoyed rising profits during the 1990s and attribute this to banks' increasing market power gained by adopting new technologies (Berger & Mester, 2003).

Advances in technologies have allowed service providers to incorporate many different technologies into the delivery of their services. These technologies have been implemented in the service encounter for the customer to use with varying degrees of success. The factors influencing consumer attitudes towards and adoption of self-service technologies (SSTs) across three different technologies used in the banking industry reveal that service attributes related to trust, quality, and time are major attributes that influence attitudes toward each of these technologies and offer an

Table 1. E-money products and transactional values in developing countries (Bank for International Settlements, 2000)

Country	Name of System	Type of System	# of Card Issues or Home PC Users (in thousands)	Volume of Daily Purchase or Transaction (in thousands)	Value of Daily Transaction (USD'000)	Reported Period
Brazil	Visa Cash SIBS	Card based	135.1	1.29	4.5	1996-1999
Hong Kong	Octopus Mondex Visa Cash	Card based	6,110.0	3,900.0	3,670.0	1999
Singapore	Cash Card	Card based	3,156.6	276.1	177.2	1999
Thailand	Micro Cash SB Smart Card	Card based	75.7	1.1	1.6	1999

explanation of the varying degrees of acceptance found among consumers (Curren & Mueter, 2005). Further on the issue of technology adaptation Lassar, Manolis, and Lassar (2005) examine the relationships between consumer innovativeness, self-efficacy on the Internet, Internet attitudes, and online banking adoption, while controlling for personal characteristics. While results confirm the positive relationship between Internet-related innovativeness and online banking, they also surprisingly show that general innovativeness is negatively related to online banking (Lassar et al., 2005). Availability of computers in the selected developing countries and rate of penetration of Internet services are exhibited in Table 2.

Bank characteristics such as asset size, number of employees, number of full service locations, areas of lending, and return on assets largely influence the technology diffusion process and adaptation at the customer levels. It has been observed in a study that a number of bank composition and operations variables behaved statistically independently between size variables (assets, number of employees, and number of branches) and wide area network access. The survey data also indicate that return on assets and network system variables are independent. Therefore, networks systems have not had a direct impact on the bottom line (Zhu, Scheuermann, & Babineaux, 2004).

Customer Value Management

The customer values for banking services are shaped more by habits, reinforcement effects, and situational influences than strongly held attitudes. However, the aggregate returns on the customer value towards the new product from the perspective financial institution may be manifesting in enhancing the market share and services coverage, and augmenting profit in a competitive environment. The academics, consultants, and business people speculated that marketing in the new century would be very different from the time when much of the pioneering work on customer loyalty was undertaken (Churchill, 1942; Brown, 1953; Cunningham, 1961; Tucker, 1964; Frank, 1967). Yet there exists the scope for improving the applied concepts, as there have been many changes over conventional ideologies. It has been observed in one of the studies that the customer values are created through individual perceptions, and organizational and relational competence (Johnson,

Table 2. Computer and Internet penetration rates 2004 (Chinn & Fairlie, 2006)

Country/Group	Computers per 100	Internet Users per 100
China	4.08	7.23
India	1.21	3.24
Brazil	10.71	12.18
Mexico	10.68	13.68
Thailand	6.00	11.25
Malaysia	19.16	38.68
Developing Countries	3.68	5.95
Transition Countries	11.89	13.98
Developed Countries	56.64	51.83
World	12.24	13.65

Martensson, & Skoog, 2001). Management of business relationships is a key strategic success factor to fully utilize the market potential. The goal of relationship development has been defined as the ability to attract, maintain, and enhance new customer relations (Berry, 1983). Contributions to this area have developed a number of models for relationship management (Zeithaml, Berry, & Parasuraman, 1988), and a common denominator of these models is that firms need to adjust to market conditions. This involves, for instance, narrowing perceptional gaps to adjust workflows in the organization or to activate the customer as a relationship partner.

The value concept in the above relationship governs the customer portfolio decision in terms of formulation of recursive utility over time. It shows that the optimal portfolio demand for products under competition varies strongly with the values associated with the brand, industry attractiveness, knowledge management, and ethical issues of the organization. The extent of business values determines the relative risk aversion in terms of functional and logistical efficiency between the organization and supplier, while the switching attitude may influence the customers if the organizational values are not strong and sustainable in the given competitive environment (Rajagopal, 2006a).

A study examines the success of product pricing practices and the conditions upon which success is contingent, discussing three different pricing practices that refer to the use of information on customer value, competition, and costs respectively. The study argues that the success of these practices is contingent on relative product advantage and competitive intensity. The study reveals that there are no general “best” or “bad” practices, but that a contingency approach is appropriate (Ingenbleek, Debruyne, Frambach, & Verhallen, 2003). Value and pricing models have been developed for many different products, services, and assets. Some of these are extensions and refinements of convention models’ value-driven pricing theories (Gamrowski & Rachev, 1999; Pedersen, 2000). Also there have been some models that are developed and calibrated, addressing specific issues such as model for household assets demand (Perraudin & Sorensen, 2000). The key marketing variables such as price, brand name, and product attributes affect customers’ judgment processes and derive inference on its quality dimensions leading to customer satisfaction. The experimental study conducted indicates that customers use price and brand name differently to judge the quality dimensions and measure the degree of satisfaction (Brucks, Zeithaml, & Naylor, 2000).

The value of corporate brand endorsement across different products and product lines, and at lower levels of the brand hierarchy, also needs to be assessed as a customer value driver. Use of corporate brand endorsement either as a name identifier or logo identifies the product with the company and provides reassurance for the customer (Rajagopal & Sanchez, 2004). A perspective from resource-advantage theory (Hunt & Morgan, 1995) is used to formulate expectations on the degree to which the use of information on customer value, competition, and costs contribute to the success of a price decision. It is argued that the success of these practices is contingent on the relative customer value the firm has created and the degree to which this position of relative value is sustainable in the competitive marketplace. These expectations are empirically tested on pricing decisions with respect to the introduction of new industrial capital goods.

The studies that advocate the models of building customer value through traditional relationship marketing discuss the long-term value concepts to loyal customers. Most importantly, these are expected to raise their spending and association with the products and services of the company with increasing levels of satisfaction that attribute to values of customers (Reichheld & Sasser, 1990). In the most optimistic settings, such value creation is observed to generate new customers for new products in view of the customer relationship and value management strategies of the firm (Ganesh, Arnold, & Reynolds, 2000). In the high customer value framework, the firm ensures diminished costs to serve (Knox, 1998) and exhibits reduced customer price sensitivities. A database-driven approach, customer tenure in reference to the length of a customer's relationship, and values retention with a company have often been used to approximate the loyalty construct (Ganesh et al., 2000; Reinartz & Kumar, 2000, 2002). Hence the relationship marketing with a customer value orientation thrives on the concept that raises the length of the customer-company relationship, which contributes in optimizing the profit for the firm (Reichheld & Sasser, 1990). However, the contributions of long-life customers were generally declining, and in a non-contractual setting, short-life but high-revenue customers accounted for a sizeable amount of profits (Reinartz & Kumar, 2000).

The role of customer value has been largely recognized over time by the financial institutions as an instrument towards stimulating market share and profit optimization. The customer values for a new product of a financial institution in competitive markets are shaped more by habits, reinforcement effects, and situational influences than strongly held attitudes. A strong and sustainable customer value associated with a new product launched by a financial institution may also lead to building customer loyalty in the long run. An analysis of the new product-market structuring based on customer value may be developed well within the microeconomic framework of financial institutions. The aggregate returns on the customer value towards the banking services from the perspective of a financial institution may be observed manifesting in enhancing the market share and services coverage, and augmenting brand in a given market. The value of a customer may be defined in reference to a firm, as the expected performance measures are based on key assumptions concerning retention rate and profit margin, and the customer value also tracks market value of these firms over time. The value of all customers is determined by the acquisition rate and cost of acquiring new customers (Gupta, Lehmann, & Stuart, 2003).

It is increasingly gaining significance that the financial value of a firm depends on intangible assets such as brands, customers, employees, and knowledge, which are beyond the balance sheet. The authors demonstrate this method by using publicly available data for five firms—one well-established firm (Capital One), for which traditional financial valuation models work well, and four Internet firms (Amazon, Ameritrade, eBay, and E*Trade), for which traditional financial models have difficulty. The results indicate that cutting acquisition costs may not be the most effective way to improve value. Furthermore, to the extent that customers are assets, the market may be incorrect in treating customer acquisition costs as current expenses rather than as investments. Authors also find that 1% improvement in retention has an almost five times greater impact on customer value than 1% improvement in discount rate or cost of capital. Financial analysts and company managers spend considerable time and effort measuring and managing discount rate because they understand its impact on firm value. However, the results show that it is perhaps more important not only for marketing managers but also for senior managers and financial analysts to pay close attention to a firm's customer retention rate (Gupta et al., 2003).

In the process of enhancing the customer value for the new products, a financial institution may simultaneously use intensive customer value for technology-based banking services and intensive customer relationship management (CRM) strategies to the competitive sales and marketing strategies. The integrated impact of CRM, sales, and marketing strategies at different stages of service attractiveness would contribute to the customer value and influence the aggregate returns on the customer value derived at various stages of service attractiveness of the financial institutions. However, a financial institution may need to compute the trend of customer value for all the services in its product line, and measure the variability in the customer values perceived for its new services. The customer values are broadly reflected in the competitive gains, perceived values, and extent of association with the financial services and level of quintessence with the customer relationship management services of the organization.

FRAMEWORK OF ANALYTICAL CONSTRUCT

Technology and Profit Optimization Equilibrium

Let us assume that banks with conventional wisdom, without access to improved services technology, function at a steady state. Profit in a financial firm largely depends on the financial performance in terms of long-term gains in the market at the price of services offered by the firm. The financial performance in financial institutions like banks may be set by the lower and upper limits ranging from 1 to infinite, which can be measured in reference to predetermined scale of performance of the firm (e.g., number of accounts, volume of lending, repayments, overdue status, spread of accounts in different services, operational cost, technology cost, gross profit, net profit, spillover costs, and the like). While measuring the performance of a financial firm, it is important to consider the cost of technology involved in delivering the services that contribute to the profit of the firm. The operational equilibrium at the given prices using the existing technology for optimizing profit may be expressed for individual banks as:

$$z_0 = q_0^{\max 1-\infty}(pq_0) - \alpha_c q_0^{\beta_c} \tag{1}$$

wherein (z_0) is profit of the banks, p is price, (q_0) denotes the financial performance of the bank which may also be determined as out of the organization, and ($\alpha_c > 0$) and ($\beta_c > 1$) represent the cost parameter in application of the existing technology. In the above equation (α_c) and (β_c) denote the constants of fixed and variable cost respectively. The variables discussed in the above equation are the basic operational drivers in a financial firm aiming at incremental profit through delivering high customer value supported with improved technology. Hence, equation (1) can be considered as the basis of the further derivations in the model, and the profit optimization solution may be derived considering equation (1). By following elementary calculus, we obtain the following equation:

$$q_0 = \left[\frac{p}{\alpha_c \beta_c}\right]^{\frac{1}{\beta_c - 1}} \tag{2}$$

When new technology with significant improvements over the conventional is implemented at a given time t, an individual bank may optimize its profit and decide on adoption of innovative practices or otherwise. Hence:

$$z_1 = q_0^{\max 1-\infty}(pq_1) - \frac{\alpha_c}{\gamma}(q_1)^{\beta_c} - c' \tag{3}$$

where (z_1) represents profit and (q_1) denotes the performance of the bank after adoption of new technology, the cost savings incurred by the adoption of new technology is indicated by (γ), and (c') expresses the period cost of adoption of new technology by the banks. The performance optimization of an individual bank may be derived solving the above equation as:

$$q_1 = \left(\frac{\gamma p}{\alpha_c \beta_c}\right)_t^{\frac{1}{\beta_c - 1}} \tag{4}$$

$$z_1 = pq_1\left(\frac{\beta_c - 1}{\beta_c}\right) - c' \tag{5}$$

Thus, an individual bank will adopt new technology if ($z_1 \geq z_0$) with the threshold size of adoption (q'') at a given time and business environment. This situation may be expressed as:

$$z_1 \geq z_0 \Rightarrow q'' = \frac{c'}{p\left(\frac{\beta_c - 1}{\beta_c}\right)\left(\gamma^{\frac{1}{\beta_c - 1}} - 1\right)} \qquad (6)$$

It may be observed from the above equation that the size of requirement for adoption suggests that large banks have an advantage in conceiving and implementing the new technology leading to further adding value. This process is induced in large banks through customer services and various value augmentation approaches pertaining to customer relations management. Assuming bank size distribution as (D_b) and threshold size of adoption as (q''), the role of aggregate adoption of new technology may be expressed as:

$$A_t = 1 - D_b(q'') = \frac{1}{1 + \left(\frac{kq''}{Eq_0}\right)^{1/g}} \qquad (7)$$

whereas (A_t) represents rate of aggregate adoption of technology, (Eq_0) and g are mean and Gini Coefficient respectively, and k is the constant. Accordingly a proposition may be drawn for the above equation that the rate of technology adoption (A_t) increases with the customer demand in reference to various satisfaction parameters, average bank productivity, and cost savings factor (γ). However (A_t) decreases with the increase in the cost of adoption of new technology (c'). Over time, banks adopt the new technology, the average bank size keeps increasing, and the aggregate rate of adoption augments stochastically to a new state of equilibrium. During a transitional stage at a given time t, financial institutions run into critical size requirement (q'') ripping the size into two parts—conventional and new fangled—which reveals ($q_{0t} \leq q''_t$).

Over time, (q'') may face stronger challenges than existing due to the internal and external environmental shifts in reference to change in customer demand, decrease in the cost of technology adoption, banking deregulation, and so forth. Consequently, the new technology becomes accessible to the smaller banks, and the overall technology-profit equation moves to a new state of equilibrium. Hence, future innovation in technology may be adopted by smaller banks at a probability of marginal change in the profit during the technology gestation period. Therefore, at each time ($t \geq 0$), the optimization behavior of a bank may imply:

$$q''_t = \max(q_{0t}, q_{1t}) + \omega(q''_{t-1}) \qquad (8)$$

where (q''_t) represents maximum value of a bank with new technology and ω is a discount factor. It implies that in order to increase overall performance of the bank or a financial institution, a simple dynamic path at the initial time (0) works out to be a decision for technology adoption. Accordingly, the customer value associated with the performance of a bank using innovative technology may be expressed as:

$$V_t^{\theta} = \exp(c', \gamma, D_b)_t^{\lim 1-\infty} + \max(q_0, q_1, q'', A_t) + \mu V_{t+1}^{\theta} \qquad (9)$$

In the above equation (V_t^{θ}) denotes the customer value with adopted technology in a bank at tine t, and (μ) represents the mean of the cognitive variables in reference to perceived values of the customers over the period of effective usage of new technology. As regards the value parameters for banking technology adoption and diffusion, a financial institution may attain many equilibrium paths over different time lags. However, the major determinants for technology adoption for banks include cost of technology adoption, profit impact of technology, operational area and size of the organization, cost-saving probabilities, and customer value. The technology and innovation keep rising from time (t+1) to shift the equilibrium of profit and customer values to a new state, leading to change in overall efficiency of the organization. Therefore, financial losses may emerge as a result of *ex ante* adoption of new technology with overestimation of the profit targets.

Measuring Customer Value

The customer values for goods and services are largely associated with the retail store brands and customer services offered therein. The beginning of customer preferences is the basic discrete time that helps a customer in making a buying decision and maximizing the value of product. Ofek Elie (2002) discussed that the values of products and services are not always the same and are subject to a value lifecycle that governs the customer preferences in the long run. If customers prefer the product and service for N periods with Q as value perceived by the customer, the value may be determined as $Q>N$, where Q and N both are exogenous variables. If every customer receives higher perceived values for each of his or her purchases, the value-added product is $q \geq Q$, where q refers to the change in the quality brought by innovation or upgraded technology. The customer may refrain from buying the products if $q \leq Q$; that does not influence his buying decisions. However, a strong referral R may influence the customer values, with an advantage factor β, which may be explained by price or quality factor. In view of the above discussion, it may be assumed that customer preferences have high variability that increases the value factors in customer decisions:

$$D'_{bn} = \sum_{t=1}^{N} \rho^t (C_t, \hat{Z}) + \rho^{N+1} Q_t \qquad (10)$$

where D_{bn} is expressed as initial buying decision of the customers, (ρ) is quality of services, C_t represents consumption, $\hat{Z}$ is a vector of customer attributes (*viz.* preferential variables), and Q_t is the value differences perceived by the customer with and without technology-based services.

A customer value is a dynamic attribute that plays a key role in buying and is an intangible factor to be considered in all marketing and selling functions. The value equation for customer satisfaction may be expressed as a function of all value drivers, wherein each driver contains the parameters that directly or indirectly offer competitive advantages to the customers and enhance the customer value.

$$V' = K_s, K_m, K_d, K_c [\prod \{V(x,t,q,p)\}] \qquad (11)$$

In the above equation V' is a specific customer-value driver; K are constants for services (K_s), margins (K_m) retained by the banks for providing services (which is also commonly known as commission), services spread (K_d) in reference to inter- and intra-branch movements, and cost to customers (K_c); x is volume of operations; t is time; q is organizational quality; and p denotes price. The perceived customer value (V) is a function of price (p) and non-price factors including organizational quality (q) and volume (x) in a given time t. Hence, $\prod$ has been used as a multiplication operator in the above equation. The quality of the product and volume are closely associated with the customer values. The total utility for the conventional services goes up due to economy of scale as the quality is also increased simultaneously ($\partial_v/\partial_x>0$). The ∂ customer value is enhanced by offering a larger volume of product at a competitive price in a given time ($\partial_v/\partial_p>0$) and ($\partial_v/\partial_t>0$). The conventional products create lower values to the customers ($\partial_v/\partial_x<0$) while the innovative products, irrespective of price advantages, enhance the customer value ($\partial_v/\partial_x>0$). The value addition in the conventional services deliver lower customer satisfaction as compared to the innovative products (Rajagopal, 2005). Such transition in the customer value, due to shift in the technology, may be expressed as:

$$V'_{hj} = a\left[\sum \frac{T_p}{(1+V_p)^{(1+j+i)}}\right] + b(X_j) \qquad (12)$$

In this equation V'_{hj} represents enhancements in customer value over the transition from conventional to innovative products, *a* and *b* are constants, T_p denotes high-tech and high-value products, V_p represents value of product performance that leads to enhance the customer value, the volume is denoted by *X*, and j is the period during which customer value is measured (Rajagopal, 2006b).

Besides the high-tech and high-value products, the customers and companies may also find scope of enhancing values with appropriate promotional strategies. The customer values often get enhanced by offering better buying opportunities that reflect on short- and long-term gains. Let us assume that the competitive advantage in existing products over time is G_x that offers j^{th} level of satisfaction through various sales promotion approaches adopted by the company. Such market situation may be explained as:

$$G_x = [r_1 m_1; r_2 m_2; r_3 m_3; ......; r_j m_j] \qquad (13)$$

where r_j denotes the j^{th} level of satisfaction (j = 1,2,3,….,n) and m_j is the number of customers attracted towards buying the product. It may be stated that competitive advantage for the existing products of a firm over time is determined by the level of satisfaction derived by the customers and number of customers favoring the buying decisions for the products in a given market. The parameters of customer satisfaction may include product innovativeness, perceived use value, sales promotion, influence of referrals, and price and non-price factors. The competitive advantage of a firm is also measurable from the perspective of product attractiveness to generate new customers. Given the scope of retail networks, a feasible value structure for customers may be reflected in repeat buying behavior ($\hat{R}$), which explains the relationship of the customer value with the product and associated marketing strategies. The impact of such customer value attributes in a given situation may be described as:

$$\sum_{j=1}^{n} r_j m_j = \hat{R} \qquad (14)$$

The repeat buying behavior of customers is largely determined by the values acquired on the product. The attributes, awareness, trial, availability, and repeat (AATAR) factors influence the customers towards making re-buying decisions in reference to the marketing strategies of the firm. The decision of customers on repeat buying is also affected by the level of satisfaction derived on the products and number of customers attracted towards buying the same product, as a behavioral determinant.

Customer Value Enhancement Through Banking Technology

Let us assume that $(x_0, x_1, x_2, \ldots x_{n-1}, x_n)$ represents customer value at different stages of banking services attractiveness, increasing with reference to the derived advantage from the competing products in a given market at a given time (*t*). In the process of enhancing the customer value for the new products, a firm may use intensive customer value for banking products; a financial institution may simultaneously use intensive customer relationship management (CRM) and the competitive strategies in reference to the new technology used in a bank. The integrated impact of CRM, sales, and marketing strategies at different stages of product attractiveness would contribute to the customer value. Such an aggregated customer value represented by R_n can be measured by a firm. Hence, the R_n can be calculated with the following operation:

$$A(R_n) = f(x_0)\Delta x + f(x_1)\Delta x + f(x_2)\Delta x + ... + f(x_{n-1})\Delta x \qquad (15)$$

Further simplifying and substituting the values of equations (9) and (12) in this equation, we get:

$$A(R) = A(R_n)_{\lim n \to \infty} + \sum_{km}^{jm} [(\Delta v' + \Delta b')(\Delta s)]^t + V_t^\theta + V'_{hj} \qquad (16)$$

In the above equation A(R) represents the aggregate returns on the customer value derived at various stages of banking services attractiveness and quantitative changes in the volume of banking products positioned by a bank, repeat buying, and market coverage in terms of changes in the market shares of the financial institutions. The aggregate returns on the customer values may be measured by a firm for not only the existing products in the market, but also for the new products in the potential markets $A(R_n)_{\lim n \to \infty}$. The number of customers attracted towards the new product promotion, influence of referrals, and augmented perceived use values derived by the customers may be the major factors contributing to determining the potential markets for the new products. However, a bank may identify the potential markets in reference to its banking products and branch expansion policies. Besides, a firm may need to compute the trend of customer value for all the products in its product line, and measure the variability in the customer values perceived for its banking products.

The model explains that the value-based customer portfolios would enhance the **customer value** as the product efficiency viewed from the **customer'**s perspective—that is, as a ratio of outputs (e.g., resale **value**, reliability, safety, comfort) that the customers obtain from a product relative to inputs (price, running costs) that the customers have to deliver in exchange. The derived efficiency **value** can be understood as the return on the customer's investment. Products offering a maximum **customer value** relative to all other alternatives in the market are characterized as efficient. Market partitioning is achieved endogenously by clustering products in one segment that are benchmarked by the same efficient peer(s). This ensures that only the products with a similar output-input structure are partitioned into the same sub-market. As a result, a sub-market consists of highly substitutable products. The customer values are reflected in their competitive gains, perceived use values, volume of buying, and level of quintessence with the customer relationship management services of the organization. If these variables do not measure significantly, there emerges the development of switching attitude among the customers. If the organizational values are low, the customer relationship may be risk averse due to weak dissemination of information and technology-based values to the customers.

GENERAL DISCUSSION AND FUTURE DIRECTIONS

Few contributions address the measurement of the customer value as an intangible asset of the financial institutions, though substantial literature is available discussing the customer relations and loyalty-building perspectives. In view of growing customer demand for innovative technology with quality banking services to accelerate the information and transaction process, it may be observed that greater household access to the Internet drives a higher Web site adoption rate. There are many information and transaction access outlets in developed western countries and developing countries of Latin America and the Caribbean which include phone banking, mobile services, and Internet banking portals. However, greater household access to the Internet and mobile devices in banking operations may negatively relate to local average bank assets. A possible explanation is that once the customers have access to the information and transactions on Internet and mobile devices, they would form a relationship with a bank outside of their region/country which may have a negative impact on the size of banks in their region.

Over time, due to internal and external changes in the organizational environment in reference to customer demand, technology progress, and improvements in banking regulation, the innovation diffuses into smaller banks. The major factors affecting technology adoption and augmenting include mean bank size, per capita income, household access to Internet, average bank age, bank loan specialization, competitive advantages in banking products, product-mix of banks, self-service technologies, cost of adoption, level of customer satisfaction, and customer density in the region availing banking services. The costs of accessing electronic banking services need to be reduced for wider coverage of customers on e-banking bay. Comprehensive knowledge dissemination and trust play a pivotal role in creating customer value, in absence of which knowledge barriers may limit the size of the market to a subset of bank customers in the short term. Therefore, once a bank has made the decision to adopt new technology for improving its services and optimizing profit, the bank will learn to depend on market-specific demand characteristics.

The common services such as brokerage and asset management services, personal banking services, checking accounts, and services bills collections are standardized and homogeneous, hence self-service technologies can be considered as a substitute to a branch transaction regardless of the issue of complementarity of the entire bundle of banking services. Exploring the synergy between online and off-line channels in general reveals that a bank typically delivers standardized, low-value-added transactions such as bill payments, balance inquiries, account transfers, and credit card lending through the inexpensive Internet channel, while delivering specialized, high-value-added transactions such as small business lending, personal trust services, and investment banking through the more expensive branch channel. By providing more service options to its customers, an improved technology adoption will enable the bank to retain its most profitable customers and generate more revenue from cross-selling. Some banks, which operate on branchless concepts and depend only on the Internet, have lower asset returns than incumbent branching banks as well as new branching entrants. This is primarily due to their lower interest margins and fee income, lower levels of loan and deposit generation, fewer business loans, and higher non-interest expense for equipment and skilled labor. The financials of such banks turn robust after implementing a stick surveillance measure to sustain future competition.

An augmented and sustainable customer value builds the loyalty towards the product and brand, implying that bank managers should develop customer-driven strategies so that relationship augmentations can be achieved. This is not simply a matter of segmenting customers, but also signals the need to manage the reciprocities of relationship. It has been argued that relationships are constituted by value-creating transformations in which the customer may contribute in different ways. Relationship development is to improve these processes by capitalizing on an increasing customer involvement in adoption of new technology used in the bank. However, acquiring new customers is the easiest way to develop enhanced customer-technology relations favoring the growth of the bank.

Systematically explored concepts in the field of customer value and a market-driven approach towards new products would be beneficial for a company to derive a long-term profit optimization strategy over the period. Hence, a comprehensive framework for estimating both the value of a **customer** and profit optimization needs to be developed. On a tactical level, managers need to consider the optimum spread of customers on a matrix of product attractiveness and market coverage. This needs careful attention and the application of managerial judgment and experience to measure the value-driven performance of the product of the firm. It is necessary for the managers to understand that customer value is context dependent and there exists a whole value network to measure, not just a value chain. This value network will contain important entities far beyond the ones commonly taken into consideration in financial projections and business analyses.

CONCLUSION

The framework for measuring the customer values discussed in this chapter provides analytical dimensions for establishing the long-term customer relationship by the banking institution and to optimize its technology levels. The model discussed in this chapter provides a holistic view of the customer value by proposing ways to measure the different variable associated in reference to adoption of new technology in banking services. The model assumes that a high functional value integrated with the triadic entities—banking institution, technology, and customer—which would raise the market power of the organization, sustain decisions of customer portfolios and develop long-term relationships thereof. Customer value in terms of satisfaction is one of the indicators for building profit-oriented strategies in a banking institution. Customer value concepts may be applied by the firms to evaluate the product performance in the given market and determine the approach for competitive advantage. Customer relationship is an important tool for capitalizing on customers through their involvement in new technology used in the banking institution. However, enhanced customer-technology relations favoring the growth of the bank largely depend on acquiring new customers for long-term sustainability.

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Chapter XII
Data Warehousing and Analytics in Banking: Concepts

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ABSTRACT

In an increasingly competitive market, banks are constantly searching for sustainable competitive advantage to help them maintain their edge against competition. Over the years, banks have tried various drivers for competitive advantage, none of which were sufficient barriers for competitors. Understanding the behavior of their customers and using this knowledge to drive the interaction with customers is the most sustainable competitive advantage banks can obtain. Data warehousing and analytics provide banks with the ability to obtain customer knowledge, and the same infrastructure can be used for multiple business applications.

INTRODUCTION

Conventionally, banks were product oriented. The customer was treated as a mere appendage to the product sold. In the 1990s this trend started changing, especially with the advent of the Internet age. Customers became savvier with the availability of abundant information on the Internet. Banks began looking at alternate options to gain competitive advantage.

Competitive Advantage

How different are banks from other businesses? Well, not really very different from the shareholder's perspective. Like in any other business, it involves taking calculated risks to earn a return on investments made. However, the significant difference is that the key commodity the bank deals in is *money*. Additionally, banks are one of the most leveraged businesses in the world—the capital adequacy ratio (CAR) specified by Bank for International Settlements (BIS) or local monetary authorities is typically around 8-10%. The capital adequacy ratio is a measure of the amount of a bank's capital expressed as a percentage of its risk-weighted credit exposures. In other words, banks are allowed to gear themselves up very high.

In certain aspects, banks can be considered complex businesses. For instance, most of the products in banks have long tenures. For example, most home loans or mortgages are likely to be for 10 years or more. Banks have to contend with unpredictable cash flows. Activities that impact cash flows like loan repayments or a depositor's action when a deposit is due for maturity are determined by many factors including interest rates and solvency of the customers. Interest rate is a significant factor that affects the profitability of banks. What this basically means is that banks are more like super tankers rather than fast boats. They cannot change course instantly. Any course correction has to be planned and executed at a speed that does not result in the tanker capsizing! What this implies is that any strategy a bank plans to adopt has to be well thought out. More importantly, if something goes wrong, course correction could become difficult. This implies that banks have to build a sustained differentiation model while considering the competition, as they cannot change their course often and fast enough.

Let us examine the key trends banks have followed in terms of building competitive differentiators. Since the 1980s banks have used various strategies for creating differentiation. The most common drivers for differentiation are products, services, and channels. Product as a driver for differentiation means that banks compete with each other to bring new products to the market. Service as a differentiator was employed during the early 1990s, before getting swamped by channels with the explosion of Internet and connectivity. In the late 1990s banks rushed to create multiple channels for customers to transact with, which included, apart from traditional channels like Branch and ATM, electronic channels like tele-banking, mobile banking, and Internet banking. Quite often, a channel was introduced with a me-too mentality—introducing a channel because my competitor is doing the same! A good example is the introduction of mobile banking by all the local banks in Singapore in the late 1990s. With the high penetration of mobile phones among the population, every bank rushed to provide mobile banking as an alternative channel touting user-friendly conveniences like checking your balance while you are on a bus! What seemed obvious later, but not apparent at that time, was that in a small geography like Singapore with branches and ATMs emerging at every corner, mobile banking became a 'nice-to-have' rather than 'must-have' facility. In a short time, practically all the banks withdrew the mobile banking channel.

Service is another competitive differentiator banks employ to attract customers. Depending upon the customer relationship with the bank, one can find service offerings like chauffeuring to collecting and banking checks that are beyond the conventional realm of banking.

The common drawback for all these drivers of differentiation—products, services, and channels—is that they can all be replicated easily by another bank. Hence the competitive advantage a bank gets through any of these methods is temporary, until the competitor bank catches up.

Sustainable Competitive Advantage

What then can be considered as a sustainable competitive advantage? Any advantage that cannot be easily replicated by a competitor bank is the characteristic of sustainable competitive advantage. Knowledge and insight of its customers then is the true sustainable competitive advantage for any bank. Let us examine this concept in some detail. By analyzing customer behavior the bank can learn about their preferences and drivers for behavior. This knowledge can be used to customize products and services. For example, analyzing patterns in credit card transactions and matching them up with other interactions like customer complaints could exhibit leading behavioral indicators for credit card cancellations. This information can then be used to create an attrition prediction model which can predict which cardholders are likely to cancel their credit card in the near future. Sending an appropriate offer to retain them *before* they quit would be very effective in preventing attrition. Similarly, based on a combination of demographic information and the customer's transaction details, it is possible to determine which stage of the lifecycle the person belongs—bachelor, getting married, bought a new house, and so forth. This insight can be used to tailor customer services as well as customize offers for new products. A traditional bank would use recent history of customer behaviors relating to credit card payment dues to determine whether to accept or decline the request for penalty fee waiver. Generally, if the bank finds that the customer is a chronic late payer of monthly dues, they would enforce late payment penalty fee. Picture an alternate scenario: based on the total customer relationship and profitability, as well as projected future profitability if it is determined that the customer is a high lifetime value customer, the bank can choose to offer a special grace period to such customers or even waive the late fee in total!

From the customers' perspective, as they get accustomed to offers and services that fit closely with their expectations, the affinity between the bank and customer goes up. This is a sustainable differentiator vs. a competitive bank that would not have ready access to their customers' transaction and other behavioral data. Using knowledge and insight into customer behavior as the competitive differentiator is synchronous with the change banks are trying to implement—to move towards a customer-centric organization from the traditional product-centric or branch-centric focus.

In this chapter we are going to look at the related technologies called data warehouse (DW) and analytics, which are being employed by banks to gain customer knowledge and insight. The suitability of this technology for getting competitive advantage will be explained, and at the end of this chapter the reader will get acquainted with the concept of data warehouse, gain awareness of the key technologies in a data warehouse, as well as future trends, supported by a case study of a successful banking data warehouse implementation. The distinction between a data warehouse and analytics will be elaborated wherever appropriate. Any reference to data warehouse in this chapter should be interpreted to include both data warehouse and analytics.

CUSTOMER KNOWLEDGE AND INSIGHT

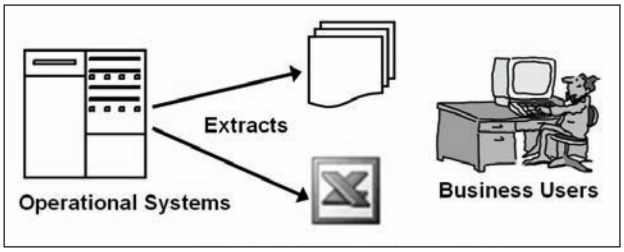
What is required to obtain customer knowledge and insight? Obviously, data—a lot of it. An access to historical data of transactions and other behavioral data is required. Once the data is made available, various tools or technologies are needed that can enable business users to derive knowledge and insight about customers. These would normally encompass query tools, reporting tools, statistical tools, and business rule engines as some of the common capabilities.

Some of the early solutions to handle this requirement are explained below.

Providing the Business Users with an Extract of Data

In the typical scenario, based on the business users' requirements, programmers would write programs to extract data from operational systems and provide them in the form of files. These files were then used by business users to perform their queries and analysis. Depending upon the sophistication of users and requirements, tools that were used to analyze the data included spreadsheet software and statistical analysis software. The

Figure 1. Extract processing



universal availability of Microsoft Excel had accelerated this trend, with business users utilizing Excel's statistical analysis capability and pivot table functionality to analyze the data.

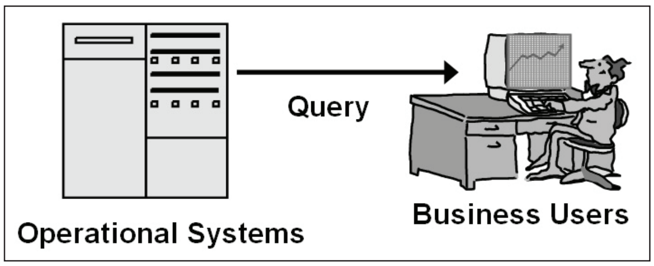
Allowing Users to Access Operational Data for Analysis

Some of the banks created reporting and analysis databases that mirrored operational system databases. Query tools and statistical analysis tools were provided to access these databases so that the business users could analyze the data. The advent of Graphical User Interface-based query tools was a major contributor to this trend.

Challenges of These Approaches

- **Lack of historical data:** Operational systems tended to keep only the current relevant information rather than a history of older data. For example, if the income of the customer increased from \$100,000 per annum to \$120,000 per annum, operational systems usually update the annual salary field to store only the current salary. While such an approach would be perfectly fine in the context of day-to-day business operations, this is not acceptable in the context of obtaining insights and knowledge, based on data. The income at a given point of time has an influence on the individual behavior at that point of time, and hence keeping track of changes to what are normally called 'static' data is essential.
- **Granularity of data:** Operational systems tend to keep data in the most granular, that is, detailed level. However, in order to obtain insights, data are generally viewed in aggregates rather than at a detailed level. For example, aggregating data like *amount spent at each merchant category* by customer attributes like *age, gender, number of dependents,* and so forth is frequently done to study if there is a correlation between the customer attributes and amount spent.

Figure 2. Operational system query



Such aggregation requires querying large volumes of transaction-level data before answers can be provided. This tended to be a performance challenge, especially since operational systems were not designed for query and analysis.

- **Operational system not designed for query and analysis:** The operational system's design principles were oriented towards fast capture of data rather than fast retrieval or query of data. Concepts like third normal form in relational database design were meant to optimize the database design to ensure lack of redundancy while increasing the speed of data entry. Such design techniques were inherently not appropriate for query and retrieval in most database architectures.
- **Lack of integrated data:** Operational systems are typically organized by a specific business function or product. For example, a typical bank may be using Vision Plus for credit card processing and a custom-built application for loan application processing. When business users want customer-level insights, it typically involved integrating data from various such operational systems. The integration challenge is not only an issue of lack of one application that housed all data, but also lack of integrated data definitions. For example, one operational system may use 1 and 0 to indicate *male* and *female* gender, while another operational system may use M and F to indicate *male* and *female* gender.

Definition of a Data Warehouse

In the early 1980s, Bill Inmon propounded the concept that a separate database was required for the purpose of obtaining insight and knowledge, which could be used for supporting decision making in organizations. Not only that a separate database was required, but it had to be designed with different principles compared to operational systems. He coined the term 'data warehouse' (Inmon, 1996) to define such databases. He is called as the 'father of data warehouse' for spawning an entirely new paradigm of housing and accessing data for query and analysis purposes.

What Is a Data Warehouse?

According to Inmon (1996), a data warehouse is a *subject-oriented, integrated, non-volatile,* and *time-variant* collection of data in support of management's decisions. A data warehouse is organized around subject areas like customer, channels, profitability, and so forth, vs. operational systems that are typically organized by applications like credit card, loans, and so forth. *Integrated* indicates not only integration of data from multiple sources, but also integrated definition of data elements. Non-volatility is a key requirement of a data warehouse—that is, whatever is loaded into the data warehouse cannot be amended at a later point in time. This is an essential requirement since query results have to be consistent regardless of how often the same query is executed. Time variance mandates the need to timestamp data so that the time currency of data can be known. The example of annual salary changing over a period of time, explained earlier, is a good example of data that is time variant. In short, practically all the data in the data warehouse is time variant.

While there have been alternate definitions for data warehouse, Inmon's definition is generally considered as the industry standard definition and has stood the test of time. With due humility, the author would like to suggest a minor amendment to this definition—replace 'management's decisions' with 'decision making at all levels in the organization'. The author strongly feels that the use of a data warehouse ecosystem for decision making has gone beyond management users to include decision making at all levels in the organization.

The reader needs to be cognizant of a few other definitions as well: datamart and operational data store (ODS). Datamart is defined as a subset of the data warehouse, typically designed to satisfy a department or single user group (Inmon, 1996). Typical datamarts in the context of banking include customer profitability, regulatory reporting, Basel II compliance, credit risk management, and so forth.

ODS is defined as an architectural construct that is subject oriented, integrated (i.e., collectively integrated), volatile, and currently valued. Further, it contains only corporate detailed data (Inmon, 1995). ODS is built if there is a need for an integrated data source for operational purposes rather than any strategic or decision-making purpose.

DATA WAREHOUSE ARCHITECTURE

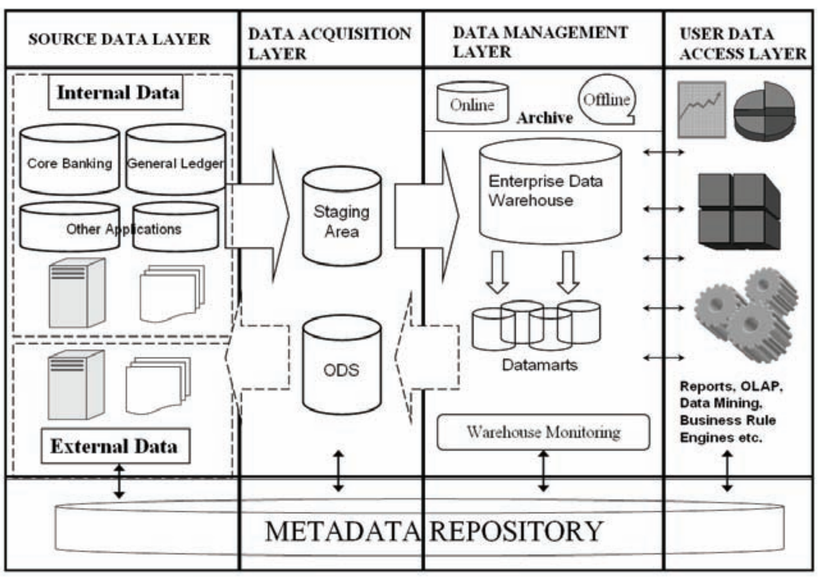
While there are many versions and variations of data warehouse architectures, certain common elements prevail. Figure 3 shows a generic logical data warehouse architecture that can be applied to most banks and financial institutions.

Let us examine the key architectural components. At a high level, the data warehouse architecture is divided into four layers: source data layer, data acquisition layer, data management layer, and user data access layer.

Source Data Layer

This layer consists of the various potential sources of data to the data warehouse ecosystem. Source data can be broadly classified into two categories, internal and external. Internal refers to data that is generated in various forms within the organization. The most common type of internal data, which also forms the bulk of the source data, is the various operational applications within the bank. Core banking applications, General Ledger, and the Obligor (customer) rating system are examples of operational applications in a bank. Apart from source data that resides in operational applications, any bank would typically have data that may reside outside operational applications. Typical examples would be loan applications (in the case of banks that have not automated loan

Figure 3. Architecture of a typical data warehouse



application processing) and targets assignment to relationship managers. Such data needs to be brought into structured electronic format before they can be fed into the data warehouse, for which reason in some cases data capture programs may need to be created.

External data are those data that are external to the bank. Typical examples include interest rates (e.g., LIBOR), macro economic indices, and share prices. Depending upon the source of external data, they may be available in structured electronic format. XML has emerged as the most popular format for exchange of data between organizations. Similar to internal data, if the data is not available in structured electronic format, data capture programs may need to be created to capture them.

Apart from structured data, unstructured data are also increasingly becoming a valid source to the data warehouse. Unstructured data like e-mails, phone transcripts, chats, and so forth are required for potential usage like fraud detection and SOX compliance.

The recommended method of taking data out of the source data layer is the 'push' method. That is, each source of data 'pushes' the requisite changed data at the predefined time period to the data acquisition layer. The 'push' is typically done to standard file structures. Normally, it is recommended that the corresponding source system team own the programs that push the data. This will ensure that impact analysis of any changes to source systems will cover the data warehouse push programs also.

It is recommended that the push happens from a backup database instead of the actual operational system database since usages of operational system databases are typically 24x7 in the case of banks.

Data Acquisition Layer

Data pushed from the source data layer is processed in the data acquisition layer. Data is first brought into a scratch pad area called a staging area where data acquisition activities like data cleansing, data integration, and validation take place. The staging area is typically a relational database, though in some cases it can be designed as flat files also. Typically, the staging area is not accessible to end users. An optional component of the data acquisition layer is the operational data store (ODS). The ODS is considered as an optional component since not all banks may need an ODS.

In the architecture diagram, solid block arrows represent data acquisition flows. While in theory, data acquisition can be performed by custom-developed programs using languages like SQL or C, the recommended approach is to use data acquisition software that has benefits like reduced development time, collection of metadata, and ability to perform impact analysis. Common data acquisition software includes Informatica, Datastage (IBM), Oracle Warehouse Builder (Oracle), and SQL Server Data Integration Services (Microsoft).

Data acquisition tools are also called ETL (extract, transform, and load) tools. The key capabilities of data acquisition tools are enumerated under ETL. The data acquisition tools normally have the capability to natively extract common types of data storage like databases and file systems. Sophisticated tools would also include native access to standard applications like SAP. Transformation is the stage where data cleansing, data integration, and application of business rules happen. While ETL tools generally support rule-based data cleansing, purpose-built data cleansing tools like Trillium may be required for more sophisticated cleansing (e.g., de-duping of customer records using heuristic rules).

Data Management Layer

The data management layer consists of the storage aspect of the data warehouse architecture. Enterprise data warehouse (EDW), datamarts, near-line or online archival, and off-line archival are typical components of the data management layer.

While relational database management systems (RDBMSs) are the most common technology used in storage of data, many vendors have created data warehouse-specific extensions or versions. Among the DBMSs that are either solely meant for a data warehouse or substantially used in the data warehouse environment are Teradata, Sybase IQ, and IBM Redbrick.

Data modeling tenet to follow in data warehouses is a big debate with roughly two camps—one camp promoting normalized data models and another camp promoting dimensional modeling or star schema modeling. Dimensional modeling was popularized by Ralph Kimball, Reeves, Ross, and Thornthwaite (1998). A full discussion of the two methods is beyond the scope of this chapter. Briefly stated, the most commonly accepted global approach is to model the ODS and EDW layers using a normalized modeling approach and datamarts using the dimensional modeling approach.

Depending upon the architecture, the datamarts can consist either entirely of RDBMSs or a mix of RDBMSs and multidimensional databases. Popular vendors of multidimensional databases include Hyperion (now acquired my Oracle) and Cognos.

User Access Layer

This is the layer that provides analytics capability to end users. This layer is where the various end users access components reside. An alternate name for the user access layer is business intelligence (BI). BI is a term coined by Gartner and defined as the process of transforming data into information, and through discovery, transforming that information into knowledge, which would help in effective decision making. Some industry participants differentiate data warehousing as independent of business intelligence. That is, the data warehouse is differentiated as the components and activities that lead up to the creation of the data management layer, while usage of the data warehouse falls under business intelligence. In this chapter, the phrase 'data warehouse' is used to indicate data warehouse and business intelligence/analytics.

At a high level, business intelligence can be defined to consist of two categories of capabilities:

- Query, reporting and analysis
- Advanced analytics

QUERY, REPORTING, AND ANALYSIS

This category of capability consists of the ability to perform ad hoc query of the data in the data warehouse as well as multidimensional analysis. Also included in this category are production quality report generation and other forms of presentation of prepackaged information like dashboards, alerts, e-mail blasts, and so forth.

Multidimensional analysis is typically done using OLAP concepts. OLAP stands for OnLine Analytical Processing (a term coined to be direct contrast to OLTP). OLAP can be loosely defined as a set of principles that provide a dimensional framework for decision support. A dimensional framework is used to visualize business in the form of dimensions or perspectives and metrics or facts.

Popular vendors for OLAP querying and reporting include Hyperion (Oracle), Business Objects, SAS, Cognos, Oracle BI Enterprise Edition (Oracle), Micro Strategy, and Pro Clarity (Microsoft).

ADVANCED ANALYTICS

When the quantum of data items is large, as is the case in banks, it becomes difficult for business users to spot a trend or identify correlations using querying and multidimensional analysis. Advanced analytics includes data mining and statistical software that is used to identify correlations among large data sets and make predictions based on correlations identified.

Berry and Linoff (1997) define data mining as the process of exploration and analysis, by automatic or semiautomatic means, of large quantities of data, in order to discover meaningful patterns and rules. To expand further, there are six types of activities that can be done using data mining (Berry & Linoff, 2000). The six types of activities are grouped under two categories called *directed data mining* and *undirected data mining.*

Directed data mining consists of building a model that describes one variable of interest based on other data items. The three directed data mining activities are classification, estimation, and prediction.

Classification would involve assigning a new object to one of the predefined classes. The characteristics of predefined classes would have been derived based on historical data. Examples of usage of classification in banking include classifying a loan application as high/medium/low risk and classifying a new customer into a predefined segment.

Unlike classification, which provides a discrete outcome, estimation will provide continuously valued outcomes. Typically, estimation is used in conjunction with classification to solve business requirements. For example, a bank may use estimation to determine the expected length of a relationship and use classification to assign different lifetime value segments.

While any classification or estimation is predictive in nature, prediction is given as a separate category to emphasize the objective of model building. Typically, the same techniques that are used for classification and estimation are used for prediction also.

Undirected data mining aims to identify relationships among the data items without any specific target variable as objective. The three undirected data mining activities are affinity grouping, clustering, and description.

Affinity grouping or association rules are used to determine what goes together. For example, it can be used to determine which product combinations are normally opted for by customers—personal loan and mortgage loan may be identified as one group.

Clustering is similar to classification except that there are no predefined segments. Segments or clusters are formed when the clustering activity is performed. For example, clustering credit card transactions could reveal distinctive clusters with homogenous buying behavior.

Description and visualization are used to describe the data to improve our understanding. Visualizing ATM usage in the form of a geographic map would give an instant understanding of the distribution of ATM loads in a manner that no amount of reports can provide.

There are various data mining techniques and algorithms that can be used across the above six activities. Some of the common techniques and algorithms are neural networks, rule induction, decision trees, and logistic regression. A full discussion of the various techniques and algorithms is beyond the scope of this chapter.

Intelligent Miner (IBM), Enterprise Miner (SAS), and SPSS/Clementine are some popular vendors of data mining products apart from the embedded data mining capabilities of RDBMSs like Oracle and SQL Server.

Closing the Loop

The architecture shows dashed block arrows pointed to the left of the diagram. These represent flow of data back to the operational system or other sources of data. This concept is called *closing the loop,* wherein the insights gained in the data warehouse are taken back to operational systems to support decision making and manage customer experience. Typical examples of data that are taken back to operational systems include customer lifetime value score, attrition indicator, repayment behavior score, and so forth.

Other Components of Architecture

Metadata is a key component of the data warehouse that typically gets ignored in many implantations leading to lots of pain at a later time. Metadata can simply be defined as data about data. Metadata is the detailed definition of anything related to the data warehouse ecosystem. It will include definition of source systems, data acquisition rules, data warehouse and datamart definitions, and end user layer definition, among others (Marco, 2000). The key requirement for metadata is the need to capture the definition in business terms. Metadata is typically used for requirements like impact analysis, for end users to understand what data are available and how it was derived, and so forth. The metadata environment normally consists of a repository to store metadata, interface tools to extract or exchange metadata with tools like data acquisition tools, data modeling tools, OLAP tools, and a navigator for users to access the metadata. Popular metadata tools include Metadata Manager (Informatica) and Metastage (IBM).

Warehouse monitoring (Inmon, Welch, & Glassey, 1997) is the aspect of monitoring the ecosystem of a data warehouse with an objective of identifying usage trends, performance trends, and capacity planning. While there are data warehouse-specific monitoring tools like Teleran, monitoring at a high level for performance and successful execution of programs can be done using system monitoring solutions like HP Open View, CA Unicenter, and IBM Tivoli. Data warehouse-specific monitoring tools are useful because they can identify both frequently used data as well as unused data, which then can be used to determine performance tuning measures as well as purging policies. They can also be used to implement a chargeback mechanism to end user departments.

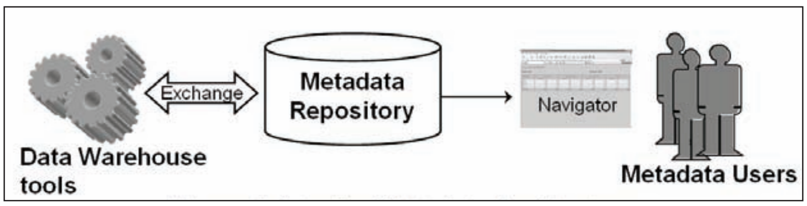
WHAT IS THE DATA WAREHOUSE USED FOR?

We started by establishing the premise that customer insight gained by using a data warehouse is the source for sustainable customer differentiation in banks. Let us get into details by examining some of the key usage areas of a data warehouse in a bank.

Customer Relationship Management (CRM)

This is perhaps the most important usage or benefit of a data warehouse in a bank. This could be termed as the *strategic* (in contrast with regulatory) application of data warehousing. CRM is not a new term—it is the concept of customer centricity that most industries have embraced, albeit with mixed success. To put it simply, CRM as a concept identifies the most valuable customers (MVCs) of the organization and provides them with differentiated and customized services and products,

Figure 4. A typical metadata architecture



thus increasing the relationship value (Peppers & Rogers, 1997). In other words, CRM recognizes that all customers hold varying classes of value to the organization and hence have to be treated differently based on their potential worth.

Initially, many CRM implementations failed due to an over emphasis on technology, while missing out on the strategy and apparently underestimating the need for change management in culture. This is probably the appropriate time to introduce the different types of CRM: operational CRM and analytical CRM. Operational CRM maintains transactional focus upon customer management to drive operational efficiency. Examples of operational CRM include contact center campaign management and sales force automation. While operational CRM is important, the benefits of operational CRM become static after sometime, chiefly because it addresses 'how to' but not 'what to'. For example, while contact center software can provide capabilities to create cross-sell scripts, what is not within its realm is which customer to target for cross-sell at what point in time and what is the appropriate product or service to cross-sell. It is at this juncture that the concept of analytical CRM takes root.

Analytical CRM uses the data warehouse ecosystem to derive the rules for implementing operational CRM. For example, segmenting the customers and identifying the next best product to cross-sell along with response scoring, using data mining (Berry & Linoff, 1997) is the activity done in the data warehouse ecosystem which is then used to drive which product can be cross-sold to which customer in operational CRM. Table 1 gives some of the key components of operational and analytical CRMs to differentiate them.

A typical analytical CRM architecture inclusive of the interaction points with operational CRM is shown in Figure 5.

The key components of the architecture are:

a. **Marketing datamart:** Also called customer intelligence datamart, this would provide the historical perspective of the complete relationship with the customer. The contents of marketing datamart are typically aggregated data and would include derived data like customer scores (e.g., lifetime value score), results of surveys (risk profile, needs and wants), and so forth.
b. **Analytics:** Customer analytics is the component of analytical CRM that provides tools and technologies for analyzing customer data to derive customer insights. This would typically include OLAP technologies as well as data mining tools. The models for calculating scores like customer lifetime value are derived here.
c. **Campaign management:** These tools automate planning and optimal execution of campaigns. They should contain capabilities

Table 1. Differences between analytical and operational CRM

Operational CRM	Analytical CRM
Campaign Management	Attrition Modeling
Contact Centers	Behavioral Modeling
Customer Service	Customer Lifetime Value
Internet Banking	Historical Profitability Calculation
Sales Force (Relationship Manager) Automation	Needs Analysis
	Response Scoring
	Risk Analysis

to define a campaign, attach targets and cost (e.g., cost per customer acquisition), and schedule and execute a campaign by extracting data from the marketing datamart. Some of the popular campaign management tools include SAS, Unica, Siebel, and SAP.

d. **Event processing engines:** These optional components are typically part of campaign management tools, which are used to identify unusual or exceptional events (normally based on transactions) to initiate a response. For example, an unusual cash deposit into an account could trigger a call from the bank to offer investment advice.

e. **Touchpoint enablers:** These represent technologies that are used to integrate the outcome of analytical CRM with operational CRM. Typical examples include e-mail servers to send mail offers, integration to contact center software to create call scripts, a relationship manager portal to display leads generated, and so forth.

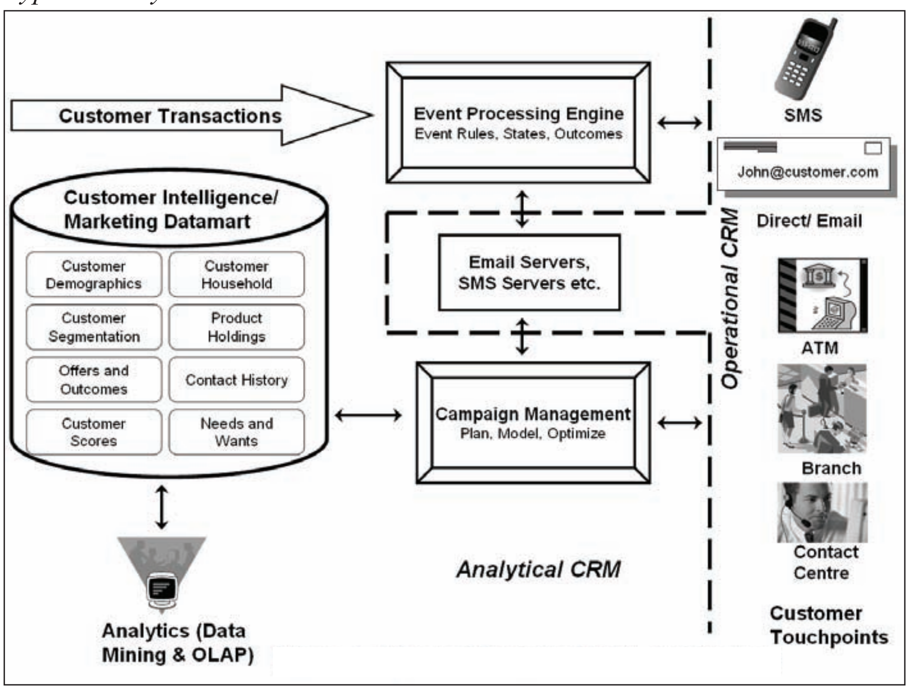
A point to note is that typically, transactions are not stored as part of the marketing datamart. The event processing engines typically contain storage capabilities where statistical profiles of transactions that pass through it are stored, rather than the actual transactions.

Another significant point about this architecture is that it can cater to any form of customer management rather than just marketing. For example, by interfacing with credit risk management datamart instead of marketing datamart, the same architecture can be used for managing debt collection activities.

Statutory Compliance

The data warehouse ecosystem covers both regulatory reporting and associated analytics for compliance. Statutory compliance from both the local Monetary Authority and the BIS perspective is a key utility of a data warehouse. Most banks pur-

Figure 5. A typical analytical CRM architecture



suing the new capital accord by BIS—popularly called Basel II—use a data warehouse by default for statutory compliance. By definition, Basel II compliance focuses heavily on historical data and statistical modeling. Statistical models must be based on historical data to determine the probability of default (PD) and hence identify loss given default (LGD). Most advanced banks are opting for the internal ratings-based (IRB) approach, starting with *foundation IRB* with an objective of implementing *advanced IRB* (AIRB). Some mature banks are directly opting for the AIRB approach.

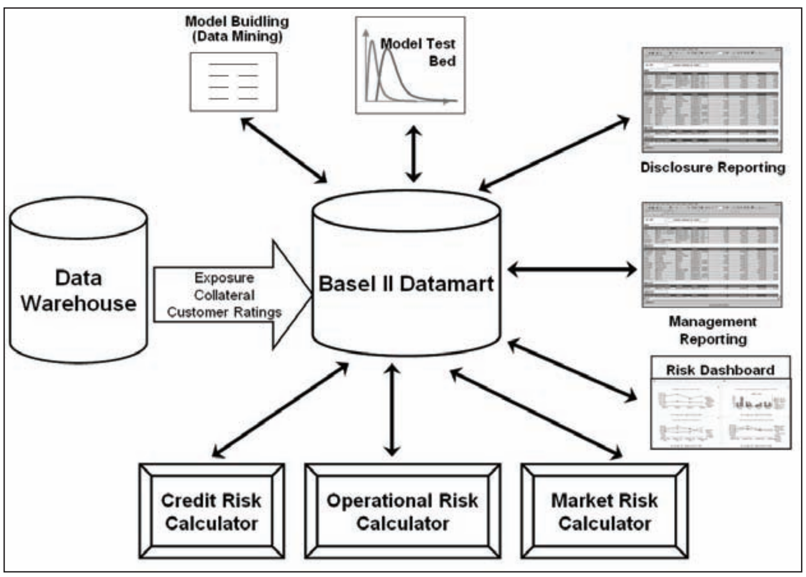
The AIRB approach to a large extent and foundation IRB to some extent requires extensive data with historical perspective (Ceulebroeck & Wallis, 2002). The PD and LGD models are statistical models that need to be developed based on historical delinquency data. Basel also requires that the developed models be back tested to validate their predictive capabilities. Data warehouse environments contain both historical data as well statistical tools (data mining), and hence they are the ideal ecosystem to implement Basel II compliance. Depending upon the size of the bank and complexity of operations, there can be a dedicated data warehouse for Basel II compliance, or it can be a datamart in the data warehouse ecosystem. The architecture of a typical Basel II compliance initiative is shown in Figure 6.

Calculators or engines that calculate economic capital based on probability of default (PD), loss given default (LGD), and exposure at default (EAD) are available from vendors like SAS, SAP, and Sunguard. Some banks have adopted the approach to develop their own calculators using custom-built programs.

Other Applications

Asset liability management (ALM), profitability (customer, channel, business unit, and product), channel performance management, delinquency prediction, attrition modeling (especially credit cards), anti money laundering (AML), SOX compliance, and fraud detection are some of the examples of applications of a data warehouse in banking.

Figure 6. A typical Basel II architecture



Some sample applications using advanced analytics are given below, some of which would overlap under the categories of analytical CRM or statutory compliance.

- **Customer lifetime value:** Apart from historical profit, banks are keen on knowing where the customers' future profit potential stands. This concept is called customer lifetime value (CLV). Using logistic regression or proportional hazards regression, the probability of customer 'survival'—that is, estimating the duration of a future customer relationship—would be determined. Based on the expected survival length, the potential future value based on historical profit can be computed. Proportional hazards regression will also indicate how the predictor variables may affect the probability of survival, which can be used for customer retention campaigns.
- **Attrition modeling:** Banks want to predict the likelihood of a customer terminating a facility with them to move to a competitor. Credit cards are good examples of products that invite high attrition from customers. Based on past historical data of attrite customers, attrition models can be created which are then used to predict a potential attrition well before the customer actually terminates. Decision trees are ideal to create attrition models, as the resultant models can be understood by business users as well as easy to deploy.
- **Credit scoring:** When a customer applies for a credit product (e.g., credit card, house mortgage), banks need to assess the probability of the account turning delinquent. Data mining can be used to create models based on historical delinquency data, which are then used to score a customer applying for a credit facility.
- **Propensity modeling:** Sales and marketing teams in banks want to predict customers' facility requirements such as opening a new facility or asking for a credit limit increase. Conceptually this is similar to attrition modeling, which is a case of propensity to churn.
- **Customer segmentation:** As part of understanding the customer behavior, customer segmentation models are created based on multiple target variables. For example, customer segments can be identified based on credit card spending. If a particular segment is a high-frequency, high-value spending segment, then the profile of that segment can be used to identify other customers that exist in the bank with the same profile, but who do not spend as much as the identified segment.

CONCLUSION

To conclude, we established that customer knowledge and insight will provide sustained competitive advantage to banks. The technology of data warehousing is the key enabler to obtain customer knowledge and insight. A well-designed data warehouse and analytics infrastructure can be used to support multiple business applications in the bank.

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Chapter XIII
Data Warehousing and Analytics in Banking:
Implementation

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ABSTRACT

Data warehousing and analytics represent two of the foremost technologies that can be used by banks to obtain sustainable competitive advantage. Adopting the right implementation methodology is critical to ensuring successful implementation. Alternate implementation methodologies, typical challenges in implementation, and critical success factors apart from real-life case studies are discussed here as learning points to aid in successful implementations. Future proofing implementations are critical to avoid rework, and hence some key emerging trends have also been discussed.

INTRODUCTION

Business users in banking use data warehouse and analytics as key enablers to achieve sustainable competitive advantage. While there is considerable debate on the definition of success as well as on the various surveys that provide statistics on the failure rate, there is no argument on the fact that data warehouse and analytics implementations have the potential to fail if inappropriately implemented. The author advocates the view that success of a data warehouse and analytics implementation should be measured by the positive impact to the top line and bottom lines of the bank instead of assessing technical factors alone. Hence a technically successful data warehouse that has the right data, made available at the right time to the right users is still a failure if it does not end up increasing the top line and/or bottom line.

CHALLENGES IN IMPLEMENTATION

Data warehousing is often touted as a high-risk implementation. According to many surveys, a large majority of data warehouse implementations are considered failures. The definition of failure and the authenticity of the survey results can be a point of debate. However, it is generally accepted that data warehouse implementations can go wrong more often than not. Some of the key challenges in data warehouse implementations are listed below, with specific reference to banking implementations:

- **Ability to define user requirements:** Defining the requirements for a data warehouse becomes a challenge when considering the maturity levels of the users. This is because, unlike an operational system, the users do not have an 'old system' or manual equivalent to refer back to, to help them define what would be best suited to their current requirements. This being a relatively new paradigm, not all users are mature enough to define what they want. One potential mitigation option is to use packaged data warehouses that would encapsulate the best practices in terms of banking data models and reporting templates. Vendors like IBM, Teradata, Oracle, and Satyam offer such packaged data warehouse solutions.
- **Data reconciliation:** Since the data warehouse is also used for regulatory and compliance initiatives, there is a need for validating the accuracy of loaded data. This is different from data warehousing when applied in other industries where accuracy can be conceded to an extent, as most analysis happens at aggregate levels. The recommended method of data reconciliation and validation for banking data warehouses is to validate the loaded data against general ledger balances. For example, the outstanding balance amount of loan accounts should be matched against the general ledger chart of the account into which the loan account balances are posted. This requires the ability to identify the charts of accounts into which key measures are posted in the general ledger.
- **Poor data quality:** Data quality is a major challenge in banks, as the data elements that are valuable in a data warehouse environment like customer demography are not considered necessary for day-to-day banking operations. From the operations perspective, what are needed are customers' identification and contact details, which will allow the bank to contact the customers and send statements. For instance, data items like annual income are considered unnecessary from the operations perspective, whereas they are very critical in the data warehouse environment to develop predictive models. With the push towards customer centricity in banks, there is a greater thrust to get clean data in banks. This challenge is mitigated by a combination of business rules to clean data when it is brought to the data warehouse (English, 1999) and change in business processes to get more updated and clean data.
- **Lack of organizational readiness:** Too many banks failed to get the business benefit of data warehousing, upon treating it as an IT project. Business users must be mature enough to use the data warehouse to achieve their business objectives and goals. This requires a change in culture and business processes. If the change management in culture, process, and compensation is not addressed as part of implementation, it would lead to a failed implementation, with ROI hardly visible (Adelman, Bischoff, & Dyché, 2002).
- **Long timeline:** In many banks, IT departments treat data warehouse implementations as infrastructure initiatives resulting in long project timelines. The resultant impact is that the users lose interest and develop alternative options. The right way to implement the data warehouse is to break into granular implementation tracks, with each track tied to a specific business objective or need. The ideal timeline for each iteration

should be three to four months, though in certain cases, six months can be considered as acceptable.

- **Adoption chasm:** This is defined as the inability of business users to successfully adopt (use) the data warehouse. An empirical study among banks in Taiwan (Hwang, Ku, Yen, & Cheng, 2004) concluded that support from top management, size of the bank, effect of internal business champion, internal needs, and competitive pressure influenced the adoption of the data warehouse technology by business users.

The Data Warehouse Institute (TDWI) is the premier professional body for data warehouse professionals. Its Web site http://www.tdwi.org/ consists of its famous series of "Ten Mistakes to Avoid" articles under various categories related to data warehousing. These articles are a good supplement to this section of the chapter.

CRITICAL SUCCESS FACTORS

While we saw some examples of what can go wrong in an implementation, some of the critical success factors that can be used to ensure successful implementation are given below:

- **Business sponsor:** The data warehouse should be sponsored and driven by business users and not by the IT department.
- **Start with a high reward area:** The first implementation should be a highly visible and high reward area, as it will ensure that management attention is established and further commitment is obtained.
- **Iterative implementation:** Do not try to boil the ocean—that is, do not implement the data warehouse as a single implementation. It is better done iteratively, with each iteration tied to a specific business objective or business initiative.
- **End user involvement:** Unlike conventional application development, users must be involved throughout the project. They can play a vital role during the design and development process to iteratively provide inputs on aspects like data cleansing rules. The 'build it and traffic will follow' principle does not work in data warehouse implementations.
- **Get the right skills:** Data warehouse development involves a totally different mindset and different rules of the game. Make sure that the right talent is recruited or the right vendors are engaged. Otherwise, the data warehouse will end up looking like a mirror of the operational system!
- **Clean and integrated data:** Loading the data warehouse with data that is not clean or validated will result in users losing faith in it. Appropriate validation routines would ensure that correct data is loaded.

IMPLEMENTATION METHODOLOGY

Data warehouse and analytics implementations deserve a different methodology compared to normal IT application projects. Given below are some key reasons as to why a separate methodology is required:

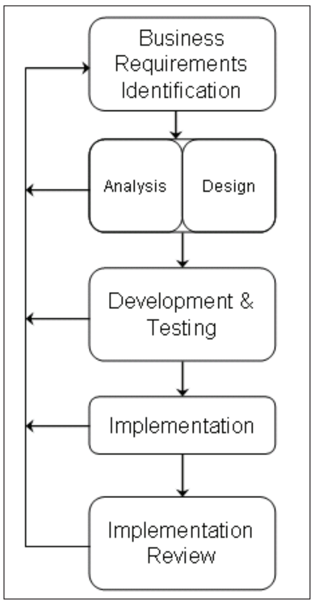
- Activities that are not normally performed in operational applications are critical in data warehouse and analytics projects (e.g., source system analysis, data cleansing, data integration, and data movement).
- Business users often expect results in short timeframes to ensure quick return on investment (ROI).
- Different technologies and approaches are adopted (e.g., dimensional modeling, ETL, and OLAP technologies).

Various methodologies have emerged that are an adaptation of conventional methodologies. A discussion of all possible methodologies is beyond the scope of this chapter. However, iterative methodology (Inmon, 1996), which is a common factor of most successful methodologies, has been described, apart from an emerging methodology.

Iterative Methodology

Data warehouse requirements tend to evolve as users get more sophisticated, based on experience. Hence a strict waterfall methodology will not work as the users may not be able to define all the requirements in one phase. Long implementation timeframes are a challenge given user expectations of fast turnaround times. Hence, most authors recommend an iterative methodology of developing a data warehouse. A typical iterative methodology is shown in Figure 1. It is generally recommended that a time box approach to iterative development be adopted and to limit the scope to what can be implemented within the accepted time box. An ideal time box in the context of banks could be between 60 to 90 days. Hence each iteration should be limited to a timeframe between 60 and 90 days with the scope adjusted appropriately to ensure it fits the chosen timeline. This is one key difference compared to a traditional waterfall methodology (at first glance the iterative methodology shown in Figure 1 may look like a waterfall methodology) wherein the scope is generally fixed and timeline is decided based on scope. Another key difference when compared to the waterfall methodology is that any of the previous phases can be revisited based on the learning in a current phase. For example, if data discovery performed during the analysis phase results in new understanding of the business or data quality, the business requirements identification phase needs to be revisited.

Figure 1. A typical iterative methodology



Data Mining Methodology

In a poll conducted by KDnuggets™ (2006), CRISP-DM was shown as the most popular methodology for data mining. Figure 2 shows a graphical depiction of the results of the methodology.

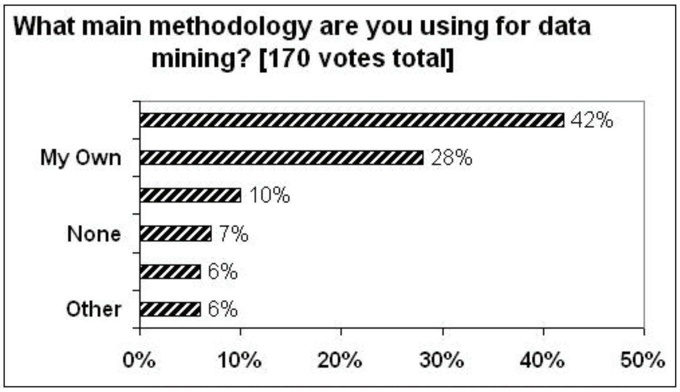
CRoss Industry Standard Process for Data Mining (CRISP-DM) is an industry and tool-neutral data mining process model. Key project partners involved in developing CRISP-DM are Teradata, SPSS, Daimler Chrysler, and OHRA Verzekering en Bankk Groep B.V., The Netherlands (*http://www.crisp-dm.org/Partners/index.htm*).

The CRISP-DM process model is an iterative methodology for data mining (http://www.crisp-dm.org/Process/index.htm), and Figure 3 shows a graphical depiction. A detailed description of this methodology is beyond the scope of this chapter; interested readers can get more details at http://www.crisp-dm.org.

Agile Development Methodology

There have been attempts to adopt agile development methodology (http://agilemanifesto.org/

Figure 2. Data mining methodology poll results



and http://www.agilealliance.org/) in data warehousing and analytics. Briefly, agile development methodology involves adopting frequent release cycles (in days or weeks rather than months) and deep involvement of end users in the entire process. There are many agile development frameworks and of these, two widely used frameworks are the Microsoft Solutions Framework (MSF) and Extreme Programming (XP). While a detailed description of agile development is beyond the scope of this chapter, in brief, it involves an iterative, multi-release framework with fixed release schedule. Resource triangle, which consists of three dimensions—requirements, time, and resources—is a zero sum game. Any change to one dimension (e.g., fewer resources than planned) would require changes to at least one other dimension. Typically, the project team will meet daily along with business users to check on the resource triangle and decide what changes need to be affected to any of the dimensions. Since fixed release schedule is a key criterion, any scope that could not be met in the current release would be postponed to the next release rather than changing the release schedule. At times the deliverable could be released with known bugs rather than extend the timeline to solve the bugs.

Adelman (2004) cautions:

Figure 3. CRISP-DM process model

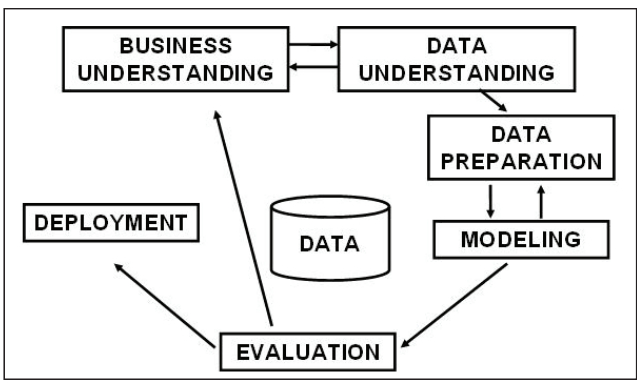


Table 1. Technology stack components

Technology Stack Component	Technology
Data Warehouse Database	IBM DB400 in AS400
ETL	Informatica PowerCenter
Metadata Manager	Informatica
End User Reporting & Analysis	Business Objects, Crystal Reports, Cognos
Budgeting and Planning	Hyperion System 9
Data Mining	SAS & IBM Intelligence Miner
Datamart Databases	Oracle, SQL Server, DB400
Scheduler	Control-M
Data Transport	Connect Direct
Data Modeling	All Fusion ERWIN

Be careful that you don't minimize the efforts involved in properly defining your business requirements, cleaning up your data, implementing an appropriate architecture, fully training your user community, and thoroughly testing. If your 'agile development methodologies' are short of these activities, you will deliver a substandard data warehouse.

The bottom line is that usage of agile development methodology in data warehousing and analytics is an emerging trend, and to avoid costly rework one has to use it with caution.

DETAILED CASE STUDY

Business Scenario

A large South Asian bank was at a crossroads in the early 1990s. The local government thrust was on consolidation in the local banking sector, which forced local banks to merge in order to gain size for effective international competition. The bank decided to acquire banks in the region as a strategy to turn itself into a regional bank vs. being a predominantly single country bank. It began by acquiring a local bank in its home country, followed by another acquisition in a neighboring country.

IT Scenario

To align with the business strategy of becoming a regional bank, the CIO opted for a strategy of creating hubs of excellence for IT applications and business processing. The home country or headquarters was chosen as the hub for core banking applications. This meant that the core banking for all country operations in the region were consolidated into servers in the home country onto a single platform and application. High-speed networks allowed users and operations in the various countries to access the central environment.

The acquisitions resulted in the bank having multiple data warehouse environments. To align with the 'hubs of excellence' strategy, the bank was required to consolidate the data warehouse environments. There was also a need to assess the various technologies and applications in the data warehouse ecosystem, and to design an architecture that optimized the utilization of the various applications. The data warehouse design had to be reviewed in the context of the bank's business strategy, of opting for regional bank status, along with its IT strategy to create hubs of excellence. To complete the list of drivers, Basel II compliance deadlines were looming and the impact of compliance initiatives on the data warehouse ecosystem was another factor to consider.

The bank engaged a local consulting firm to review the current data warehouse environment and design an architecture that aligned with the business and IT strategies.

Recommendations

The study involved examining the existing inventory of the data warehouse ecosystem and performing a critical review of all major components. There were a few contenders for the enterprise data warehouse layer in the new architecture. These included the incumbent data warehouse and packaged application from an external vendor which was the foundation for determining profitability. The key recommendations were:

- The bank could opt for a dependent data warehouse architecture, wherein a central global data warehouse (GDW) would feed clean and consistent data to various downstream applications and datamarts. The centralized GDW would serve as the 'one version of truth' in the organization.
- For regional operations, there was a need for a single customer view across the region from both the strategic and compliance perspective. Hence, the bank would need to design a new data model catering to this requirement, as none of the existing data warehouses or packaged applications could satisfy the requirement.
- Countries that had significant volumes of data or regulatory restrictions would have their own satellite data warehouse and satellite data acquisition (ETL) environments. They would also feed the central GDW for group-level analysis and compliance purposes. A country-specific satellite data warehouse was recommended, as the nature of activities that happened in the data warehouse environment (unpredictable query patterns, large volume of data extracted during queries, etc.) meant that network bandwidth could get severely clogged.
- Packaged applications like profitability determination, local regulatory reporting, and collections management would take clean data from GDW instead of directly accessing the source operational systems.
- Basel II compliance requirements like modeling, risk datamarts, compliance reporting, and capital calculators would be treated as downstream applications taking data from GDW instead of independently building a separate parallel environment. In other words, both strategic and compliance information needs of the bank would be sourced from a single environment.
- The GDW would start as a monthly load frequency environment eventually moving to a daily load. In the meantime, the staging area would be refreshed on a daily basis to provide data to downstream applications like collections management which required data on a daily basis.
- Certain derived data needed to be updated in operational applications (closing the loop) to support decision making at operational levels.
- The implementation roadmap was drawn up with multiple phases where each phase would be used to support one or two business objectives or initiatives.

Implemented Architecture

Based on the recommendations, the architecture implemented in the bank is shown in Figure 4.

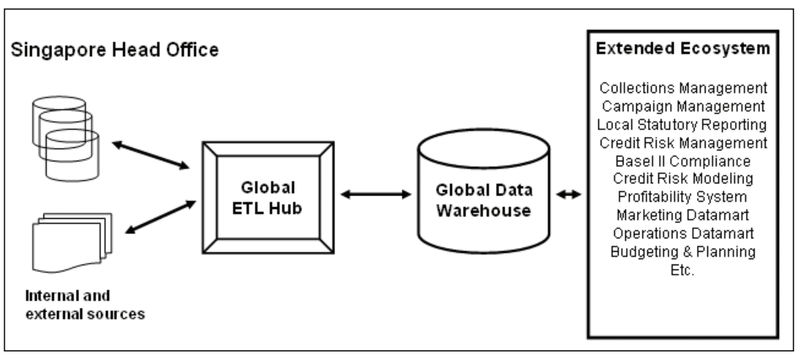
The overseas subsidiaries data was brought to the global ETL hub and loaded into the global data warehouse for use at the head office to perform group-wide operations like risk management. Depending upon the size of the group institution, business users either directly accessed their own data in the global data warehouse or had their own data warehouse infrastructure containing only their country data. The significant technology stack components used in this implementation are given in Table 1.

Challenges Faced

Some of the key challenges faced in implementing the new architecture were:

- **Regulatory hurdles:** Many of the financial regulators in the region forbade carrying customer data outside of the country. This conflicted with the 'hub of excellence' concept. The solution involved obtaining customer clearance as well as specific approvals from regulatory bodies. Where approvals could not be obtained, the matter was resolved by masking or scrambling customer-sensitive information (e.g., ID numbers), which passed the scrutiny of regulatory bodies. At the group level, information is generally required as an aggregate and hence scrambling of customer identification information did not severely impede business functionality.
- **Data quality:** As mentioned earlier, maintaining data quality is a typical challenge of any banking data warehouse implementation. Exception identification and defining workflow as part of the data acquisition process were mitigatory steps. The workflow process handled routing of 'dirty' data to respective owners for cleansing. This augmented the rule-based cleansing.
- **Data reconciliation:** The approach adopted was reconciliation against general ledger data. However, the challenge lay in accurately identifying the chart of account into which the metrics would be posted. For example, the loan system would maintain the chart of account for each facility into which the outstanding amount was posted and the outstanding amount would be posted into a separate chart of account if the facility turned delinquent. This challenge was mitigated in the data acquisition process by maintaining a cross-reference table supplemented by business rules.
- **Customer segment:** Defining the customer segment was a challenge because the business rules were not straightforward. A customer's segment is determined either by the nature of the customer or by the product or by the business unit. For example, in general, any corporate organization is considered a

Figure 4. High level architecture



corporate segment. However, credit cards were handled by the retail segment, and credit cards issued to corporations were also considered part of the retail segment. In other words, the product definition took precedence over the customer definition. This was handled by a combination of business rules during data acquisition and data modeling.

- **Data definition:** Some data definition varies between operational application and analytical requirement. For example, days past due (DPD) would be defined as the number of days past the repayment date in the operational system. However, in the data warehouse, what was more critical was banding the DPD into buckets of one month, two months, and so forth. Transferring from one definition to another required a careful definition of business rules, as a monthly definition is based on the calendar month and not on every 30-day count becoming one month!
- **Performance:** This was a major challenge, considering that data for multiple countries was loaded into a single data warehouse. The challenges included the batch time available to load, data from different countries arriving at different timelines, ensuring minimal inconvenience to users who may be using the application during data loading, and query performance. The performance challenge was mitigated with a combination of design activities, which included using database-specific features like partitioning and indexing. This was apart from data acquisition design, which was optimized to reduce the impact on source system and data warehouse batch windows.

Key Benefits

Some of the key benefits that accrued as a result of implementation of the proposed new architecture using the GDW are listed below:

- A collections application that was implemented took the data feed from the data warehouse. This enabled the bank to proactively define collection strategies to reduce non-performing loans and improve the recovery of bad debts. This resulted in a big business initiative of reduced NPLs and increased collections efficiency, directly contributing to the bottom line of the bank.
- **Customer scoring:** By performing statistical modeling and scoring customers on various parameters like repayment behavior and attrition score, the bank was able to obtain business benefits. These included increased loan quality (by using repayment behavior score as part of application processing) and reduced attrition, hence increasing customer lifetime value (through attrition prevention campaigns based on attrition scores). The validity and predictability of the scoring model and the score card elements were tracked in the data warehouse and were instrumental in fine tuning the models.
- Business was able to view the entire customer relationship in a single environment which enabled them to analyze and execute initiatives at customer level instead of product level. This improved the customer centricity and resulted in increased customer lifetime value.
- The marketing users were able to gain insights on the behavior of the customer and drive campaigns that resulted in increased use of facilities and cross-sell initiatives. For example, based on insight gained on utilization patterns and repayment behavior, the proactive limit increase was offered to a select group of customers which resulted in higher utilization and hence increased profitability.
- By opting for a unified data warehouse architecture, IT was able to support stra-

tegic and compliance initiatives like Basel II compliance with a reduced investment compared to its peers.

OTHER IMPLEMENTATION EXAMPLES

Scotiabank

The Bank of Nova Scotia (Scotiabank) implementation details were obtained from the Web site of SAS Institute International (http://www.sas.com/success/scotiabank.html).

Scotiabank is a large Canada-based international financial services group. Scotiabank opted for SAS solutions in the areas of customer relationship management and database marketing to strengthen its capabilities in risk management, cost control, and customer satisfaction. Scotiabank worked with SAS to create a capability that combines SAS predictive modeling and SAS marketing optimization to create multi-channel offer selection and targeting solution.

Scotiabank had the capability to target customers for specific campaigns based on profitability and propensity to respond. In response to business needs, they wanted to build a capability that allowed business users to look at multiple campaigns simultaneously and predict which customer should be targeted for which product. This is a critical capability, as at any point in time, the bank would be executing multiple campaigns, and if the bank has to be customer centric, it should not 'carpet bomb' the customer with multiple offers at the same time. Also, the marketing resources of banks are not unlimited and hence optimal target customer identification is critical, to avoid high campaign costs. The implemented SAS solution had the capability to create predictive and profitability models, in addition to business rules, to identify which customers should be targeted with which offers along with expected incremental profit. By adopting this technique, Scotiabank was able to improve marketing ROI by 50% in some campaigns, compared to using traditional selection techniques.

Leading Bank in South Asia

This is an example of a failed data warehouse and analytics implementation. The bank in question is based in a South Asian country and is among the largest retail banks in that country with around 8 million customers. The bank's journey in data warehousing started in the late 1990s when a multinational vendor was invited to create a blueprint for data warehouse and analytics implementation for the bank. The blueprint involved implementing data warehouse and analytics in phases, starting with customer data and a liabilities product in the first phase. The bank selected a range of technologies that are required for the implementation of a data warehouse and engaged a local vendor for implementation. The first phase was implemented in approximately six months and included about one year's worth of historical data. The bank continued to enhance the data warehouse using internal resources and the local vendor. Approximately one year after the implementation of the first phase, the CIO approached the CEO with a large budget request to enhance the data warehouse with asset products data. The CEO rejected the request citing that he did not see any visible business impact of the data warehouse.

The business users were found to be using an old PC-based system for their reporting needs and hardly any usage of the data warehouse was observed. An external consultant was tasked to find out what went wrong. Following were the key findings:

- Business users did not have prior experience using data warehouse and analytics, and hence were not in a position to provide proper requirements. The local vendor engaged also had no prior experience and hence could not add value in the requirements definition phase. This resulted in a data warehouse that was largely driven by known reporting requirements which were already being satisfied in some form or other by existing initiatives.

- With IT and the vendor leading the way, business user involvement in the implementation process was minimal, and as a result the users felt no sense of ownership or commitment to use.
- While training was conducted for business users on the technical aspects of the data warehouse, there was no major effort to teach them on how to use data warehouse and analytics for decision-making purposes. That is, the connection between business strategies and technology capabilities was not made obvious.
- Relying heavily on an external vendor led to vendor-driven direction, which satisfied their own vested interests.
- The end user layer (analytics) was not user friendly. The users had to be 'IT friendly' in order to use the analytics tools.
- Lack of metadata definitions contributed to end users having a poor understanding of what was available in the data warehouse.
- Data warehouse design was sub-optimal, resulting in performance challenges when queries were executed. Users gave up after waiting many hours for queries to complete.

The bank subsequently brought in another vendor experienced in implementing data warehouse and analytics in banks. By executing business initiatives that were tightly coupled to the data warehouse capabilities, they restored the confidence in the data warehouse. Some of the business initiatives included selecting target customers for marketing campaigns by performing needs analysis. About six months later, the CEO gave the go ahead for the next major phase of data warehouse enhancement.

DOES EVERYONE NEED A DATA WAREHOUSE?

One of the frequently asked questions is whether every bank needs a data warehouse and what the prerequisites are for building one. Most banks are moving away from product-based applications to core banking applications that cater for customer information files (CIFs) with all banking products in one application. Let us address a few questions relating to core banking here.

The first question is, if a bank has implemented core banking, does it need a data warehouse? The simple answer is 'yes'. While the core banking may cater to a single customer view in terms of containing all customer-related data in one application, there are other fundamental technical drivers that make core banking unsuitable for decision-making needs. One reason is that the database design of core banking applications is more tuned towards fast data processing (insert/update/delete) and not data analysis. Another reason is that to handle trend analysis, the data needs to be kept in the data warehouse for a longer period than what is typically done in core banking systems. Moreover, the core banking application cannot be loaded with end user queries as it will severely impact the performance for banking operational needs. Additionally, for decision making, often data external to the organization needs to be analyzed in conjunction with the internal data, and hence a separate repository (read data warehouse) is required to hold internal and external data in an integrated manner.

The second question is whether core banking implementation is a pre-requisite for data warehouse implementation. The answer is 'no'. If the core banking is already implemented, it does simplify the process of implementing a data warehouse, but it is not a mandatory pre-requisite. If fact, many banks have used data warehousing to create the single customer view, which was subsequently used to drive the core banking implementation.

The key driver for opting for data warehousing in banking should come from business. Typical business drivers include a strong competitive marketplace, regulatory compliance requirements, and pressure on profits. These business drivers apply regardless of whether core banking is implemented or not and whether the country of operation is an emerging country or developed country. Most banks tend to be in such situations and hence it is safe to assume that all banks require data warehouse and analytics in some form or other.

EMERGING TRENDS

Data warehousing is a relatively new concept—about 25 years old. However, its rapidly changing technology landscape with the inclusion of new concepts embraces new developments in the IT field. The data warehouse has evolved substantially since it was originally defined by Bill Inmon. Hence, Bill developed a revised architecture called DW 2.0 ™ in 2006. According to DW 2.0 (Inmon, 2006), data warehouse architecture consists of four sectors: interactive sector, integrated sector, near line sector, and archival sector. A more detailed discussion of this definition is deferred until a greater dissemination and acceptance of the new definition happens. Some of the key emerging and future trends, from a technical perspective, are explained below.

Right-Time Enterprise

Gartner coined the term *right-time enterprise* (RTE) and defined RTE as an enterprise that competes by using up-to-date information to progressively remove delays that hamper management and execution of its critical business processes. The goal of RTE is to reduce the time between an event occurring and a decision based on the data of the event getting executed. There are three latencies involved in the decision cycle. The latency between a business event and data getting stored in an RTE environment is called data latency. The latency between data getting stored and any analysis done (manual or automated) is called analysis latency. Once analysis is done and using the information or knowledge gained from the analysis, the time taken for decision making is called decision latency (Hackathorn, 2003). The

Figure 5. A typical RTE architecture

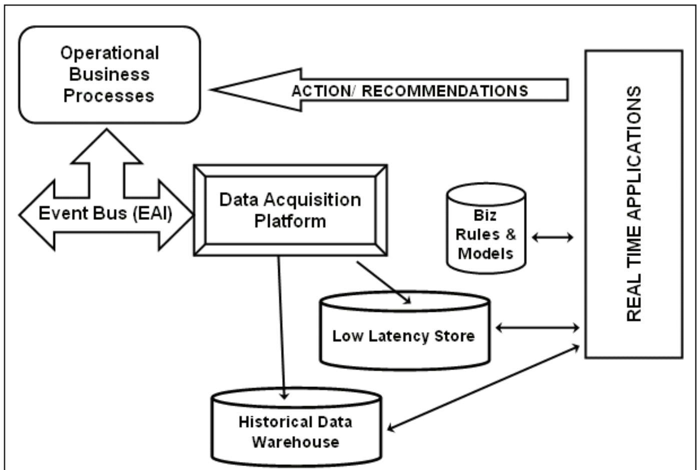


Figure 5. A typical RTE architecture

objective of RTE is to reduce the action distance, in other words reduce all types of latency.

A typical RTE architecture is shown in Figure 5.

The key points to note in the architecture are that data flows into the RTE environment in the form of event messages through event bus or message queues—which are normally enterprise application integration (EAI) tools. Most data acquisition tools have connectors that allow them to read data from message queues. Low latency store is a temporary storage area (which may not always be required) before real-time applications act on the message. Real-time applications include real-time querying and analysis as well as predictive applications like fraud detection. In this architecture, as soon as the business process happens, the data corresponding to the business process is dropped into the event bus, which appears in the RTE environment almost instantaneously. This data is now available for manual analysis as well as automated analysis and decision making by real-time applications. The actions or recommendation by predictive applications are communicated back to the operational business processes through the same event bus or message queue.

Business Activity Monitoring

Business activity monitoring (BAM) is a part of real-time enterprise (White, 2003). The component of RTE that is used for real-time (or more appropriately right-time) performance management is called BAM. It is meant for operational business management unlike the data warehouse, which is more for strategic business management. A simple BAM architecture consists of a low latency store, BAM server, and engines for acting upon output of the BAM server. In most cases, the data warehouse is part of the architecture to provide the historical perspective. BAM server processes operational events and analyzes them based on business rules. Depending on the business rules, actions are taken by the appropriate engine. A simple form of BAM involves updating dashboards or consoles that are viewed by operators or other personnel. Alternately, rule engines can process BAM server output to take actions like triggering an operational activity or sending a message to a business user.

One example of usage of BAM in banking is operational risk management using dashboards and alerts. Another example is real-time loan application analysis comparing against the customer's historical data and the bank's overall risk allowances.

The key advantage of BAM is that it places monitored events in context, which could be:

- **Historical and seasonal:** What is normal now, that is, at this point in time?
- **Business context:** Is this event that is happening critical? How does it have a role in the overall business process?
- **Organizational context:** Who in the organization is interested in this event?

An example of how context will be applied in the BAM environment can be illustrated under operational risk management. Rapid depletion of the currencies in ATM hoppers at a rate much higher than normal rates is an unusual event. However, if it is determined that it is the eve of Christmas, then this event is treated as a normal event because history shows that cash withdrawal is high on the eve of holidays.

Other Trends

Some of the other key trends are:

- **BI and business process integration:** Contrary to traditional BI, which involves analysis in a separate environment and influencing business processes in the business operations environment, BI would increasingly get embedded as part of business process. Dynamic pricing for loans that involve calculating impact on regulatory capital on the fly is an example of BI embedded in business process.

- **Embedding BI functionality into databases:** Most database vendors like Microsoft and Oracle are progressively embedding BI functionality into the database engines. The type of BI functionality that gets embedded in the databases includes data mining and OLAP. This trend is expected to accelerate and aid the emergence of applications that embed BI or predictive analytics as part of them. Embedded BI applications are a key requirement to support embedding BI in business processes.
- **Service-oriented architecture and Web services:** These are increasingly becoming architectural requirements in data warehouses. Most of the newer tools support SOA and the Web services paradigm.
- **BI applications:** There is a push to integrate BI into business processes with a result in BI applications, that is, applications that embed BI capabilities like predictive analytics.
- **Open source:** Open source data warehouse tools have started appearing and are expected to mature in the next decade or so, resulting in more cost-effective deployments.
- **Ubiquitous analytics:** BI will move from dedicated BI tools and applications to more ubiquitous capabilities. Microsoft has already started the trend by embedding the BI functionality on Microsoft Office products.
- **Unstructured content:** There is an increasing need for integrating unstructured data in the data warehouse leading to convergence of BI tools and unstructured content analysis tools like search engines. Statutory requirements like SOX mandate the need to store unstructured data like e-mails and telephone conversations in the data warehouse. Apart from statutory requirements, strategic usage of data warehouse and analytics also demands unstructured data, as the analytics become more sophisticated in the quest to acquire more knowledge based on data. For example, to understand the difference between successful and unsuccessful cross-sell opportunities, the contact center agent's call transcripts need to be integrated with the structured data. The biggest challenge in integrating unstructured data into the data warehouse lies in digitizing the unstructured data, which are typically in the form of Web content (e.g., Web site content or chat room transcripts), audio (call transcripts), and paper formats.

CONCLUSION

Data warehouses are by and large difficult-to-implement initiatives; however, following a few key critical success factors and avoiding known pitfalls will ensure successful implementations. The future of data warehouse use in banking lies in making the bank a real-time enterprise with an objective to reduce the time between an event occurring and the time for associated decision making to happen.

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Chapter XIV
A Reference Model for Savings Bank

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ABSTRACT

With approximately 17,490 well-defined modeling objects, the SKO[1]-Datenmodell[2] is probably the most extensive reference data model in German for the banking area. So far, this reference data model has been used in about 30 projects describing different subject areas. The detailed project data models that have been derived from these projects have been reintegrated into the generic reference data model, as far as the results are applicable to the entire Sparkassen-organisation. The SKO-Datenmodell was initially developed approximately 15 years ago. It is derived from the financial services data model[3] (FSDM), which has been provided by IBM. The FSDM is a reference data model which is generally valid for the banking area. In contrast to the FSDM, the SKO-Datenmodell is specialized for the requirements of the Sparkassenorganisation. The basic elements of the reference data model are a conceptual design of data model abstraction levels, an extensive methods and procedures handbook with precise quality requirements and an integrated tool support by m1[4] and Rochade.[5] The different levels of the SKO-Datenmodell and the use of these levels in practice are described in this chapter.

THE CONCEPTUAL DESIGN OF LEVELS OF THE SKO-DATENMODELL

The SKO-Datenmodell covers approximately 80% of the business data that are required by application development projects in the Sparkassenorganisation. The data model is subdivided into the five levels A, B, C, C' and D (Figure 1). The A-Level is a very compact level with business data. This level covers the architecture view. The following levels become more extensive and the contents

Figure 1. The levels of the SKO-Datenmodell

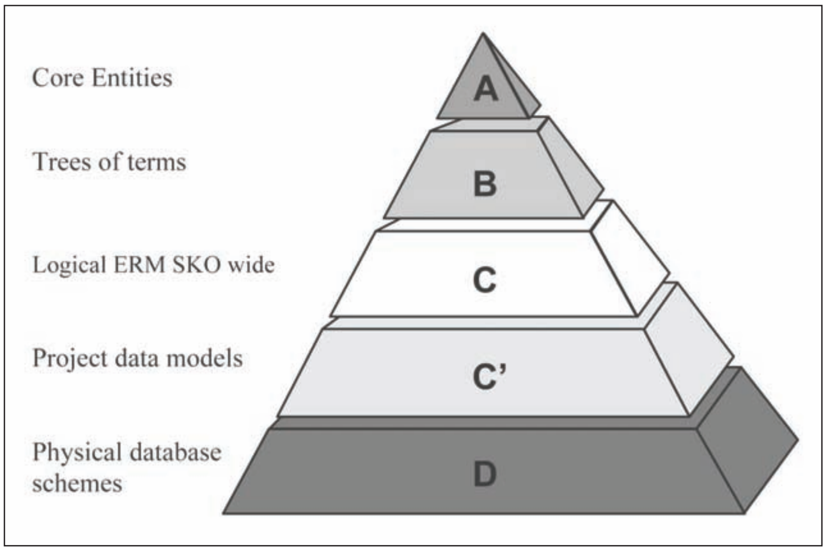


Table 1. The core entities of the A-Level

Core entity	Definition	Example
Involved Party	An involved party is an individual, an organization, an organization unit or a community of involved parties about which the financial institution wishes to maintain information to enable a good cooperation.	Individual, organization
Event	An event is an activity or an occurrence about which the financial institution wishes to keep information as a part of managing its business.	Order, booking, advisory talk
Business Direction Item	A business direction item is an externally or internally caused regulation which helps to regularize the business of an involved party and to define its framework for action.	Enterprise objective, legal guidelines
Classification	A classification is a definition of dividing features for business information and their structure.	Account, unit of measure, market segment
Condition	A condition is a single requirement or a combination of requirements, which are necessary for the processing of the businesses of a financial institution.	Fee, maturity, interest rate
Location	A location is a bounded area or a point where something is addressed to or where something can be found.	Town, address
Product	A product is a service which is offered or sold by the financial institution or its competitors. It can also be a service which is offered to the financial institution.	Consumer loan, custodianship in a safe deposit box
Resource Item	A resource item is every object which is owned, managed and/or used for the business of the financial institution or which is of special interest for the financial institution.	Building, manual
Arrangement	An arrangement is a potential or a real conclusion of a contract between two or more Involved Parties.	Product arrangement, employment arrangement

become more and more detailed in the direction of a technical view.

The content of the levels A, B and C are developed and maintained by a central group hosted by the SIZ[6]. The models of these three levels are available for all members of the Sparkassen-organisation. The C' and Dlevel contents are developed by the various projects of the joint use centers of the Sparkassenorganisation.

The A-Level (Architecture View)

The *A-Level* of the SKO-Datenmodell consists of nine *core entities* (Table 1). These core entities represent containers for the business terms in the banking area. The business terms are assigned to their proper places on the highest level. Each term belongs only to one of the nine core entities. Each core entity has a detailed definition and description as well as examples to support the classification.

The nine core entities are a useful instrument at the beginning of application development projects. During the definition of requirements, the project contents can be delimited by assigning the business terms to the core entities. However, the A-Level is also a good place to define responsibilities in a project. In one of the last application development projects with the SKO-Datenmodell, the project teams had been organized by the core entities. The "customer relationship management" team was responsible for the core entities involved party, location and resource item. Arrangement and account (classification) had been covered by the "arrangement management" team and product and condition by the "product management" team.

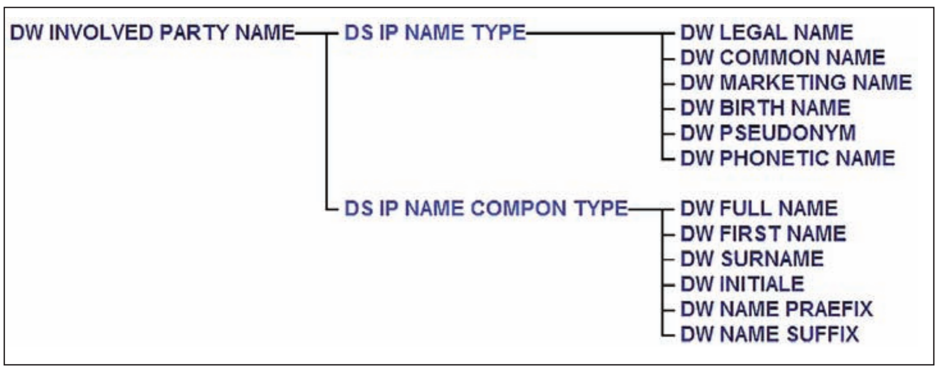
In this case of having several teams, close communication between the data modelers of each team is important during the development of the project data model.

The B-Level (Business View)

The *B-Level* of the SKO-Datenmodell is a specialization of the A-Level. Each of the nine core entities is decomposed into a *tree of terms.* Such a tree of terms at the B-Level consists of a *classification hierarchy*, a *description hierarchy* and a *relationship hierarchy.* This hierarchical structure allows the detailed classification of business terms. With this specialization of the nine core entities, it is possible to cover the demand for information in a financial institution. The actual version of the SKO-Datenmodell contains 7,500 objects at the B-Level.

The construction elements of the B-Level are *scheme* and *value.* Each B-Level-hierarchy

Figure 2. Extract of the description hierarchy of the core entity involved party with the tool m1



starts with a value. Then, schemes and values alternate. Figure 2 shows a part of the description hierarchy of the core entity involved party (IP). The abbreviation DW stands for description value. DW marks the term as a value of a description hierarchy. In the same way, the schemes are marked with DS. This abbreviation stands for description scheme. The example shows two schemes for the classification of "involved party name." The scheme "DS IP NAME TYPE" distinguishes between several kinds of names like "birth name," "marketing name" or "legal name." The second scheme, "DS IP NAME COMPONent TYPE," shows the different components of names like "first name," "surname" or "full name." The name "Max Miller" can be the legal name of an Involved Party as well as the marketing name. Furthermore, "Max Miller" can be filed as first name "Max" and surname "Miller" or as full name "Max Miller." The example shows that a term, found by the modeling, can be described by several categories.

On the B-Level, the same rule as on the A-Level applies: Every value and every scheme has to be described by a definition and some examples. This is necessary to enable the correct classification of terms and to avoid synonyms and homonyms. The given examples especially facilitate the use of the model for business professionals.

After an analysis of the context, each term is put in its proper place in one of the hierarchies by using suitable modeling principles. If a business term is a specialization of a core entity, it belongs to the classification hierarchy of this core entity. An "entry" is a specialization of an event and therefore belongs to the classification hierarchy of the core entity event. All the values that describe or identify a core entity—like the "involved party name" or the "account number"—are part of the description hierarchy of the corresponding core entity. Therefore, the "involved party name" belongs to the description hierarchy of the core entity "involved party." "Account number" belongs to the description hierarchy of the core entity "classification," because account is a subtype of classification. The relationship hierarchy contains all terms, which describe relationships within a core entity as well as relationships between two core entities. The relationship "involved party is customer of an involved party" is part of the relationship hierarchy of the core entity "involved party." The relationship "involved party is supplier of resource item" is included in the relationship hierarchy of the core entity "involved party" as well as in the relationship hierarchy of the core entity "resource item."

The model of the B-Level is a very good assistance for conversations with the business department. The simple construction also allows a business professional without modeling knowledge to find business terms very fast. The model also facilitates the navigation within the SKO-Datenmodell.

In application development projects, the model of the B-Level supports the definition of requirements. Moreover, the trees of terms support the clarification of business terms. The selection of terms of the B-Level model allows a simple and fast definition of the project scope. Because the reference model is already filled with terms and definitions, the specification process of a concrete project will be sped up. This definition of the project contents is the basis for the development of the project data model with the C-Level model of the SKO-Datenmodell.

The B-Level is not only useful in projects that develop new applications. The B-Level model also supports package integration, migration and re-engineering projects. Migration projects use the model as a neutral medium. The data models of applications that have to be migrated get an association to the B-Level model to define derivation rules from old to new.

The C-Level (Logical ERM Organization-Wide)

The *C-Level* of the SKO-Datenmodell consists of a logical *entity relationship model* (ERM). This level considers structural aspects. The actual SKO-Datenmodell version 3.1 contains the following elements on the C-Level:

- 1023 entities
- 2100 attributes
- 938 domains
- 5014 domain values
- 704 relationships
- 215 subtype sets

The business content of the entity relationship model is mainly derived from the B-Level hierarchies. A number of rules define the derivation mechanism. Each element of the model has a detailed description as well as examples.

Also, on the C-Level business aspects are decisive. Technical considerations do not influence the modeling. Generic structures, which cover a large area, help to reduce the complexity of the model.

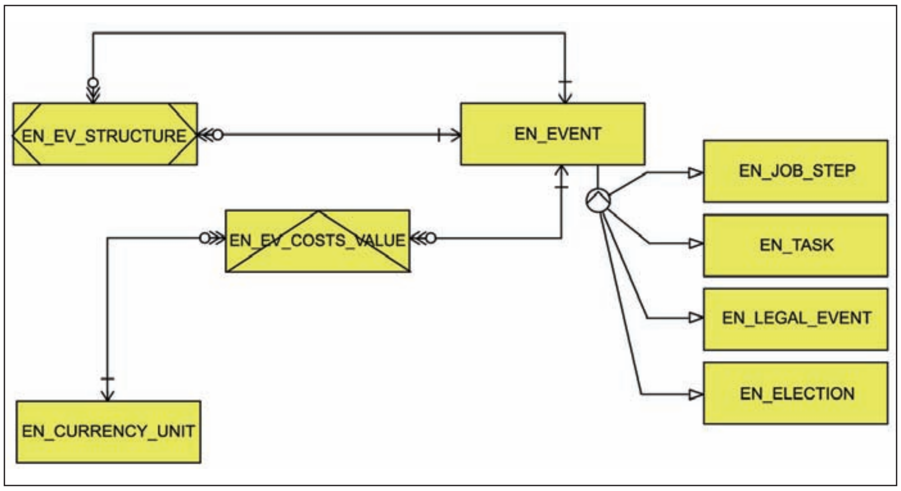
This extensive entity relationship model is primary a communication basis for data modelers and developers. The user should be familiar with the data model based application development techniques. Application development projects use the model as a basis for the development of the project data models. The elements of the B- and C-Level models are linked with a so-called level trace. This trace allows the tool-supported selection of the data model extract that is relevant to the project, based on the scope definition on the B-Level. This C-Level extract is the basis for the project data model.

However, this is not the only use of the C-Level. The entity relationship model of the SKO-Datenmodell can also be the foundation for the development of an own enterprise-wide data model. For example, the German savings bank Hamburger Sparkasse has developed their enterprise-wide data model based on the SKO-Datenmodell.

The C'-Level (Logical ERM Subject Area View)

The logical data models of the different application development projects are located on the *C'-Level* of the SKO-Datenmodell. These project data models are parts of the C-Level model that are either extended specifically to the business or

Figure 3. Extract of the C-Level model with the tool Rochade (core entity Event)



reduced. In contrast to the C-Level, which has the emphasis on structure, the C'-Level concentrates on the modeling of a specific subject area or of one project. Because of this strong orientation on a special subject area, C'-Level models are much more detailed than the entity relationship model of the C-Level. Not only data modelers and developers can use the models of the C'-Level. In addition, business professionals with modeling knowledge can use these models, because of the subject area view.

During the development of a C'-Level model, application-specific and/or technical aspects will be added to an extract of the C-Level model. One example for the modeling of technical aspects on the C'-Level is the modeling of a special concept for historical data.

Most of the project data models on the C'-Level are entity relationship models. However, they do not have to be entity relationship models just because this notation has been used for the model on the C-Level of the SKO-Datenmodell. The use of the notation depends on the modeling standards and the application development standards in the projects as well as on the project type.

In a card management project, experiences with object-oriented application development using the SKO-Datenmodell have been made. To also cover the modeling of systems for planning purposes, the project "OLAP modeling with the SKO-Datenmodell" was realized. The results of this project have been integrated in the *Methods and Procedures Handbook* of the SKO-Datenmodell.

The outcomes of the A-, B- and C-Levels are created and maintained by a central data administration group. But the models of the C'-Level are results of the application development projects of the various joint use centers. Experienced SKO data modelers support these projects.

The SKO data modelers collect new findings into a database during the project work. The entries of this database are used for revision and extension of the B- and C-Level models of the SKO-Datenmodell. If generally applicable, these findings are included in the SKO-Datenmodell during a so-called maintenance project. The result of such a maintenance project is always a new version of the SKO-Datenmodell. The members of the Sparkassenorganisation each get a new version. In order to follow the changes made between the versions of the model, a history and version trace will be delivered in addition. The trace helps to understand the deviations between the two model versions.

The D-Level (Physical Database Scheme)

All the previous levels of the SKO-Datenmodell have a very strong business view. Technical aspects have hardly been covered during the modeling on these levels. Now, the *physical database schemes* of the *D-Level* take the technical requirements of the database design into consideration. These technical requirements depend very much on the guidelines of the joint use centers as well as on the hardware used, database management system and the underlying application architecture. Therefore, instructions for the step from the logical to the physical database scheme are not included in the SKO-Datenmodell.

Overall Concepts (Level Independent)

In order to support communication between the logical concepts of the SKO-Datenmodell and the business community, *overall concepts* irrespective of level have been introduced, for instance, account or customer. The SKO-Datenmodell distinguishes between two different kinds of overall concepts:

- Overall concepts based on the core entities of the A-Level.

- Overall concepts which include—in addition to the core entities—modeling principles for the design of semantic connections.

The core entities with their definition and relationships are the basis for the nine overall concepts, which are based on the core entities, such as Involved Party or Arrangement.

Additional overall concepts of the SKO-Datenmodell are customer, account, managerial account, segment and trading object. All overall concepts have detailed descriptions. Table 2 shows a short definition of the additional overall concepts.

Overall concepts help the analyst and the data modeler to put the business terms and facts in their proper places. In this way, the overall concepts support the uniform comprehension of facts within the Sparkassenorganisation. They are, together with the structural criteria, a way for standardization. The overall concepts should also support the delimitation of different aspects of complex business facts.

METHODS AND PROCEDURES HANDBOOK AND TOOL SUPPORT

As pointed out in the previous section, there are several guidelines and instructions available in a methods and procedures handbook accompanying the SKO-Datenmodell. This section will introduce the *Methods and Procedures Handbook* and will describe the tools around the SKO-Datenmodell and the model management.

The Methods and Procedures Handbook of the SKO-Datenmodell

The *Methods and Procedures Handbook* covers precise modeling instructions for all model components. It describes in detail the objectives and the use of each level of the SKO-Datenmodell. Furthermore, it defines which modeling elements belong to a level and how they have to be created and described.

However, the *Methods and Procedures Handbook* not only includes guidelines, which relate

Table 2. Overall concepts of the SKO-Datenmodell

Overall concept	Definition
Customer	A customer is a connection between two involved parties. One of these involved parties has an existing or a potential business relation with the other involved party.
Account	An account is a two-sided calculation of the financial institute about requests and liabilities toward third parties based on business relations.
Managerial Account	A managerial account is an aggregation or a compacting of data of internal accounts and/or customer accounts. This data has been made available for controlling purposes of the financial institution. It can be used for further evaluation.
Segment	A segment is a specific group of objects. These objects are interesting to the financial institution in any combination because they support the institution and its business functions.
Trading Object	A trading object is a resource item, which is offered for sale or arranged to be sold by the financial institution or another involved party.

to one level, but also detailed instructions to the associations between the levels. The interaction of the modeling elements of the different levels and versions of the SKO-Datenmodell is defined with the help of so-called traces. These traces completely document the connection between the objects of the model. Moreover, they facilitate the navigation between the levels and the versions of the SKO-Datenmodell. The objects of the B and C levels are linked by a level trace. For instance, the classification value "involved party" of the B-Level model is linked with the entity "involved party" of the entity relationship model on the C. Therefore, you can see that this classification value is modeled as an entity in the C-Level model. "account number" is modeled on the B-Level as the value of the description hierarchy and on the C-Level as attribute of the entity "account".

Traces also connect different versions of the SKO-Datenmodell. The objects of the B- and C-Level models of the SKO-Datenmodell Version 3.1 are linked via traces with the objects of the previous version 3.0.

The detailed instructions in the *Methods and Procedures Handboo*k of the SKO-Datenmodell allow a homogeneous modeling with high quality standards. In addition, SKO-Datenmodell newcomers have a comprehensive reference book.

Model Management

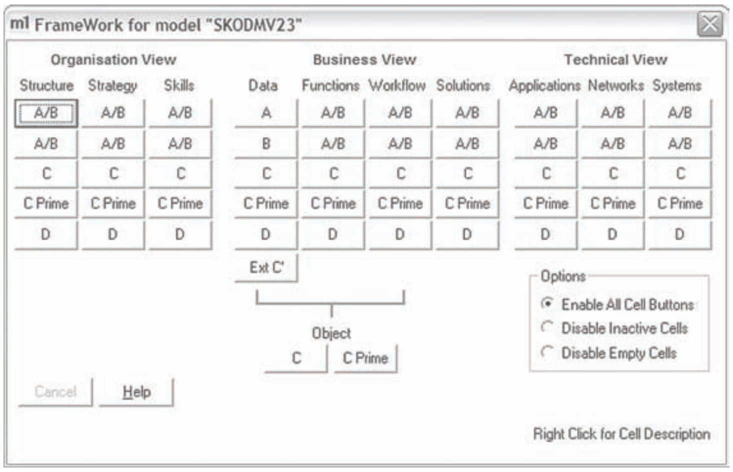
Such an extensive reference model like the SKO-Datenmodell cannot be administered and expanded without *tool support*. At present, three tools are used for the work with the SKO-Datenmodell. *Rochade* and *m1* are used for modeling and administration of the model. Whereas the SKO-Datenmodell Meta model and specialized model management applications are implemented on base of the *Rochade* repository by the model management team, the *ml* tool is being used on an "as is" basis without modifications. Moreover, a task database supports the maintenance process.

For a long time, the *Rochade tool* was used "just" as repository for the administration of the different versions of the SKO-Datenmodell and for the tool-supported quality assurance of the models. Since 2001, *Rochade* is also used for the further development of the SKO-Datenmodell because the supplier has not supported the modeling tool any longer.

A very good support for the use of the A and Blevels of the SKO-Datenmodell in application development projects is provided by the *ml* tool.

The "FrameWork Window" of m1 allows a simple navigation between the different levels

Figure 4. The FrameWork Window of m1



of the model (Figure 4). So m_1 relieves a simple entry in the SKO-Datenmodell, especially for users who have no or only limited experience with the model.

However, the tool m1 is not suited as modeling tool for the maintenance of the B and C levels of the SKO-Datenmodell. The strengths of this tool are the fast navigation between levels, very good search- and trace-functions and the function to define scopes.

In projects, the active work with the A- and B-Levels of the SKO-Datenmodell usually takes place with the *ml* tool. At the beginning of a project, the project contents will be set at the B-Level. The relevant C-Level part will be extracted based on the B-Level scope of the project contents. This step is fully supported by the m_l tool. Then the C-Level extract will be transferred in the respective modeling tool, where the development of the project data model takes place. At present, the projects use *Rochade* as the modeling and model management tool.

The *task database* is a Lotus Notes database. It has been developed to support the maintenance process for the SKO-Datenmodell. All change requests concerning the B or C levels of the SKO-Datenmodell are collected in this database. Each request has a reference to the application development project, which has made the request. Every maintenance project is planned in the task database. In addition, all changes made in such a project are documented in the database. Therefore, it is possible to reproduce which changes have been made in the new version of the SKO-Datenmodell and which application development project has made the change request.

DEVELOPMENT OF THE DATA MODEL

In 1991, the Sparkassenorganisation bought the financial services data model (FSDM) of IBM. In the following years, the model has been customized and enhanced. A mixed team of FSDM consultants and various representatives of the SKO has adapted and enlarged the tree of terms of the B-Level and the entity relationship model of the C-Level to meet the special requirements of the SKO. The A-Level of the FSDM with the nine core entities has been retained. However, the overall concepts have been developed in addition to the three levels of the FSDM. In parallel to the customization, the marketing process for the new model has been started. Moreover, scenarios for the introduction of the model have been developed and a lot of conviction work has been done. In 1995, the first release of the SKO-Datenmodell was ready for the use in the SKO.

So far, this reference model has been used in about 30 projects with the following subjects: “statement analysis, booking, clearing and settlement, (sale-) controlling, derivatives/trades, real estate consultation, lending business, customer relationship management, marketing, market research, micro geography marketing, internal organization, personnel, audit, risk control and management, cost accounting” (Kittlaus, 1999, p. 31). As far as the results of these projects have been applicable to the entire Sparkassenorganisation, the integration into the SKO-Datenmodell has taken place. At present, the SKO-Datenmodell Version 3.1 is the most recent version of the model in use.

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Section III
Risk Management

Chapter XV
A Semi-Online Training Algorithm for the Radial Basis Function Neural Networks:
Applications to Bankruptcy Prediction in Banks

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ABSTRACT

This chapter presents an algorithm to train radial basis function neural networks (RBFNs) in a semi-online manner. It employs the online, evolving clustering algorithm of Kasabov and Song (2002) in the unsupervised training part of the RBFN and the ordinary least squares estimation technique for the supervised training part. Its effectiveness is demonstrated on two problems related to bankruptcy prediction in financial engineering. In all the cases, 10-fold cross validation was performed. The present algorithm, implemented in two variants, yielded more sensitivity compared to the multi-layer perceptron trained by backpropagation (MLP) algorithm over all the problems studied. Based on the results, it can be inferred that the semi-online RBFN without linear terms is better than other neural network techniques. By taking the Area Under the ROC curve (AUC) as the performance metric, the proposed algorithms—semi-online RBFN with and without linear terms—are compared with classifiers such as ANFIS, TreeNet, SVM, MLP, Linear RBF, RSES, and Orthogonal RBF. Out of them TreeNet outperformed both the variants of the semi-online RBFN in both data sets considered here.

INTRODUCTION

Artificial neural networks (ANNs) have been applied in applications involving classification, function approximation, optimization, and control. It is well known that the two most popular architectures of ANN—multi-layer perceptron (MLP) and radial basis function network (RBFN)—are universal function approximators. RBFN and MLP can be used for a wide range of applications primarily because they can approximate any function under mild conditions. MLP is trained by supervised learning. On the contrary, the training of RBFN takes place in a hybrid manner containing both unsupervised and supervised schemes. Unsupervised training is less approximate and hence relatively fast. Moreover, the supervised part of the learning consists of solving a linear problem, which is therefore fast, with the additional benefit of avoiding the problem of local minima usually encountered in training MLP. Hence, the training of RBFN is faster than that of MLP. RBFN has just two layers of parameters (centers, widths, and weights) and each layer can be determined sequentially (Benoudjit & Verleysen, 2003).

An RBF network has two layers. Consider an unknown function $f(X)$: $R^d \to R$. In a regression context, RBFN approximates $f(X)$ by a weighted sum of d-dimensional radial activation functions (plus linear and independent terms). The radial basis functions are centered on well-positioned data points, called centroids; the centroids can be regarded as the nodes of the hidden layer. The positions of the centroids are obtained by an unsupervised learning rule. The network weights between the radial basis function layer and the output layer are estimated using ordinary least squared technique. Suppose we want to approximate the function $f(X)$ with a set of M radial basis functions $\phi_j(X)$, centered on the centroids C_j and defined by Benoudjit and Verleysen (2003):

$$\phi_j(X): R^d \to R: \phi_j(X) = \phi_j(\| X - C_j \|)$$

where ||.|| denotes the Euclidean distance, $C_j \in R^d$ and $1 \le j \le M$.

The approximation of the function $f(X)$ may be expressed as a linear combination of the radial basis functions:

$$\sum_{j=1}^{M} \lambda_j \phi_j(\| X - C_j \|) + \sum_{i=1}^{d} a_i x_i + b$$

where λ_j are weight factors, and a_i, b are the weights for the linear and independent terms respectively.

A typical choice for the radial basis functions is a set of multi-dimensional Gaussian kernels:

$$\phi_j(\| X - C_j \|) = \exp(-\frac{1}{2}(X - C_j)^T (X - C_j))$$

Moody and Darken (1989) proposed, as unsupervised part of the algorithm, the k-means clustering algorithm to find the location of the centroids C_j. Once the basis function parameters are determined, the transformation between the input data and the corresponding outputs of the hidden units is fixed. Then, the supervised learning part of the algorithm commences where the weights connecting the nodes in the kernel layer and the nodes in the output layer are estimated using the linear least squares technique. Accordingly, the minimization of the average mean square error yields the least square solution for the weights.

$$\lambda = \phi^+ y = (\phi^T \phi)^{-1} \phi^T y,$$

where λ, y are the row vectors of weight factors λ_j and training data outputs y_p, ϕ is $N_T \times M$ matrix of $\phi_{ij} = \exp(-\| X_i - C_j \|^2 / 2\sigma_j^2)$ values, and $\phi^+ = (\phi^T \phi)^{-1} \phi^T$ denotes the pseudo-inverse of ϕ.

Review of Work Done in Improving RBF Network

We now review earlier works where online training algorithms for RBFN were suggested. Fung, Billings, and Luo (1996) derived a new recursive supervised training algorithm, which combines the procedure of online candidate regressor selection with the conventional Givens QR-based recursive parameter estimator to provide efficient adaptive supervised network training. Mashor (2000) presented a new hybrid algorithm, moving k-means clustering algorithm for training RBFN, which positions the RBFN centers and Given's least square to estimate the weights. Sarimveis, Alexandridis, Tsekouras, and Bafas (2002) proposed training methodology based on a fuzzy partition of the input space that combines self-organized and supervised learning. The RBFN architecture and a new fast and efficient method for training such a network are used to model linear dynamical multi-input multi-output (MIMO) discrete-time systems. For a given fuzzy partition of the input space, the method is able to determine the proper network structure, without using a trial-and-error procedure. Sarimveis, Alexandridis, and Bafas (2003) presented an algorithm based on the subtractive clustering technique for training RBFN, which is faster in training times and more accurate in prediction. Dumitrescu (2003) proposed a dynamic clustering algorithm (GCDC) based on a new evolutionary optimization meta heuristics, the Genetic Chromo (GC) dynamics. This algorithm is used for designing RBFN topologies. GCDC performed the clustering of training data thereby reducing the complexity of the network. Nabney (2004) showed that the RBFN with logistic and *softmax* outputs can be trained efficiently using Fisher scoring algorithm. Han and Xi (2004) presented a new neural network called radial basis perceptron (RBP) for distinguishing different sets. RBP network is based on RBFN and MLP. RBP has two hidden layers that are connected by selective connection. They presented an algorithm to train an RBP network. The algorithm alternately applied basis functions adaptation and backpropagation training until a satisfactory error is achieved.

The primary objective of this chapter is to develop a semi-online training algorithm for the RBFN and explore its usefulness in predicting bankruptcy in banks. We accomplish this by replacing the k-means clustering algorithm by an online clustering algorithm, the evolving clustering method of Kasabov and Song (2002), which performs unsupervised learning in an online manner, while the supervised learning part of the RBFN is performed by ordinary least squares algorithm. We call the new architecture "semi-online RBFN," as the supervised part of the algorithm, being taken care of by ordinary least squares technique, involves batch processing of data.

SEMI-ONLINE RBFN

The present online training algorithm for RBFN works in two steps. In the first step, where unsupervised learning takes place on the input data, clusters are determined in just one pass using the evolving clustering method of Kasabov and Song (2002). The second step, involving supervised learning between the hidden layer consisting of kernels or radial basis functions and the output layer, is performed by employing the ordinary least squares technique. We chose to use the ordinary least squares technique and not the iterative gradient-based supervised training to justify the semi-online feature of the training algorithm in both phases. The use of the ordinary least squares technique requires batch processing of data and hence the algorithm becomes *semi-online* instead of *online*. Thus, in the supervised phase, the minimization of the average mean square error yields the least square solution for the weights.

$$\lambda = \phi^{+} y = (\phi^{T}\phi)^{-1}\phi^{T} y,$$

where λ, y are the row vectors of weight factors λ_j and training data outputs y_p, ϕ is $N_T \times M$ matrix of $\phi_{ij} = \exp(-\| X_i - C_j \|^2 / 2\sigma_j^2)$ values, and $\phi^{+} = (\phi^T \phi)^{-1}\phi^T$ denotes the pseudo-inverse of ϕ.

The architecture of the resulting semi-online RBFN is depicted in Figure 1. We developed two variants of the semi-online RBFN—(1) semi-online RBFN without linear terms, and (2) semi-online RBFN with linear terms—by choosing two different forms of the ϕ matrix. The matrix ϕ without linear terms is as follows:

$$\phi_1 = \begin{bmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1K} & 1 \\ \phi_{21} & \phi_{22} & \cdots & \phi_{2K} & 1 \\ \phi_{31} & \phi_{32} & \cdots & \phi_{3K} & 1 \\ \cdots & & & & \\ \phi_{m1} & \phi_{m2} & \cdots & \phi_{mK} & 1 \end{bmatrix}$$

Further, the matrix ϕ with linear terms is: (see Box A).

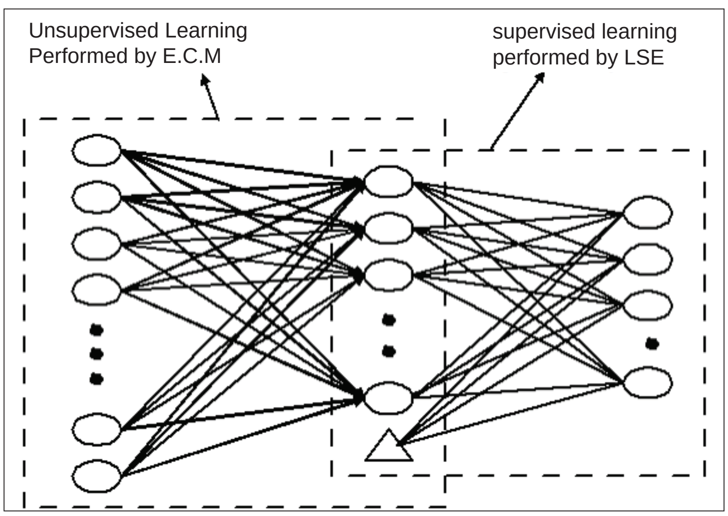
Evolving Clustering Method (ECM)

Clustering has been one of the most important tasks in the statistical learning theory (Bezdek, 1981, 1987; Vapnik, 1998). Clustering is concerned with finding the grouping of data vectors based on their similarity through defining the cluster centers and their radii, along with the membership degree to which each data vector belongs to the clusters. The exact clustering methods (such as K-means) define the membership of each vector as belonging to only one cluster (membership degree of 1) and not belonging to the rest of the clusters (membership degree of 0). Clustering algorithms are often used as parts of other methods of computational intelligence, such as data mining and learning algorithms (Kasabov & Song, 2003), a radial basis function neural network to select the kernels (Kasabov, 2001), and fuzzy inference systems where the number of possible fuzzy 'if-then' rules is determined by the number of clusters in

Box A.

$$\phi_2 = \begin{bmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1K} & x_{11} & x_{12} & \cdots & x_{1d} & 1 \\ \phi_{21} & \phi_{22} & \cdots & \phi_{2K} & x_{21} & x_{22} & \cdots & x_{2d} & 1 \\ \phi_{31} & \phi_{32} & \cdots & \phi_{3K} & x_{31} & x_{32} & \cdots & x_{3d} & 1 \\ \cdots & & & & & & & & \\ \phi_{m1} & \phi_{m2} & \cdots & \phi_{mK} & x_{m1} & x_{m2} & \cdots & x_{md} & 1 \end{bmatrix}$$

Figure 1. Semi-online RBFN architecture



the data set (Rummery & Niranjan, 1994; Heskes & Kappen, 1993; Saad, 1999).

When the online algorithms became popular over the last decade (Kasabov, 1998, 2001, 2003), the evolving clustering method emerged as one of them. Kasabov and Song (2002) proved the effectiveness of ECM in the context of designing a dynamic, evolving neuro-fuzzy inference system, called DENFIS, which is then applied to modeling and knowledge discovery tasks in bioinformatics, brain study, and intelligent machines. Indeed, many applications in the above-mentioned areas, as well as in finance, environmental study, adaptive process control, and other areas, require a fast online clustering to evolve and adapt a model incrementally and continuously to incoming data.

The ECM Algorithm

In this section, first the evolving, online, maximum distance-based clustering method, ECM, of Kasabov and Song (2002) is described. The online ECM does not involve any optimization. It is a fast, one-pass algorithm for dynamic estimation of the number of clusters and current cluster centers in a data set. It is a distance-based connectionist clustering method where the cluster centers are represented by evolved connectionist-type nodes. In any cluster, the maximum distance *MaxDist* between a sample point and the cluster center is less than a threshold value *Dthr,* which is set as a clustering parameter. This parameter affects the number of clusters to be estimated. In ECM the distance between vectors *x* and *y* denotes a *general Euclidean distance* defined as follows:

$$\|x-y\| = \left(\sum_{i=1}^{q} \left(x_i - y_i \right)^2 \right)^{1/2} \Big/ q^{1/2}$$

$$\text{where } x \text{ and } y \in R^q \qquad (1)$$

In the online clustering process, the data samples come from a data stream and the algorithm starts with an empty set of clusters. When a new cluster is created, the cluster center Cc is defined and its cluster radius Ru is initially set to zero. When more samples are presented one after another, changing their centers' positions and increasing their radii will update some existing clusters. Which cluster will be updated and how much it will be changed depends on the position of the current sample in the input space. A cluster will not be updated any more when its cluster radius Ru becomes equal to a threshold value *Dthr.* The original ECM algorithm is described in Box 1.

BANKRUPTCY PREDICTION IN BANKS

The prediction of bankruptcy for financial firms, especially banks, has been an extensively researched area since the late 1960s (Altman, 1968). Creditors, auditors, stockholders, and senior management are all interested in bankruptcy prediction because it affects all of them alike (Wilson & Sharda, 1994). The most precise way of monitoring banks is by onsite examinations. These examinations are conducted on a bank's premises by regulators every 12–18 months, as mandated by the Federal Deposit Insurance Corporation Improvement Act of 1991. Regulators utilize a six-part rating system to indicate the safety and soundness of the institution. This rating, referred to as the CAMELS rating, evaluates banks according to their basic functional areas: ***C****apital adequacy,* ***A****sset quality,* ***M****anagement expertise,* ***E****arnings strength,* ***L****iquidity,* and ***S****ensitivity to market risk.* While CAMELS ratings clearly provide regulators with important information, Cole and Gunther (1995) reported that these CAMELS ratings decay rapidly. Fraser (1976) noted that banks performed better by holding relatively more securities and fewer loans in their portfolios. Gady (1972) and Fraser (1976) showed that core deposit funding was beneficial for banks, particularly demand

Box 1.

Step 0: Create the first cluster by simply taking the position of the first sample from the input stream as the first cluster center Cc1, and setting a value 0 for its cluster radius Ru1.
Step 1: If all samples have been processed, the algorithm is finished. Else, the current input sample x_i is considered and the distances between this sample and all n already existing cluster centers Cc_j, $D_{ij} = \|x_i - Cc_j\|$, $j = 2,...,n$ are calculated.
Step 2: If any distance value D_{ij} is equal to or less than at least one of the radii Ru_j, $j = 1,2,\ldots, n$, then it means that the current sample x_i belongs to a cluster C_m with the minimum distance:

$$D_{im} = \|x_m - Cc_m\| = min\|x_i - Cc_j\|,\ j = 2,...,n$$

subject to the constraint $D_{ij} \leq Ru_j,\ j = 1, 2, ..., n.$
In this case, neither a new cluster is created, nor any existing cluster is updated. The algorithm returns to Step 1. Else—go to the next step.
Step 3: Find cluster C_a (with center Cc_a and cluster radius Ru_a) from all n existing cluster centers such that,

$$Cc_a = S_{ia} = \min(S_{ij}),\ where\ S_{ij} = D_{ij} + Ru_j,\ j = 1, 2, ..., n.$$

Step 4: If S_{ia} is greater than *2* x *Dthr*, the sample x_i does not belong to any existing clusters. Hence, a new cluster is created in the same way as described in Step 0 and the algorithm returns to Step 1.
Step 5: If S_{ia} is not greater than *2* x *Dthr*, the cluster C_a is updated by moving its center Cc_a and increasing the value of its radius Ru_a. The updated radius is set to be equal to $S_{ia} / 2$ and the new center is located at the point on the line connecting the x_i and Cc_a, and the distance from the new center to the point x_i is equal to new radius. The algorithm returns to Step 1.
Thus, the maximum distance from any cluster center to the samples that belong to it is not greater than the threshold value *Dthr*, though the algorithm does not keep any information of past examples.

deposits, which are non-interest bearing. Gady (1972) indicated that high performance banks were able to generate more interest or non-interest income than underperforming banks. Wall (1985) observed that higher profit banks rely more on equity funding. Brewer, Jackson, and Moser (1996) observed that firms used the derivative instruments to change their risk exposure. They also concluded that there was a negative correlation between risk and derivatives usage. Haslem, Scheraga, and Bedingfield (1992) determined the impact of strategies followed by individual banks related to the relative profitability performance. Kwast and Rose (1982) employed statistical cost accounting techniques to examine the relationship between bank profitability and two dimensions of operating performance pricing and operating efficiency.

A variety of statistical techniques such as regression analysis and logistic regression have been used to solve the problem of bankruptcy prediction. These techniques typically make use of the company's financial data to predict the financial state of the company (healthy, distressed, high probability of bankruptcy). Altman (1968) pioneered the work of using financial ratios and multiple discriminant analysis (MDA) to predict financially distressed firms. However, the usage of MDA or statistical techniques, in general, relies on the restrictive assumption on linear separability, multivariate normality, and independence of the predictive variables (Karels & Prakash, 1987; Odom & Sharda, 1990; Ohlson, 1980). Unfortunately, many of the common financial ratios violate these assumptions. The bankruptcy prediction problem for financial firms can also be solved using various other types of classifiers. Tam (1991) explored a backpropagation trained neural network (BPNN) for this problem and compared its performance with methods such as MDA, logistic regression, k-nearest neighbor (k-NN) method, and ID3. He concluded that the neural network outperformed other prediction techniques. Salchenberger, Mine, and Lash (1992) find that the neural network produces fewer or an equal number of classification errors for each of the forecast periods in consideration compared to the logit model. This conclusion holds for total errors, Type I errors, and Type II errors. Tam and Kiang (1992) found that a neural network generally performs better than statistical methods and decision trees. As a result, many researchers view the neural network as an attractive alternative to statistical techniques for bankruptcy prediction. Wilson and Sharda (1994) compared the performance of the neural networks vis-à-vis the MDA proposed in Altman (1968).

Lee, Han, and Kwon (1996) applied three different hybrid neural network architectures: MDA assisted neural network, ID3 assisted neural network, and a self-organizing map-assisted feed forward neural network. The hybrid neural networks performed much better than the stand-alone prediction models. Further, they concluded that the SOM-assisted feed forward neural network outperformed other hybrids. Bell (1997) reported that neural networks and logistics regression performed equally well in the prediction of commercial bank failures. Jo, Han, and Lee (1997) used MDA, a case-based forecasting system (CBFS), and neural networks for predicting the bankruptcy of Korean firms; they demonstrated that neural networks outperform MDA and CBFS. This study also revealed that CBFS was inappropriate for bankruptcy prediction. Swicegood (1998) also employed MLFF-BP NN with two hidden layers to solve this problem. Olmeda and Fernandez (1997) solved the bankruptcy prediction problem for Spanish banks. They employed the backpropagation trained neural network, logistic regression, multivariate adaptive regression splines (MARS), C4.5, and MDA as standalone models as well as in various combinations in the multiple voting scheme devised by them to construct an ensemble system. They found that neural networks outperformed all other models while operating in the standalone mode; and the combination of neural network, logistic regression, C4.5, and MDA performed the best among all the combinations. In another study, Alam, Booth, Lee, and Thordarson. (2000)

Table 1. Average results of 10-fold cross validation for Spanish bank data

Classifiers	Accuracy	Type I Error	Type II Error	Sensitivity	Specificity
Semi-Online RBF with X	**58.31**	**33.76**	**49.67**	**66.24**	**50.33**
Semi-Online RBF without X	**88.32**	**11.43**	**31**	**88.57**	**69**
Orthogonal RBF	**40.83**	**2.5**	**92.67**	**97.5**	**7.3**
Linear RBF	**75**	**48.28**	**9.83**	**51.71**	**90.17**
RSES	**92.5**	**12.5**	**2.5**	**87.5**	**97.5**
SVM	**82.5**	**13.45**	**14.33**	**86.55**	**85.67**
MLP	**80**	**33.93**	**9.83**	**66.1**	**90.17**
TreeNet	**77.96**	**13.45**	**7**	**86.55**	**93**
ANFIS	**63.34**	**55.55**	**21**	**44.45**	**79**

used fuzzy clustering and two self-organizing neural networks to identify potentially failing banks. The results showed that both the fuzzy clustering and self-organizing neural networks are promising classification tools in the identification of potentially failing banks. McKee (2000) employed rough set theory to the problem of corporate bankruptcy prediction and concluded that it significantly outperformed a recursive-partitioning model. Atiya (2001) provided a survey of all the prediction techniques including neural networks applied to the bankruptcy prediction problem and proposed more financial indicators, in addition to the traditional ones, which he used in the design of a new neural network model. Shin, Lee, and Kim (2005) applied SVM to the problem of corporate bankruptcy prediction. They concluded that SVM outperformed the MLFF-BP in terms of accuracy and generalization, as the training dataset size gets smaller. Canbas et al. (2005) proposed a methodological framework for constructing the integrated early warning system (IEWS) that can be used as a decision support tool in bank examinations and the supervision process for detection of banks, which are experiencing serious problems.

OVERVIEW OF TECHNIQUES APPLIED IN CURRENT WORK

Adaptive Neuro Fuzzy Inference System (ANFIS)

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Using a given input/output data set, the ANFIS, available as the function *anfis* in the Fuzzy Logic Toolbox of MATLAB, constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone or in combination with a least squares type of method. This allows the fuzzy systems to learn 'if-then' rules from the data they are modeling. The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. This learning method works similarly to that of neural networks.

TreeNet

TreeNet is developed using the stochastic gradient boosting algorithm, which is an improvisation of the gradient boosting algorithm of Friedman (2002). TreeNet models are typically composed of hundreds of small trees, each of which contributes just a tiny adjustment to the overall model. In spite of the slow learning strategy, TreeNet is very fast and generally produces very good models within minutes. TreeNet, introduced by Friedman (2002), finds many real-world applications ranging from credit risk scoring, targeted marketing, fraud detection, document classification, response modeling, and bioinformatics.

SVM

Support vector machines (SVMs) introduced by Vapnik (1998) use a linear model to implement linear class boundaries by mapping input vectors linearly into a high-dimensional feature space. The linear model constructed in the new space can represent a linear decision boundary in the original space. In the new space, an optimal separating hyperplane (OSH) is constructed. Thus, SVM is known as the algorithm that finds a special kind of linear model, the maximum margin hyperplane, which gives the maximum separation between decision classes. The training examples that are closest to the maximum margin hyperplane are called support vectors. All other training examples are irrelevant for defining the binary class boundaries (Vapnik, 1998). SVM is simple enough to be analyzed mathematically since it can be shown to correspond to a linear method in a high-dimensional feature space linearly related to input space. In this sense, SVM may serve as a promising alternative, combining the strengths of conventional statistical methods that are more theory-driven and easy to analyze and machine learning methods, which are more data-driven, distribution-free and robust. Recently, the SVM approach was introduced to several financial applications such as credit rating, time series prediction, and insurance claim fraud detection. In this work, SVM is implemented using the tool LIBSVM, which is an integrated software for support vector classification, regression, and distribution estimation. It supports multi-class classification.

Rough Set-Based Classifier (RSES)

Rough set theory proposed by Pawlak (1982) is based on the assumption that with any object of the given universe, there is some information associated, and objects characterized by similar information are indistinguishable or indiscernible. The indiscernibility relation indicates that we are unable to deal with single objects, but we have to consider clusters of indiscernible objects or equivalence classes of the indiscernibility relation. In rough set theory, a pair of precise concepts—namely, lower and the upper approximations—replaces any vague concept. The lower approximation consists of all objects that surely belong to the concept while the upper approximation contains all objects that possibly belong to the concept. Approximations are two basic operations in the rough set theory. Rough sets can be applied for inducing decision rules from data or to solve classification problems. RSES 2.2—Rough Set Exploration System 2.2 is a software tool that provides the means for analysis of tabular data sets with use of rough set theory (Bazan, 2000). The RSES system is freely available at http://logic.mimuw.edu.pl/~rses.

Orthogonal RBFN

To design Orthogonal RBF network (OrthoRBF), the "newrb" function from the MATLAB Neural Network toolbox was employed here, which was earlier used by Bhatt and Gopal (2004). This function uses the orthogonal least squares algorithm of Chen, Cowan, and Grant (1991) in the supervised part of the RBFN. Initially, the RBF network has no neurons. The following steps are repeated until the network's mean square error falls below a specified error goal or the maximum number of neurons are reached.

1. The network is simulated.
2. The input vector with the greatest error is found.
3. A radial basis neuron is added with weights equal to the vector.
4. The pure linear layer weights are redesigned using orthogonal least squares algorithm to minimize error.

EXPERIMENTAL METHODOLOGY

The bankruptcy prediction problem is a two-class classification problem. Each instance is mapped to one element of the set {p, n} of positive (bankrupt) and negative (non-bankrupt) class labels. A classification model or classifier is a mapping from instances to predicted classes. Some classifiers produce a continuous output (e.g., an estimate of an instance's class membership probability) to which different thresholds may be applied to predict class membership. Other models produce a discrete class label indicating only the predicted class of the instance. Given a classifier and an instance, there are four possible outcomes. If the instance is *positive* and it is classified as *positive,* it is counted as a *true positive (TP)*; if it is classified as *negative,* it is counted as a *false negative (FN).* If the instance is *negative* and it is classified as *negative,* it is counted as a *true negative*

(TN); if it is classified as *positive*, it is counted as a *false positive (FP)*. Given a classifier and a set of instances (the test set), a two-by-two confusion matrix, shown in Figure 2 (also called a contingency table), can be constructed representing the dispositions of the set of instances.

From a confusion matrix several common metrics can be calculated. The numbers along the major diagonal represent the correct decisions made, and the numbers off this diagonal represent the errors—the confusion—between the various classes.

The True Positive rate (also called hit rate and recall) of a classifier is estimated as: TP rate = TP/(TP+FN) = Sensitivity = positives correctly classified/total positives. The False Positive rate (also called false alarm rate) of the classifier is: FP rate = FP/(FP+TN) = 1-Specificity = negatives incorrectly classified/total negatives.

Type I and Type II Errors

In order to evaluate and compare the performance of all the classifiers considered in this chapter, we present the Type I and Type II errors produced by each of them and then plot and study the ROC curves. The Type I error is defined as the classification of a bankrupt bank as non-bankrupt, whereas Type II error refers to the classification of a non-bankrupt bank as bankrupt. The total error type is the average of Type I and Type II errors. In general, Type I error is more serious than Type II error. However, the studies on both the datasets (Olmeda & Fernandez, 1997; Rahimian, Singh, Thammachote, & Virmani, 1996) indicate that no misclassification costs are attached to Type I and Type II errors. Consequently, in this study, it is assumed that the cost of committing a Type I error and a Type II error is one and the same.

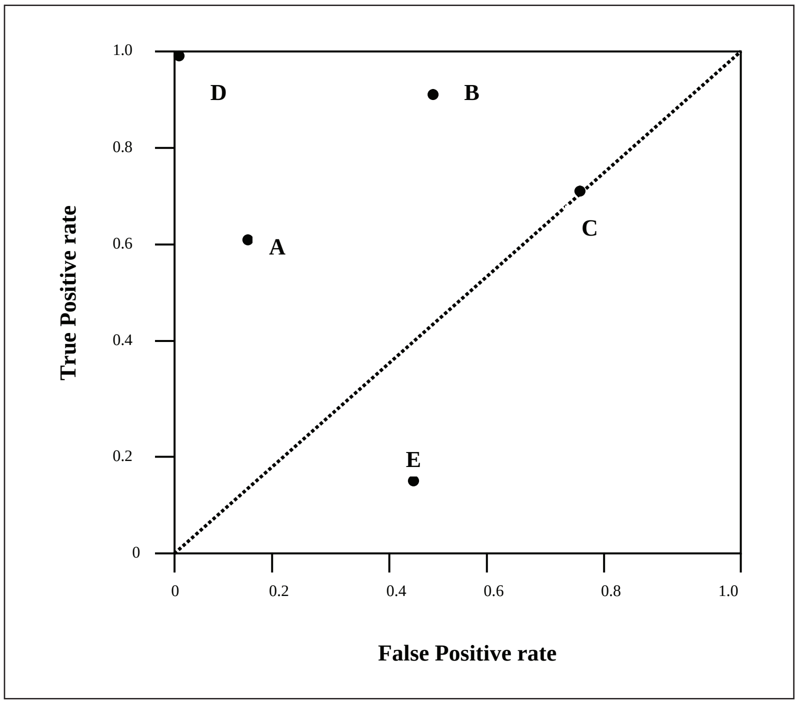
ROC Curves

The receiver operating characteristics (ROC) curve (Fawcett, 2003) is a useful technique for organizing and ranking classifiers and visualizing their performance. ROC curves are commonly used in medical decision making, and in recent years have been increasingly adopted in

Figure 2.

		True Class	
		p	**n**
Predicted Class	**Y**	**T**rue **P**ositive	**F**alse **P**ositive
	N	**F**alse **N**egative	**T**rue **N**egative
Column totals:		**P**	**N**

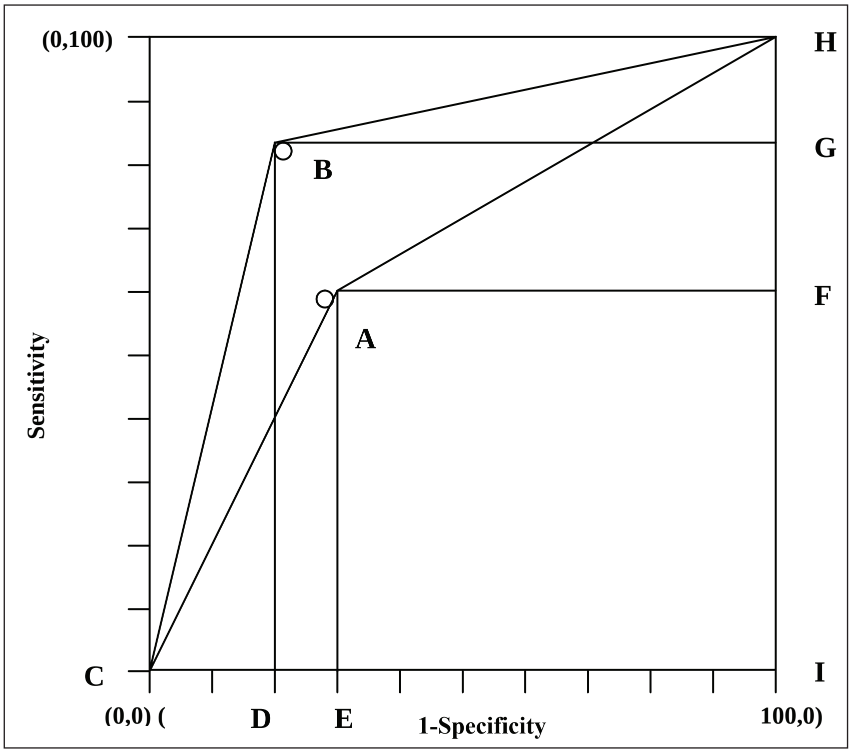
Figure 3. ROC space for different classifiers



the machine learning and data mining research communities. In addition to being a generally useful performance graphing methods, they have properties that make them especially useful for domains with skewed class distribution and unequal classification error costs. These characteristics of ROC graphs have become increasingly important as research continues into the areas of cost-sensitive learning and learning in the presence of unbalanced classes. ROC curve is a two-dimensional graph in which TP rate (Sensitivity) is plotted on the Y-axis and FP rate (1-Specificity) is plotted on the X-axis. Figure 3 depicts an ROC curve with five classifiers labeled A through E.

A discrete classifier is one that outputs only a class label. Each discrete classifier produces a (FP rate, TP rate) pair, which corresponds to a single point in ROC space. The lower left point (0,0) represents the strategy of never issuing a positive classification; such a classifier commits no false-positive errors, but also gains no true-positives. The opposite strategy of unconditionally issuing positive classifications is represented by the upper right point (1,1). The point (0,1) represents perfect classification. D's performance is perfect as shown. Informally, one point in ROC space is better than another if it is to the northwest (TP rate is higher, FP rate is lower, or both) of the latter. Classifiers appearing on the left-hand side of an ROC graph, near the X axis, may be thought of as "conservative": they make positive classifications only with strong evidence so they make few false-positive errors, but they often have low true-positive rates as well. Classifiers on the upper right-hand side of an ROC graph may be thought of as "liberal": they make positive classifications with weak evidence so they classify nearly all positives correctly, but they often have high false-positive rates. In Figure 3, A is more conservative than B. Many real-world domains are dominated by large numbers of negative instances, so performance in the far left-hand side of the ROC graph becomes more interesting.

Figure 4. AUC of two classifiers A and B



Area Under ROC Curves

An ROC curve is a two-dimensional depiction of classifier performance. To compare classifiers we often want to reduce ROC performance to a single number representing average expected performance. A common method is to calculate the area under the ROC curve, abbreviated as AUC (Fawcett, 2001). Since the AUC is a portion of the area of the unit square, its value will always be between 0 and 1.0. However, because random guessing produces the diagonal line between (0, 0) and (1, 1), which has an area of 0.5, no realistic classifier should have an AUC less than 0.5. When AUC is equal to 1, the classifier achieves perfect accuracy if the threshold is correctly chosen and a classifier that predicts the class at random has an associated AUC of 0.5.

Another interesting point of the AUC is that it depicts a general behavior of the classifier since it is independent of the threshold used for obtaining a class label. The AUC has an appealing statistical property that the AUC of a classifier is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance. Figure 4 shows calculating the area under the ROC curve for two discrete binary classifiers A and B. Here the AUC of A is sum of the areas of Triangle-CEA, Rectangle- EAFI, and Triangle FAH. However, the AUC of B is the sum of the areas of Triangle-CDB, Rectangle- DBGI, and Triangle GBH. The classifier that has more area under the ROC curve is the better than the other. Here, the AUC of classifier B is greater than the AUC of A. So, classifier B is better than classifier A.

RESULTS AND DISCUSSION

We demonstrated the efficacy of the semi-online RBFN on two bankruptcy prediction datasets taken from literature. The Spanish banks' dataset is reported in Olmeda and Fernandez (1997). The Spanish banking industry suffered the worst crisis during 1977-1985 resulting in a total cost of $12 billion. In order to develop bankruptcy prediction models, Olmeda and Fernandez (1997) considered the following financial ratios as predictor variables: *current assets/total assets, current assets-cash/total assets, current assets/loans, reserves/loans, net income/total assets, net income/total equity capital, net income/loans, cost of sales/sales, and cash flow/loans.* The data of ratios used for the failed banks were taken from the last financial statements before the bankruptcy was declared, and the data of non-failed banks was taken from 1982 statements.

The U.S. banks' data is obtained from Rahimian et al. (1996). They considered the following financial ratios as predictor variables: *working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value of equity/total debt, and sales/total assets.* Altman (1968) in his seminal study used these rations. Rahimian et al. (1996) obtained the data of 129 firms from the Moody's Industrial Manual, where 65 firms went bankrupt during the period 1975-1982.

We compared the performance of the two variants of semi-online RBFN with that of ANFIS, Linear RBFN, Orthogonal RBFN, TreeNet, LIBSVM, RSES 2.2, and MLP. The effectiveness of all the techniques was tested using the 10-fold cross-validation method on both the data sets. In the 10-fold cross-validation, the data set is divided into 10 subgroups of approximately equal size. Then, a model is trained with nine subgroups, and the leftover group is used to test the performance of the model. This process is repeated until all the subgroups are tested in turns one at a time. Consequently, this methodology requires 10 different training sessions for each model. The hope is that after 10-fold cross-validation, the error variance over all the folds gets evened out. Further, consistently good performance on all the 10 folds indicates the power, reliability, and stability of the model. Hence, 10-fold cross-validation is considered the most authentic method of testing a model. We did not compare our results with

Table 2. Average results of 10-fold cross validation for U.S. bank data

Classifiers	Accuracy	Type I Error	Type II Error	Sensitivity	Specificity
Semi-Online RBF with X	**76.19**	**22.42**	**29.37**	**77.58**	**70.63**
Semi-Online RBF without X	**87.38**	**11.96**	**14.4**	**88.04**	**85.59**
Orthogonal RBF	**55.95**	**7.92**	**83**	**92.08**	**17**
Linear RBF	**77.26**	**11.19**	**32.19**	**88.81**	**67.81**
RSES	**95.89**	**13.43**	**42.86**	**86.57**	**57.14**
SVM	**86.42**	**11.25**	**15.31**	**88.75**	**84.69**
MLP	**87.38**	**8.29**	**18.64**	**91.71**	**81.36**
TreeNet	**88.33**	**7.28**	**16.06**	**92.72**	**83.94**
ANFIS	**92.03**	**5.04**	**10.22**	**94.96**	**89.79**

those of Olemda and Fernandez (1997), because they did not perform 10-fold cross-validation in their study.

The results of the present study in terms of the accuracy (classification rate), Type I error, Type II error, Sensitivity, and Specificity are presented in Tables 1 and 2.

The ROC curve is drawn and the Area under the ROC curve (AUC) is computed in order to rank the classifiers according to their performance. In the ROC space, the left top corner area is called ROC heaven and the lower right corner area is called ROC hell. The classifiers that fall below the line joining the points (0,0) and (100,100) are treated as worst classifiers. The classifier is said to be good if it produces less Type I and Type II errors. This becomes evident from the AUC. In fact, the larger the AUC, the better the classifier is

Table 3. AUC of different classifiers applied on Spanish banks data

Classifiers	AUC	Rank
Semi-Online RBF with X	**0.583**	**8**
Semi-Online RBF without X	**0.787**	**4**
Orthogonal RBF	**0.524**	**9**
Linear RBF	**0.709**	**6**
RSES	**0.925**	**1**
SVM	**0.861**	**3**
MLP	**0.781**	**5**
TreeNet	**0.897**	**2**
ANFIS	**0.617**	**7**

Table 4. AUC of different classifiers applied on U.S. banks data

Classifiers	AUC	Rank
Semi-Online RBF with X	**0.841**	**6**
Semi-Online RBF without X	**0.868**	**3**
Orthogonal RBF	**0.545**	**9**
Linear RBF	**0.783**	**7**
RSES	**0.718**	**8**
SVM	**0.867**	**4**
MLP	**0.865**	**5**
TreeNet	**0.883**	**2**
ANFIS	**0.924**	**1**

Figure 5.

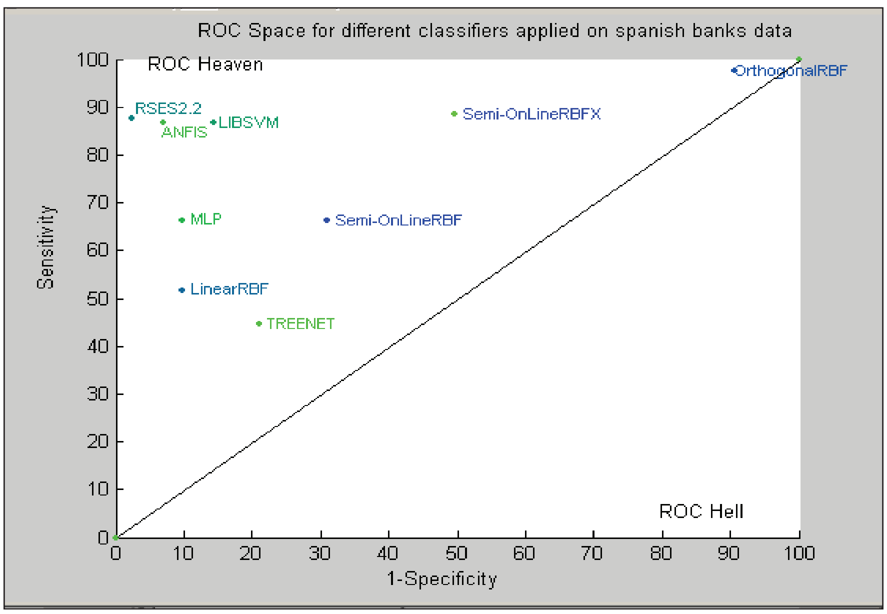
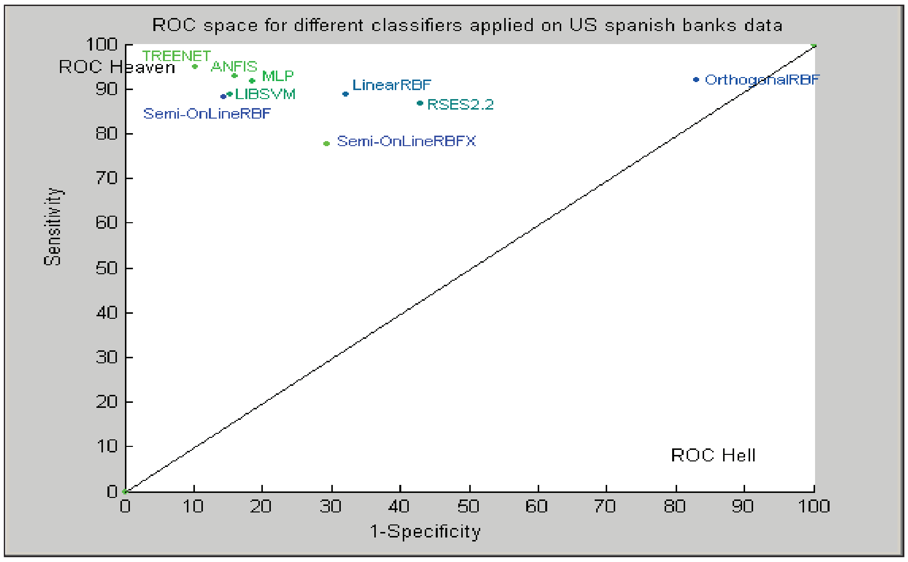


Figure 6.



said to be. Accordingly, the classifiers are ranked in Tables 3 and 4.

The results and the ROC curve for the Spanish banks data are presented in Table 1 and Figure 5 respectively. The AUC values for different classifiers for the Spanish banks data are presented in Table 3. Thus, in the case of Spanish banks data, based on the AUC values, the ranking of the classifiers in descending order is RSES, TreeNet, SVM, semi-online RBF without linear terms, MLP, Linear RBFN, ANFIS, semi-online RBF with linear terms, and Orthogonal RBFN.

The results and the ROC curve for the U.S. banks data are presented in Table 2 and Figure 6 respectively. The AUC values for the U.S. banks data for different classifiers are presented in Table 4. Thus, in the case of U.S. banks data, based on the AUC values, the ranking of the classifiers in descending order is ANFIS, TreeNet, semi-online RBF without linear terms, SVM, MLP, semi-online RBF with linear terms, Linear RBF, RSES, and Orthogonal RBF.

Thus, in both data sets TreeNet outperformed the semi-online RBF without linear terms. But, among the neural network classifiers, semi-online RBF without linear terms outperformed others, and depending on data, it outperformed the other classifiers also.

CONCLUSION AND FUTURE DIRECTIONS

A semi-online algorithm for training radial basis function neural networks is proposed based on an online, evolving clustering algorithm for the unsupervised training part of the RBFN. The supervised training part of the RBFN is taken care of by the ordinary least squares estimation technique that involves batch processing. Thus, the supervised learning part of the RBFN is left unchanged just to retain the semi-online nature of the algorithm. Two variants are developed for the supervised training part of the network: (1) with linear terms, and (2) without linear terms. The resulting neural network is called semi-online RBFN here. Two bankruptcy prediction problems were solved using the proposed algorithm to demonstrate its effectiveness. The performance of the semi-online RBFN was compared with that of the MLP, ANFIS, LIBSVM, RSES 2.2, Linear RBFN, Orthogonal RBFN, and TreeNet by considering AUC as the criterion. Ten-fold cross validation was conducted for all the techniques. The results indicate that semi-online RBF without linear terms outperformed the semi-online RBFN with linear terms and other neural network architectures used in this study. Based on the results, it is inferred that for classification problems, the semi-online RBFN without linear terms can be used as an effective alternative to other neural network techniques.

As regards future directions, generalized radial basis functions can be used in place of the simple radial basis functions and ridge regression estimates can be used in place of linear least square estimates in the supervised training part of the algorithm. These changes hopefully may improve the average classification rates of the semi-online RBFN network. Further, 'if-then' rules can be extracted from the trained semi-online RBFN. These rules being humanly comprehensible would serve as an early warning expert system for bankruptcy prediction problems in banks and firms. Another idea could be to develop a fuzzy version of the semi-online RBFN.

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Chapter XVI
Forecasting Foreign Exchange Rates Using an SVR-Based Neural Network Ensemble

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ABSTRACT

In this study, a triple-stage support vector regression (SVR)-based neural network ensemble forecasting model is proposed for foreign exchange rates forecasting. In the first stage, multiple single neural predictors are generated in terms of diversification. In the second stage, an appropriate number of neural predictors are selected as ensemble members from the considerable number of candidate predictors generated by the previous phase. In the final stage, the selected neural predictors are combined into an aggregated output in a nonlinear way based on the support vector regression principle. For further illustration, four typical foreign exchange rate series are used for testing. Empirical results obtained reveal that the proposed nonlinear neural network ensemble model can improve the performance of foreign exchange rates forecasting.

INTRODUCTION

Foreign exchange rates are one of the most important indices in the international monetary and financial markets. With the collapse of the Bretton Woods system and the implementation of the floating exchange rate system in the 1970s, the fluctuation of foreign exchange rates becomes larger and larger. High volatility of foreign exchange rates also creates an opportunity to gain profit for traders. So far the foreign exchange market has become the largest and most liquid of the financial market, with an estimated $1 trillion traded everyday (Yao & Tan, 2000). Naturally to gain more profits, the traders must accurately predict the movement direction of foreign exchange rates. Driven by profits, foreign exchange rates modeling and forecasting has been a research focus in the last few decades (Yu, Wang, & Lai , 2005a). However, foreign exchange rates are affected by many highly correlated economic, political, and even psychological factors. The interaction of these factors is very complex (Yao & Tan, 2000). For these reasons, the foreign exchange rates have the characteristics of high volatility, irregularity, nonlinearity, and complexity. Therefore, foreign exchange rates forecasting is regarded as a rather challenging task.

Although predicting foreign exchange rates is very difficult, research challenge and profit inspiration still attracts much attention from researchers and practitioners. Accordingly, a great number of forecasting methods have been developed by many experts. Traditionally, statistical methods such as Box-Jenkins (1976) models dominate the time series forecasting. However, Refenes, Zapranis, and Francis (1994) indicated that traditional statistical techniques for forecasting have reached their limitation in practical applications with nonlinearities in the dataset such as stock indices. Similarly, for the highly volatile foreign exchange markets, traditional statistical modeling is also insufficient since it is hard to capture the nonlinearity hidden in the foreign exchange rates. As a result, many emerging artificial intelligent techniques, such as artificial neural networks (ANNs), were widely used in foreign exchange rates forecasting and obtained good prediction performance. For example, De Matos (1994) compared the strength of a multilayer feed-forward network (MLFN) with that of a recurrent network based on the forecasting of Japanese yen futures. Kuan and Liu (1995) provided a comparative evaluation of the performance of MLFN and a recurrent neural network (RNN) on the prediction of an array of commonly traded exchange rates. Tenti (1996) directly applied the RNN to exchange rates forecasting. Hsu, Hsu, and Tenorio. (1995) developed a clustering neural network (CNN) model to predict the direction of movements in the USD/DEM exchange rate. Their experimental results suggested that their proposed model achieved better forecasting performance relative to other indicators. In a more recent study by Leung, Chen, and Daouk (2000), the forecasting accuracy of MLFN was compared with the general regression neural network (GRNN). The study showed that the GRNN possessed a greater forecasting strength relative to MLFN with respect to a variety of currency exchange rates. Similarly, Chen and Leung (2004) adopted an error correction neural network (ECNN) model to predict foreign exchange rates. Yu, Wang, and Lai (2005b) proposed an adaptive smoothing neural network (ASNN) model by adaptively adjusting error signals to predict foreign exchange rates and obtained good performance.

Recently, some hybrid forecasting models have been developed that integrate neural network techniques with many conventional forecasting methods such as econometrical models and some emerging intelligent models such as genetic algorithm to improve prediction accuracy. A few examples in the existing literature are presented. Yu et al. (2005a) also designed a hybrid model integrating neural network and generalized linear auto-regression (GLAR) to predict three main currencies: British pounds, German marks, and Japanese yen. Lai, Yu, Wang, and Huang (2006) hybridized neural network and exponential smoothing for foreign exchange rates forecasting. Empirical results with real data sets indicated that the hybrid model could provide an effective way to improve the forecasting accuracy achieved by either of the models used separately. Shazly and Shazly (1999) designed a hybrid model combining neural networks and genetic training to the three-month spot rate of exchange for four currencies: the British pound, the German mark, the Japanese yen, and the Swiss franc. The experimental results reported revealed that the networks' forecasts outperformed predictions made by both the forward and futures rates in terms of accuracy and correctness.

Different from previous studies, Zhang and Berardi (2001) adopted a different approach. Instead of using single network architecture, their research investigated the use of ensemble methods in exchange rate forecasting. Essentially, the study proposed using systematic and serial partitioning methods to build ensemble models consisting of different neural network structures. Results indicated that the ensemble network could consistently outperform a single network design. Similarly, Yu et al. (2005a) also designed a neural network-based nonlinear ensemble model. In their article, single neural network forecasting result, traditional linear model forecasting result, and hybrid model forecasting result as inputs for another neural network in a nonlinear integration way. Experimental results obtained revealed that their proposed nonlinear ensemble model outperformed single model and hybrid model simultaneously presented in this study.

The basic idea of the ensemble forecasting model is to use each model's unique feature to capture different patterns in the data. Both theoretical and empirical findings suggest that combining different methods can be an effective and efficient way to improve forecast performances. In their pioneering work on combined forecasting, Bates and Granger (1969) showed that a linear combination of forecasts would give a smaller error variance than any of the individual methods. Since then, the studies on this topic (i.e., combined forecasts) have expanded dramatically. Makridakis et al. (1982) claimed that combining several single models has become common practice in improving forecasting accuracy ever since the well-known M-competition in which a combination of forecasts from more than one model often leads to improved forecasting performance. Likewise, Pelikan, De Groot, and Wurtz (1992) and Ginzburg and Horn (1994) proposed combining several feed-forward neural networks to improve time series forecasting accuracy. More literature can be referred to a comprehensive review and annotated bibliography provided by Clemen (1989). Actually, the combination forecasting model is equivalent to the ensemble forecasting model in the general sense. But the word "ensemble" is preferable to "combined" in terms of the explanation of Yu et al. (2005a).

Although some ensemble techniques including *linear ensemble*, for example, simple average (Benediktsson, Sveinsson, Ersoy, & Swain, 1997), weighted average (Perrone & Cooper, 1993), and stacked regression (Breiman, 1994), and *nonlinear ensemble*, for example, neural-network-based nonlinear ensemble (Yu et al., 2005a), have been presented, there are still some difficulties in the neural network ensemble forecasting. First of all, for linear ensemble techniques, it is not necessarily suitable for all the situations. In some cases, it is hard to capture nonlinear patterns hidden in different ensemble members with linear ensemble techniques. Secondly, for nonlinear ensemble techniques, there is only one nonlinear ensemble way: neural network-based nonlinear ensemble (see Yu et al., 2005a). Nevertheless, it is well known to us that there are some shortcomings such as local minima and over-fitting in neural network training and learning. Based on the above two aspects, it is necessary to introduce a new neural network ensemble forecasting model for foreign exchange rates prediction. For this reason, this chapter will formulate a multistage neural network ensemble forecasting model for exchange rates prediction in an attempt to overcome the two main difficulties mentioned above. This model utilizes the support vector regression (SVR) technique to combine different neural network models. The proposed novel nonlinear ensemble model is actually an SVR-based nonlinear ensemble forecasting approach.

The main objectives of this chapter are two-fold: (1) to show how to predict exchange rates using the proposed nonlinear ensemble model; and (2) to display how various methods compare in their accuracy in forecasting foreign exchange rates. In view of the two objectives, this chapter mainly describes the building process of the proposed nonlinear ensemble model and the application of the nonlinear ensemble forecasting approach in foreign exchange rate forecasting between the U.S. dollar and four other major currencies—British pounds, German marks, euros, and Japanese yen—while comparing forecasting performance with different evaluation criteria.

The rest of this chapter is organized as follows. The next section describes the motivation of neural network ensemble as a foreign exchange rates forecasting tool. We then present the building process of the SVR-based neural network ensemble model in detail. For illustration purpose, empirical analysis of the four main currencies' exchange rates is reported next, and finally, some main conclusions, managerial implications, and future research directions are offered.

NEURAL NETWORK ENSEMBLE AS A FOREIGN EXCHANGE RATES FORECASTING TOOL

Originally, foreign exchange rates were only determined by the balance of payments. The balance of payments was merely a way of listing receipts and payments in international trades for a country. Usually receipts result in a demand for the domestic currency and a supply for foreign currencies, while payments involve a supply of the domestic currency and a demand for foreign currencies. The balance was determined mainly by the import and export of traded goods. At that time predicting foreign exchange rates was not very difficult. With the time past, currencies are more affected by interest rates and other demand-supply factors. In 1973, the fixed foreign exchange rate mechanism was abandoned and a flexible floating exchange rate system was introduced by industrialized countries. With the further liberation of world trade, exchange rates fluctuation becomes stronger and stronger. Increased foreign exchange trading, and hence speculation due to liquidity and bonds, had also contributed to the difficulty of exchange rates prediction (Yao & Tan, 2000).

As earlier noted, to maximize profits from the liquidity market, a trader must accurately predict the movement direction of the foreign exchange rates. Thus more and more "good" forecasting techniques are used by different traders. With the advancement of computer technologies, traders do not only rely on a single technique to provide future information about financial markets, but use a variety of techniques to obtain multiple prediction results. Traditional time series analysis techniques based on the linear assumption do not perform satisfactorily on the economic and financial time series with nonlinearity. For handling this major challenge, the development of new methods, or the modification or integration of existing techniques, which can accurately predict series whose patterns or relationships vary over time, are required. In this study we utilize the neural network ensemble forecasting techniques to perform this foreign exchange rates prediction.

Initially, the generic motivation for ensemble forecasting procedure is based on the intuitive idea that by integrating the outputs of several individual predictors, one might improve on the performance of a single generic one (Krogh & Vedelsby, 1995). However, this idea has been proved to be true only when the ensemble predictors are simultaneously accurate and diverse enough, which requires an adequate trade-off between the conflicting conditions (Yu, Lai, Wang, & Huang, 2006).

Neural networks provide a natural framework for ensemble forecasting. This is so because a neural network is a very unstable learning method—that is, small changes in the training set and/or parameter selection can produce large changes in the predicted output. This diversity of neural networks is naturally a by-product of the randomness of the inherent data and training process, and also of the intrinsic non-identifiability of the model (many different but a priori equally good local minima of the error surface). For example, the results of many experiments have shown that the generalization of single networks is not unique. In other words, the neural network's results are not stable. Even for some simple problems, different structures of neural networks (e.g., different number of hidden layers, different number of hidden nodes, and different initial conditions) result in different patterns of network generalization. In addition, even the most powerful neural model still cannot cope well when dealing with complex data sets containing some random errors or insufficient training data. Thus, the performance for these data sets may not be as good as expected (Naftaly, Intrator, & Horn, 1997; Carney & Cunningham, 2000).

The limitations on improving the performance of a single neural network and the instability of the results of a single network have hampered the development of better neural network forecasting models. Why can the same training data applied to different neural network models or the same neural models with different initialization lead to different performance? What are the major factors affecting this difference? Through the analysis of error distributions, it has been found that the ways neural networks have of getting to the global minima vary, and some networks just settle into local minima instead of global minima. In any case, it is hard to justify which neural network's error reaches the global minima if the error rate is not zero. Since the number of neural models and their potential initialization is unlimited, the possible number of results generated for any training data set applied to those models is theoretical infinite. The best performance we get is typically only the best one selected from a limited number of neural networks, that is, the single model with the best generalization to a testing set. One interesting point is that, in a prediction case, other less accurate predictors may generate a more accurate forecast than the most accurate predictor. Thus it is clear that simply selecting the best predictors according to their performance is not the optimal choice. More and more researchers have realized that merely selecting the predictor that gives the best performance on the testing set will lead to losses of potentially valuable information contained by other less successful predictors. The limitation of single neural network suggested a different approach to solving these problems that considers those discarded neural networks whose performance is less accurate as potential candidates for new neural network models: a neural network ensemble forecasting model. An accurate predictor is defined as a well-trained predictor whose performance is better than any randomly generated results on the input values (Hansen & Salamon, 1990).

In addition, another important motivation behind ensemble forecasting integrating different neural network models is based on the fundamental assumption that one cannot identify the true object or process exactly, but different models may play a complementary role in the approximation of this process. In this sense, an ensemble model is generally better than a single model.

BUILDING PROCESS OF THE SVR-BASED NEURAL NETWORK ENSEMBLE FORECASTING MODEL

In this section, an SVR-based neural network ensemble forecasting model is proposed for exchange rates prediction according to the motivation of neural network ensemble forecasting. The formulation of this proposed SVR-based neural network ensemble model is composed of three stages. In the first stage, multiple single neural predictors are generated in terms of diversification. In the second stage, an appropriate number of neural predictors are selected from the considerable number of candidate predictors generated by the previous phase. In the final stage, selected neural predictors are combined into an aggregated output in a nonlinear way based on the support vector regression principle.

Generating Single Neural Network Predictor

There are two different ways to generate individual neural predictors: homogeneous models using the same network type, and heterogeneous models using the different network type. As mentioned earlier, we need to generate some diverse neural predictors or error-independent neural predictors.

For *homogeneous* neural network model generation, several methods have been investigated for the generation of ensemble members making different errors (Sharkey, 1996). Such methods basically rely on varying the parameters related to the design and to the training of neural networks. In particular, the main methods include the following four aspects:

1. **Different network architecture:** By changing the number of hidden layers and the number of nodes in every layer, different neural networks with different architectures can be created.
2. **Different training data:** By re-sampling and preprocessing time series data, we can obtain different training sets, thus making different network generations. There are six techniques that can be used to obtain diverse training data sets: bagging (Breiman, 1996), noise injection (Raviv & Intrator, 1996), cross-validation (Krogh & Vedelsby, 1995), stacking (Wolpert, 1992), boosting (Schapire, 1990), and input decimation (Tumer & Ghosh, 1996).
3. **Different learning algorithm:** By selecting different core learning algorithms, different neural networks can also be generated. For example, a multi-layer feed-forward network can use the steep-descent algorithm or Levenberg-Marquardt algorithm or other learning algorithms.
4. **Different initial conditions:** Neural network ensemble members can be created by varying the initial random weights, learning rate, and momentum rate, from which each single neural network model is trained.

For *heterogeneous* neural network model generation, we can create neural network ensemble members by using different neural network types. For example, multi-layer perceptrons (MLPs), back-propagation networks (BPNs), radial basis function (RBF) neural networks, and probabilistic neural networks (PNNs) can be used to create the ensemble members. In addition, neural ensemble members could be created using a hybridization of two or more of the above methods, for example, different network types plus different training data (Sharkey, 1996). In this chapter study we adopt such a hybridization method to create ensemble members. Once some individual neural predictors are created, we need to select some representative members for ensemble purposes.

Selecting Appropriate Ensemble Members

After training, each individual neural predictor has generated its own result. However, if there are a great number of individual members, we need to select a subset of representatives in order to improve ensemble efficiency. As Yu et al. (2005a) claimed, not all circumstances are satisfied with the rule of “the more, the better.” Thus, it is necessary to choose an appropriate method to determine the number of individual neural network models for ensemble forecasting purpose. Generally, we select some models with error weak correlation for homogeneous neural models, whereas we need to select a few typical representatives for heterogeneous neural models.

Yu et al. (2005a) utilized a principal component analysis (PCA) technique to select the appropriate number of ensemble members and obtained good performance from experimental analysis. However, the PCA is a kind of data reduction technique which does not consider the correlation between dependent variable and independent variable. To overcome this problem, a conditional generalized variance (CGV) minimization method is proposed here.

Suppose there are p predictors with n forecast values. Then the error matrix $(e_1, e_2, \ldots, e_p)$ of p predictors is:

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1p} \\ e_{21} & e_{22} & \cdots & e_{2p} \\ \vdots & \vdots & & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{np} \end{bmatrix}_{n\times p} \quad (1)$$

From the matrix, the mean, variance, and covariance of E can be calculated as:

Mean: $\bar{e}_i = \frac{1}{n}\sum_{k=1}^{n} e_{ki}$ $(i = 1, 2, \ldots p)$ (2)

Variance: $V_{ii} = \frac{1}{n}\sum_{k=1}^{n}(e_{ki} - \bar{e}_i)^2$ $(i = 1, 2, \ldots p)$ (3)

Covariance: $V_{ij} = \frac{1}{n}\sum_{k=1}^{n}(e_{ki} - \bar{e}_i)(e_{kj} - \bar{e}_j)$ $(i, j = 1, 2, \ldots p)$ (4)

Considering equations (3) and (4), we can obtain a variance-covariance matrix:

$$V_{p\times p} = (V_{ij}) \quad (5)$$

Here we use the determinant of V (i.e., $|V|$) to represent the correlation among the p predictors. When p is equal to one, $|V| = |V_{11}|$ = the variance of e_1 (the first predictor). When p is larger than one, $|V|$ can be considered to be the generalization of variance: therefore, we call $|V|$ the generalized variance. Clearly when the p predictors are correlated, the generalization variance $|V|$ is equal to zero. On the other hand, when p predictors are independent, the generalization variance $|V|$ reaches its maximum. Therefore, when the p predictors are neither independent nor correlated, the measurement of generalized variance $|V|$ reflects the correlation among the p predictors.

Now we introduce the concept of conditional generalized variance. The matrix V can be reformulated with the block matrix. The detailed process is as follows: $(e_1, e_2, \ldots, e_p)$ is divided into two parts: $(e_1, e_2, \ldots, e_{p1})$ and $(e_{p1+1}, e_{p1+2}, \ldots, e_p)$, denoted as $e_{(1)}$ and $e_{(2)}$, that is:

$$E = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_p \end{bmatrix} = \begin{pmatrix} e_{(1)} \\ e_{(2)} \end{pmatrix}\begin{matrix} {}^{p_1\times 1} \\ {}_{p_2\times 1} \end{matrix} \qquad p_1 + p_2 = p \quad (6)$$

$$V = \begin{array}{cc} \begin{pmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{pmatrix} & \begin{matrix} p_1 \\ p_2 \end{matrix} \\ \begin{matrix} p_1 & \; p_2 \end{matrix} & \end{array} \quad (7)$$

where V_{11}, V_{22}, V_{12}, and V_{21} represent the variance-covariance matrices of $e_{(1)}$ and $e_{(2)}$.

Given $e_{(1)}$, the conditional generalized variance of $e_{(2)}$, $V(e_{(2)}|e_{(1)})$, can be represented as:

$$V(e_{(2)}|e_{(1)}) = V_{22} - V_{21}V_{11}^{-1}V_{12} \quad (8)$$

Equation (8) shows the change in $e_{(2)}$ given that $e_{(1)}$ is known. If $e_{(2)}$ has a small change under $e_{(1)}$, then the predictors $e_{(2)}$ can be deleted. This implies that the predictors $e_{(1)}$ can obtain all the information that the predictors $e_{(2)}$ reflect. Now we can give an algorithm for minimizing the conditional generalized variance as follows:

1. Considering the p predictors, the errors can be divided into two parts: $(e_1, e_2, \ldots, e_{p-1})$ is seen as $e_{(1)}$, and (e_p) is seen as $e_{(2)}$.
2. The conditional generalized variance $V(e_{(2)}|e_{(1)})$ can be calculated according to

equation (8). It is should be noted that here $V(e_{(2)}|e_{(1)})$ is a value, denoted as t_p.

3. Similarly, for the ith predictor (i =1, 2, …, p), we can use (e_i) as $e_{(2)}$, and other p-1 predictors are seen as $e_{(1)}$; then we can calculate conditional generalized variance of the ith predictor t_i with equation (8).
4. For a pre-specified threshold θ, if $t_i < \theta$, then the ith predictor should be deleted from the p predictors. On the contrary, if $t_i > \theta$, then the ith predictor should be retained.
5. For the retained predictors, we can perform the previous procedures (1)-(4) iteratively until satisfactory results are obtained.

Combining the Selected Members

Depending on the work done in the previous two stages, a set of appropriate ensemble members can be collected. The subsequent task is to combine these selected members into an aggregated output in an appropriate ensemble strategy. Suppose there are n individual neural networks trained on a data set $\boldsymbol{D} = \{x_i, y_i\}$ (i = 1, 2, … , n). Through training, n individual neural network outputs $\hat{f}_1(x), \hat{f}_2(x), \cdots, \hat{f}_n(x)$ are generated. The main question of neural network ensemble forecasting is how to combine (ensemble) these different outputs into an aggregate output $\hat{y} = \hat{f}(x)$, which is assumed to be a more accurate output. The general form of the model for such an ensemble predictor can be defined as:

$$\hat{f}(x) = \sum_{i=1}^{n} w_i \hat{f}_i(x) \tag{9}$$

where w_i denotes the assigned weight of $\hat{f}_i(x)$, and in general the sum of the weight is equal to one. In neural network ensemble forecasting, how to determine ensemble weights is a focus issue. As mentioned earlier, there are a variety of methods for determining ensemble weights in past studies which are presented below. Generally, there are two classes of ensemble strategies: linear ensemble and nonlinear ensemble.

Typically, linear ensemble strategies include two categories: the simple averaging (Benediktsson et al., 1997) and the weighted averaging (Perrone & Cooper, 1993). There are three types of weighted averaging: the simple mean squared error (MSE) approach (Benediktsson et al., 1997), stacked regression (modified MSE) approach (Breiman, 1994), and variance-based weighted approach (Krogh & Vedelsby, 1995).

Simple averaging method is one of the most frequently used ensemble approaches that are easy to understand and implement (Bishop, 1995; Benediktsson et al., 1997). Some experiments (Hansen & Salamon, 1990; Breiman, 1994) have shown that this approach by itself can lead to improved performance and it is an effective approach to improve neural network performance. Specifically, it is more useful when the local minima of ensemble members are different, that is, when the local minima of ensemble networks are different. Different local minima mean that ensemble members are diverse. Thus averaging them can reduce the ensemble variance. Usually, the simple averaging method for ensemble forecasting is defined as:

$$\hat{f}(x) = \sum_{i=1}^{n} w_i \hat{f}_i(x) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}_i(x) \tag{10}$$

where the weight of each individual network output $w_i = 1/n$.

Although simple averaging method is an easy-to-do ensemble approach, it treats each member equally, meaning it does not stress ensemble members that can make more contribution to the final generalization. That is, it does not take into account the fact that some networks may be more accurate than others. If the variances of ensemble networks are very different, we do not expect to obtain a better result using simple averaging (Ueda, 2000). In addition, since the weights in the combination are so unstable, a simple average may not the best choice in practice (Kang, 1986).

The simple MSE approach estimates the linear weight parameter w_i in equation (9) by minimizing the MSE (Benediktsson et al., 1997), that is, for $i = 1, 2, \ldots, n$:

$$w_{opt,i} = \arg\min_{w_i}\{\sum_{j=1}^{m}(w_i^T \hat{f}_i(x_j) - d_{ji}(x_j))^2\}$$
$$= (\sum_{j=1}^{m}\hat{f}_i(x_j)\, f_i^T(x_j))^{-1}\sum_{j=1}^{m} d_{ji}(x)\,\hat{f}_i(x_j) \quad (11)$$

where $d\,(x)$ is the expected value.

The simple MSE solution seems to be reasonable, but as Breiman (1994) has pointed out, this approach has two serious problems in practice: (1) the data are used both in the training of each predictor and in the estimation of w_i, and (2) individual predictors are often strongly correlated since they try to predict the same task. Due to these problems, this approach's generalization ability will be poor.

The stacked regression method was proposed by Breiman (1994) in order to solve the problems associated with the previous simple MSE method. Thus, the stacked regression method is also called the modified MSE method. This approach utilizes cross-validation data to modify the simple MSE solution:

$$w_{opt,i} = \arg\min_{w_i}\{\sum_{j=1}^{m}(w_i^T g_i(x_j) - d_{ji}(x_j))^2\}\ ,$$
$$i = 1, 2, \ldots, n \quad (12)$$

where $g_i(x_j) = (\hat{f}_i^{(1)}(x_j; D_{cv}), \ldots, \hat{f}_i^{(m)}(x_j; D_{cv})a)^T \in \Re^M$ is a cross-validated version $\hat{f}_i(x_j) \in \Re^M$ and D_{cv} is the cross-validated data.

Although this approach overcomes the limitations of the simple MSE method, the solution is based on the assumption that the error distribution of each validated set is normal (Ueda, 2000). In practice, however, this normal assumption does not always hold, and thus this approach does not lead to the optimal solution in the Bayes sense (Ueda, 2000).

The variance-based weighting ensemble approach estimates the weight parameter w_i by minimizing error variance σ_i^2 (Krogh & Vedelsby, 1995); all predictors are error-independent networks:

$$w_{opt,i} = \arg\min_{w_i}\{\sum_{i=1}^{n}(w_i\sigma_i^2))^2\}\ ,\ (i = 1,\ 2,\ \cdots, n) \quad (13)$$

under the constraints $\sum_{i=1}^{n} w_i = 1$ and $w_i \geq 0$. Using the Lagrange multiplier, the optimal weights are:

$$w_{opt,i} = \frac{(\sigma_i^2)^{-1}}{\sum_{j=1}^{n}(\sigma_j^2)^{-1}}\ ,\quad (i = 1,\ 2,\ \cdots, n) \quad (14)$$

The variance-based weighting method is based on the assumption of error independence. Moreover, as earlier mentioned, individual predictors are often strongly correlated for the same task. This indicates that this approach has serious drawbacks for minimizing error-variance when neural predictors with strong correlation are included within the combinatorial members.

From the above description, we find that the ensemble forecasting based on linear techniques is insufficient. Therefore, the emerging nonlinear ensemble technique is a promising solution to determine the optimal weight for neural ensemble predictor. To our knowledge, only one nonlinear ensemble approach—the neural network-based nonlinear ensemble method (Yu et al., 2005a)—is presented. This approach uses "meta" neural networks for ensemble purposes. Interested readers can be referred to Yu et al. (2005a) for further details. Experiment results obtained show that the neural network-based nonlinear ensemble approach consistently outperforms the other linear ensemble approach. However, there are several shortcomings to the neural network-based nonlinear ensemble approach. First, a neural network often traps into local minima due to the drawbacks of back-propagation algorithm. Second, a neural network can easily exhibit the over-fitting problem because of too many learning times or too many training examples. Third, neural network architecture and type heavily depend upon the user's experience. Furthermore, neural network learning by itself is "the state of the art" (Zhang, Patuwo, & Hu, 1998). To avoid these negative effects, a new nonlinear model, the support vector machine (SVM) model, is adopted to combine the ensemble members into an aggregate output.

The support vector machine (SVM) is an elegant tool for solving pattern recognition and regression problems. Over the past few years, it has attracted the attention of many researchers from the neural network and mathematical programming community. The main reason for this is its ability to provide excellent generalization performance. SVM has also been shown to be valuable in several real-world applications. For a detailed introduction to the subject, readers are referred to Burges (1998) and Vapnik (1995). Here we focus on the support vector regression (SVR) problem.

Assume that x is an input vector and z is a feature space vector that is related to x by a transformation $z = \phi(x)$. Let the training set D: $\{x_i, d_i\}$ consist of m data points where x_i is the i-th input pattern and d_i is the corresponding target value $d_i \in \mathbf{R}$. The goal of the SVM regression is to estimate a function $f(x)$ that is as "close" as possible to the target values for every object, and at the same time is as "flat" as possible for good generalization. The function f is represented using a linear function in the feature space:

$$f(x) = w \cdot \phi(x) + b \tag{15}$$

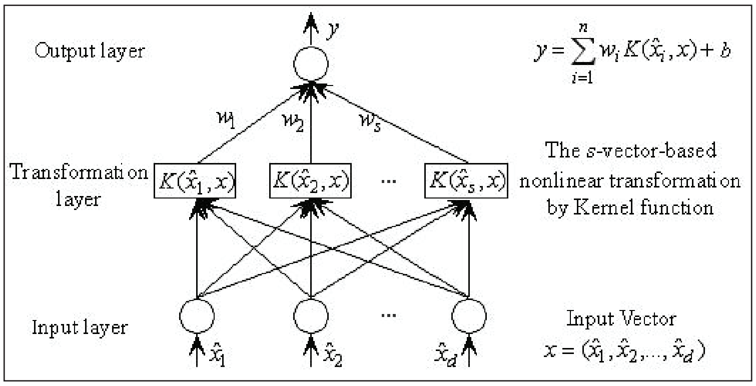
where b denotes the bias. As in all SVM designs, we define the kernel function $k(x, \hat{x}) = \phi(x) \bullet \phi(\hat{x})$, where "$\bullet$" denotes inner product in the z space. Thus, all computations will be done using only the kernel function. This inner-product kernel helps in taking the dot product of two vectors in the feature space without having to construct the feature space explicitly. Mercer's theorem (Vapnik, 1995) explains the conditions under which this kernel operator is useful for SVM designs.

Simply speaking, in an SVR model, one has to estimate the functional dependence of the dependent variable y on a set of independent variables x. The model assumes, like other regression problems, that the relationship between the independent and dependent variables is given by a deterministic function f plus some additive noise:

$$y = f(x) + \varepsilon \tag{16}$$

The current task is then to find a functional form for f that can correctly predict new cases that the SVR has not been presented before. This can be achieved by training the SVR model on a sample set, that is, a training set—a process that involves the sequential optimization of an error function. It is interesting that the structure of the

Figure 1. The basic structure of SVR ensemble forecasting model



SVR model is similar to that of neural networks, as illustrated in Figure 1. In the same way, the SVR also consists of an input layer, middle layer or transformation layer, and output layer. The difference is that every node output of the middle layer is a support vector transformed by the kernel function $k(x, \hat{x})$. Usually, the Gaussian function is used as a kernel function. Note that the SVR could overcome the important drawbacks of the neural network, such as over-fitting and local minima.

Similar to the neural network-based nonlinear ensemble forecasting model, the SVR-based nonlinear ensemble forecasting model can also be viewed as a nonlinear information processing system that can be represented as:

$$\hat{y} = f(\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n) \tag{17}$$

where $(\hat{x}_1, \hat{x}_2, \cdots, \hat{x}_n)$ is the output of single neural network predictors, $\hat{y}$ is the aggregated output or ensemble forecasting result, and $f(\cdot)$ is nonlinear function determined by SVR training. In this sense, SVR-based ensemble is a nonlinear ensemble method.

To summarize, the proposed SVR-based neural network ensemble forecasting model consists of three stages. Generally speaking, in the first stage various single neural network predictors are created based on diversity principle. In the second stage, the conditional generalized variance (CGV) minimization method is used to select the appropriate number of neural network ensemble members. In the third stage, a support vector regression model is used to integrate the selected individual neural network predictors. In such a way final ensemble forecasting results can be obtained.

EXPERTMENTAL ANALYSIS

In this section, four main currency exchange rates are used to test the proposed nonlinear ensemble forecasting model. First of all, we describe the data and evaluation criteria used in this study and then report the experimental results.

Data Description and Evaluation Criteria

In this study four foreign exchange series are selected for comparison purposes. The foreign exchange data used in this chapter are monthly and are obtained from Pacific Exchange Rates Services (http://fx.sauder.ubc.ca/), provided by Professor Werner Antweiler, University of British Columbia, Vancouver, Canada. They consist of the U.S. dollar against each of the four currencies—British pounds (GBP), German marks (DEM), euros (EUR), and Japanese yen (JPY)—studied in this chapter. We take monthly data from January 1971 to December 2000 as in-sample (training periods) data sets (360 observations including 60 samples for cross-validations). We also take the data from January 2001 to December 2005 as out-of-sample (testing periods) data sets (60 observations), which are used to evaluate the good or bad performance of prediction based on some evaluation measurement. In order to save space, the original data are not listed here; detailed data can be obtained from the Web site or from the authors.

In addition, for comparison, two typical indicators, normalized root mean squared error (*NRMSE*) and directional statistics (D_{stat}), were used in this study. Given N pairs of the actual values (or targets, x_t) and predicted values ($\hat{x}_t$), the *NRMSE* which normalizes the *RMSE* by dividing it through the standard deviation of respective series can be defined as:

$$NRMSE = \sqrt{\frac{\sum_{t=1}^{N}(x_t - \hat{x}_t)^2}{\sum_{t=1}^{N}(x_t - \overline{x}_t)^2}} = \frac{1}{\sigma}\sqrt{\frac{1}{N}\sum_{t=1}^{N}(x_t - \hat{x}_t)^2} \tag{18}$$

where σ is the estimated standard deviation of the data and $\overline{x}_t$ is the mean.

Clearly, the *NRMSE* only measure prediction in terms of levels. That is, accuracy in goodness-of-fit is only one of the most important criteria for forecasting models, the others being the profit earnings generated from improved decisions. From the business point of view, the latter is more important than the former. For business practitioners, the aim of forecasting is to support or improve decisions so as to make more money. Thus profits or returns are more important than conventional fit measurements. But in exchange rate forecasting, improved decisions often depend on correct forecasting directions or turning points between the actual and predicted values x_t and $\hat{x}_t$, respectively, in the testing set with respect to directional change of exchange rate movement (expressed in percentages). The ability to predict movement direction or turning points can be measured by a statistic developed by Yao and Tan (2000). Directional change statistics (D_{stat}) can be expressed as:

$$D_{stat} = \frac{1}{N}\sum_{t=1}^{N} a_t \times 100\% \tag{19}$$

where a_t =1 if $(y_{t+1} - y_t)(\hat{x}_{t+1} - x_t) \geq 0$ and a_t=0 otherwise, and N is the number of the testing samples.

Experimental Results

In this study four linear ensemble methods and two nonlinear ensemble approaches are implemented on four exchange rates datasets for comparison. The standard feed-forward neural networks with sigmoid-type activation functions in hidden layer were trained for each training set, then tested as an ensemble for each method for the testing set. Each network was trained with standard back-propagation algorithm for 100 iterations with a learning rate of 0.2 using the neural network toolbox provided by the Matlab software package. In addition, the best single neural network using cross-validation (CV) (Krogh & Vedelsby, 1995) method (i.e., select the individual network by minimizing the mean squared error on CV) is chosen as a benchmark model for comparison. Accordingly, the results obtained are reported in Tables 1 and 2 from the point of level prediction and direction prediction. In the two tables, a clear comparison of various methods for the four currencies is given via *NRMSE* and D_{stat}. Generally speaking, the results obtained from the two tables also indicate that the prediction performance of the proposed SVR-based nonlinear ensemble forecasting model is better than those of the single neural network model and other ensemble forecasting models for the four main currencies.

Focusing on the *NRMSE* indicator, our proposed SVR-based nonlinear ensemble method performs the best in all the cases, followed by the ANN-based nonlinear ensemble model. This indicates that the nonlinear ensemble forecasting

Table 1. The NRMSE comparison with different forecasting models

Models	GBP		DEM		EUR		JPY	
	NRMSE	Rank	NRMSE	Rank	NRMSE	Rank	NRMSE	Rank
Single ANN model	0.0686	6	0.0821	6	0.0858	7	0.0887	6
Simple averaging	0.0621	5	0.0878	7	0.0725	6	0.0976	7
Simple MSE	0.0758	7	0.0762	5	0.0676	5	0.0763	5
Stacked Regression	0.0434	3	0.0647	4	0.0564	4	0.0715	4
Variance-based model	0.0517	4	0.0616	3	0.0521	3	0.0654	3
ANN-based model	0.0393	2	0.0495	2	0.0459	2	0.0613	2
SVR-based model	0.0364	1	0.0417	1	0.0433	1	0.0581	1

models are more suitable for foreign exchange rates forecasting than the linear ensemble models and single ANN model. Of the four linear ensemble forecasting models, there is not any one model that can consistently outperform other linear ensemble models. The main reason is that every linear ensemble model has its own advantages and disadvantages, as indicated earlier. Interestingly, the *NRMSEs* of the simple averaging linear ensemble forecasting approach are not better than those of the best single ANN model based on cross-validation data for the DEM and JPY testing cases, whereas the *NRMSEs* of the single ANN are better than those of the simple MSE linear ensemble model for the GBP case, implying that the simple averaging and simple MSE-based linear ensemble forecasting models do not consider the fact that some single neural networks may be more accurate than the others.

However, the low *NRMSE* does not necessarily mean that there is a high hit ratio for foreign exchange movement direction prediction. Thus the D_{stat} comparison is necessary for practitioners. Focusing on D_{stat} of Table 2, it is not hard to find that the proposed SVR-based nonlinear ensemble forecasting model outperforms the other ensemble models and the single ANN model according to the rank; furthermore, from the business practitioners' point of view, D_{stat} is more important than *NRMSE* because the former is an important decision criterion in foreign exchange trading. With reference to Table 2, the differences between the different models are very significant. For instance, for the JPY testing case, the D_{stat} for the best single ANN model via cross-validation technique is only 63.33%, for the simple averaging method and simple MSE method it is 71.67%; the D_{stat} for the variance-based method is 78.33%, and for the ANN-based nonlinear ensemble approach, the D_{stat} is 81.67%; while for the SVR-based method, D_{stat} reaches 86.67%. Furthermore, like the *NRMSE* indicator, the proposed SVR-based nonlinear ensemble method performs the best in all the cases, followed by ANN-based nonlinear ensemble models and other four linear ensemble methods, and the poorest is the single ANN model via cross-validation technique. The main reason is that nonlinear ensemble models can capture some nonlinear patterns hidden in foreign exchange rates and the linear ensemble model cannot. Comparing the two nonlinear ensemble forecasting models, the SVR-based method seems to be more suitable than the ANN-based method. The main reason is that the SVR can overcome some inherent drawbacks of ANN.

From the experiments presented in this study, we can draw the following conclusions:

Table 2. The D_{stat} comparison with different forecasting models

Models	GBP		DEM		EUR		JPY	
	D_{stat} (%)	Rank	D_{stat} (%)	Rank	D_{stat} (%)	Rank	D_{stat} (%)	Rank
Single ANN model	71.67	6	66.67	7	66.67	7	63.33	7
Simple averaging	68.33	7	71.67	5	75.00	5	71.67	6
Simple MSE	73.33	5	70.00	6	68.33	6	71.67	5
Stacked Regression	78.33	4	76.67	4	78.33	4	73.33	4
Variance-based model	80.00	3	83.33	3	80.00	3	78.33	3
ANN-based model	86.67	2	86.67	2	88.33	2	81.67	2
SVR-based model	88.33	1	90.00	1	91.67	1	86.67	1

1. The experimental results show that the proposed SVR-based nonlinear ensemble forecasting model is consistently superior to the individual ANN model, the four linear ensemble forecasting models, as well as the ANN-based nonlinear ensemble models for the testing cases of four main currencies in terms of the level prediction measurement and direction prediction measurement.
2. The proposed SVR-based nonlinear ensemble forecasting models are able to improve forecasting accuracy significantly—in other words, the performance of the proposed SVR-based nonlinear ensemble forecasting model is better than those of all other forecasting models presented in this study in terms of *NRMSE* and D_{stat}. This leads to the third conclusion.
3. The proposed SVR-based nonlinear ensemble model can be used as an alternative solution to foreign exchange rate forecasting for obtaining greater forecasting accuracy and improving the prediction quality further in view of empirical results.

CONCLUSION AND FUTURE DIRECTIONS

This chapter proposes an SVR-based nonlinear neural network ensemble forecasting model to obtain accurate prediction results and improve prediction quality further. In terms of the empirical results, we can find that across different ensemble models for the test cases of four main currencies—British pounds (GBP), German marks (DEM), euros (EUR), and Japanese yen (JPY)—on the basis of different evaluation criteria, our proposed SVR-based nonlinear ensemble method performs the best. In the proposed SVR-based nonlinear ensemble testing cases, the *NRMSE* is the lowest and the D_{stat} is the highest, indicating that the proposed SVR-based nonlinear neural network ensemble model can be used as a viable alternative ensemble solution to exchange rates prediction.

Just such a forecasting technique highlights the managerial significance, especially for foreign exchange investment decision. For business practitioners, the main purpose of foreign exchange rates prediction is to improve investment decision in the foreign exchange market and thus gain more money. Obviously, the proposed neural network models in this study can produce a more effective prediction in terms of either level or direction. In particular, the direction prediction can almost give some direct management implication for foreign exchange investment decision. For example, at time t, one makes a specific foreign exchange rate prediction for time t+1 and finds that the t+1 prediction value is larger than the t actual value, then his/her investment decision is to buy this foreign exchange at time t. That is, if $(\hat{x}_{t+1} - x_t) > 0$ then *buy* else *sell*. This is a typical "trend-follow" strategy (Yao & Tan, 2000). Using the improved prediction, the business practitioners can effectively construct their investment strategies for foreign exchange markets. Because the SVR-based neural network ensemble model can gain more advantage than other forecasting models listed in this study, one can believe that the proposed neural network ensemble forecasting can effectively help improve foreign exchange asset management and investment decision.

In addition, this study also provides some clues for future studies. For example, other nonlinear ensemble methods, forecast horizons, prediction accuracy, and online real-time foreign exchange trading decisions can be further studied in the future. Furthermore, the proposed SVR-based nonlinear ensemble forecasting system can also be applied to other related fields, such as stock markets, crude oil markets, real option markets, and some emerging markets, which are worth exploring further in the future.

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Chapter XVII
On the New Transformation-Based Approach to Value-at-Risk:
An Application to the Indian Stock Market

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ABSTRACT

This chapter deals with the measurement of Value-at-Risk parameter for a portfolio using historical returns. The main issue here is the estimation of suitable percentile of the underlying return distribution. If returns were normal variates, the task would have been very simple. But it is well documented in the literature that financial market returns seldom follow normal distribution. So, one has to identify suitable distribution, mostly other than normal, for the returns and find out the percentile of the identified distribution. The class of non-normal distribution, however, is extremely wide and heterogeneous, and one faces a decision-making problem of identifying the best distributional form from such a wide class of potential alternatives. In order to simplify the task of handling non-normality while estimating VaR, we adopt the transformation-based approach used in Samanta (2003). The performance of the transformation-based approach is compared with two widely used VaR models. Empirical results are quite encouraging and identify the transformation-based approach as a useful and sensible alternative.

INTRODUCTION

The Value-at-Risk (VaR), in recent years, has emerged as an important tool for managing financial risks. Though originally proposed for handling 'market risk', domain of VaR application was soon found much wider, and conceptually VaR is useful in managing even other financial risks, such as credit risk and operational risk. The VaR, as a risk management tool, serves several purposes: (a) it provides a risk measure, so useful to compare risk involved in different portfolios; (b) it is a measure of potential loss from a portfolio; and (c) it is a key parameter prescribed by central banks across countries to their regulated banks to determine required capital for market risk exposure (Jorian, 2001; Wilson, 1998).

The VaR, when used for market risk, gives a single number that represents the extent of possible loss from an investment portfolio due to market swings in the future. The concept is defined in a probabilistic framework, and VaR provides a threshold on maximum loss from a portfolio in such a fashion that the instance of actual loss exceeding the threshold during a predefined future time period has certain fixed/predefined probability. In cases of other risk categories (such as credit risk and operational risk), VaR would quantify the maximum possible loss (in probabilistic sense), due to changes in corresponding risk factors. However, specification and implementation of VaR vary across risk categories. Throughout this chapter, we discuss VaR in the context of the market risk.

The VaR for a portfolio can be estimated by analyzing the probability distribution of the respective portfolio's return—the VaR simply gives a threshold return which corresponds to a suitable percentile of the underlying distribution. If returns follow normal distribution, the required percentile can be derived from the corresponding percentile of standard normal distribution (which is readily available from the standard normal distribution table) and mean and standard deviation of the observed return distribution. But in reality, financial market returns seldom follow normal distribution, and the task of estimating VaR has been a challenging one.

The empirical evidence across countries shows that distribution of financial market returns generally poses fat-tails (excess-kurtosis) and may be significantly skewed. The fat-tail distribution may occur primarily due to the 'volatility-clustering' phenomenon observed in financial markets and indicate the occurrence of large or extreme returns more frequently than predicted by normal distribution. Whereas skewed distribution would tell us to analyze the observations in two tails (i.e., large/rare negative returns in the left tail and large/rare positive returns in the right tail) differently. In either case, normality assumption to the underlying return distribution might be a potential source of error in VaR estimation. If the specific form of the non-normality were known, one would still be able to estimate VaR easily from the percentiles of the specific distributional form. But in reality the form of the underlying distribution is not known and one has to discover it from the data. The class of non-normal distributions includes all possible (in our case continuous) distributions other than normal, thus extremely wide and heterogeneous. So, while estimating VaR, one is essentially facing a decision-making problem of selecting one distributional form from a vast set of possible alternatives. A mis-specified VaR model may cost an institute heavily and the associated hazards may be covered under what is known as 'model risk'.

The conventional approaches to handle non-normality fall under three broad categories: (1) non-parametric approaches, such as historical simulation; (2) fitting suitable non-normal or mixture distribution; and (3) modeling the distribution of extreme return or modeling only the tails of return distribution. The non-parametric alternatives, like historical simulation, do not assume any specific form of the return distribution and are quite robust over distributional forms. Besides, these techniques are easy to understand and implement. But this approach suffers from the lack of analytical flexibility and several other disadvantages of what non-parametric approaches share. Alternatively, one can simply fit the parametric form of a suitable non-normal distribution to the observed returns. The class of distributional forms considered would be quite wide including, say, t-distribution, mixture of two or more normal distributions, hyperbolic distribution, Laplace distribution, and so forth, (van den Goorbergh & Vlaar, 1999; Bauer, 2000; Linden, 2001). The non-normality, particularly the excess-kurtosis problem, can also be captured through a class of conditional heteroscedasticity models. The third category, which is also parametric, takes help of extreme value theory and models either the distribution of maximum/minimum return or only the tails of return distribution. The parametric approaches are extremely useful for analytical purpose, but identification of actual/appropriate parametric form is extremely difficult.

Another sensible approach to deal with non-normality while estimating VaR, proposed recently by Samanta (2003), would involve transforming the (non-normal) return to a (near) normal variable (hence forth we call this the "transformation-based approach"). Once portfolio returns are transformed into normal variates, one would first derive suitable percentile for transformed returns, which, by construction, are (near) normal variables. The standard properties of normal distribution are useful to estimate the required percentile. Finally the percentile for transformed series can be inverted (by applying the inverse transformation) to derive the percentile of the original return, which possibly does not follow normal distribution. This chapter makes an attempt to examine the suitability of the transformation-based approach of VaR for the stock market in India. The organization of the rest of the chapter is as follows. The next section presents the concept of VaR and summarizes a number of widely used VaR estimation techniques and evaluation criteria. We follow with a discussion on the new transformation-based approach and report empirical results pertaining to the Indian stock market. We first estimate VaR numbers using the new approach and select other competing approaches of VaR estimation. Thereafter, we evaluate the performance of the new approach vis-à-vis chosen competing techniques. The final section presents concluding remarks.

VALUE-AT-RISK: THE CONCEPT, MEASUREMENT, AND EVALUATION

The Concept

The VaR is a numerical measure of the maximum amount by which a financial position in a risky category could incur losses due to, say, market swings (market risk) during a given holding period. As mentioned earlier, the measure is defined under a probabilistic framework. Let W_t denotes the total value of underlying assets corresponding to a financial position at time instance t, and the change in value of the position from time t to t+k is $\Delta W_t(k) = (W_{t+k} - W_t)$. At time point t, $X_t = \Delta W_t(k)$ is unknown and can be thought of as a random variable. Let $f(x, \beta)$ denote the probability density function of X_t, β being the vector of unknown parameters. As discussed by Tsay (2002), the VaR (at time point t) of a long-position over time horizon k with probability p—that is, 100*(1-p) percent confidence level—is defined through the identity:

$$\int_{-\infty}^{-\text{VaR}} f(x,\beta)dx = \text{p} \qquad (1)$$

The holder of a long financial position suffers a loss when $\Delta W_t(k) < 0$, and the VaR defined in equation (1) will be positive for small p (conventionally p=0.01 or 0.05). In this case, estimation of VaR depends on the left tail of the distribution of $\Delta W_t(k)$. Here VaR signifies maximum loss attached to the probability level p.

In the case of a short financial position, a loss is incurred when $\Delta W_t(k) > 0$ for underlying assets; for estimating VaR, one has to study the right tail of the distribution of $\Delta W_t(k)$. In particular, the VaR (for time horizon k with probability p) at time t would be determined satisfying the equation (2):

$$\int_{\text{VaR}}^{\infty} f(x,\beta)dx = \text{p} \qquad (2)$$

Thus, for estimating VaR, both left and right tails of the distribution of $\Delta W_t(k)$ are important; the type of financial position (i.e., whether long or short) would indicate the specific tail (i.e., whether left tail or right tail) of the distribution. One may note that the VaR with probability p defined in equation (1) is actually the percentile corresponding to left/lower tail probability p. Similarly, the one defined in equation (2) corresponds to the right-tail probability p and hence to the left-tail probability (1-p).

Sometime, VaR number is reported in association with a confidence level (instead of probability level), which simply indicates the probability that loss does not exceed VaR. The confidence level is reported in percentage form (i.e., confidence level is derived as 100 multiplied with the probability that the loss remains within VaR). Thus, the relationship between probability level p and confidence level c is described as c=100*(1-p).

Two important terminologies associated with any VaR estimate are the 'holding period' and the 'probability/confidence level'. While the terms 'holding period' refer to the (future) investment horizon, the other terminology is linked to the probability that the portfolio loss would not exceed the VaR number. It is important to note that for a given holding period, VaR number will increase (decrease) with the rise (fall) of confidence level. Similarly, for a given confidence level, VaR has positive association with the holding period—a longer holding period means higher VaR. So, the choice of 'confidence level' and 'holding period' would depend on the purpose of estimating the VaR measure.

Important Issues While Estimating VaR

As seen, VaR is defined in terms of the change/loss in value of a portfolio. In practice, distribution of return (either percentage change or continuously compounded/log-difference[1]) of the financial position is modeled and thus VaR is estimated based on percentile of the underlying return distribution. If ξ_p denotes the percentile corresponding to left-tail probability p of distribution of k-period percentage change, then k-period VaR for long and short financial positions would be $[(\xi_p/100)W_t]$ and $[(\xi_{1-p}/100)W_t]$, respectively. Alternatively, if ξ_p represents the percentile for log-return (in percent), then VaR for long and short financial positions would be $[\{\exp(\xi_p/100)-1\}W_t]$ and $[\{\exp(\xi_{1-p}/100)-1\}W_t]$, respectively.[2] The multi-period VaR may be derived based on estimated one-period VaR (under certain assumptions).

Sometimes percentiles of return distribution are termed as 'relative VaR' (e.g., Wong, Cheng, & Wong, 2003). On this perception, the VaR for change in value may be termed as 'absolute/nominal VaR'. Thus, the relative VaR using log-return series would be $[\xi_p/100]$ for a 'long position' and $[\xi_{1-p}/100]$ for a 'short position'. In our discussion, we use the single term VaR to indicate either 'nominal VaR' or 'relative VaR'; the actual understanding would be made from the contextual meaning.

Measurement of VaR: Select Available Techniques

The central to any VaR measurement exercise has been the estimation of suitable percentile of change in value or return of the portfolio. If the underlying distribution were normal, one would have simply estimated the mean and standard deviation of the normal distribution and hence estimate the implied percentiles. But the biggest practical problem of measuring VaR is that the observed return series generally does not follow normal distribution—the financial market returns are known to exhibit 'volatility clustering phenomena' and follow 'fat-tailed' (leptokurtic) distribution with possibly substantial asymmetry in tails. The deviation from normality intensifies the complexity in modeling the distribution of returns and hence estimation of percentiles and VaR. The fat-tailed/volatility clustering behavior would potentially be modeled through the class of conditional heteroscadasticity models, such as ARCH (Engle, 1982), GARCH (Bollerslev, 1986), and the approach followed in RiskMetrics (J.P. Morgan/Reuters, 1996). But such approach do not necessarily improve the quality of VaR estimates (Wong et al., 2003). There has been a plethora of techniques to handle non-normality in unconditional return distributions. Available techniques can be classified under three broad classes: (1) 'historical simulation', a model-free approach for estimating percentile; (2) parametric approach for fitting non-normal (fat-tailed and/or skewed) distribution, such as t-distribution and hyperbolic distribution; and (3) extreme value theory, which models either the distribution of extreme observations or tails of underlying distribution. Details of the methods stated above are available in standard books/papers on the topic (e.g., van den Goorbergh & Vlaar, 1993; Bauer, 2001; Sarma, Thomas, & Shah, 2003)[3], and for the sake of brevity, we briefly present two methods of VaR estimation that are considered as benchmark models in our empirical exercise.

Normal (Covariance) Method

The simplest possible VaR method is the normal (covariance) method, which assumes that returns are normally distributed. If μ and σ are mean and standard deviation respectively for return at a future date, then VaR would be calculated from the expression $(\mu + \sigma z_\alpha)$, where z_α represents the percentile corresponding to left-tail probability α of the standard normal distribution and α is the probability level attached to VaR numbers. This approach is static in a sense that it models the unconditional return distribution (van den Goorbergh & Vlaar, 1999).

As known, unconditional distribution of returns generally shows fatter tails (leptokurtosis or excess-kurtosis) than normal; this means that normality assumption to unconditional return distribution is not realistic. It is also known that fat-tails may also be a reflection of the changing conditional volatility which can be modeled under suitable conditional heteroscedastic models like exponentially weighted moving average used in RiskMetrics (J.P.Morgan/Reuters, 1996) or more advanced models like ARCH, GARCH, and so forth (Engle, 1982; Bollerslev, 1986; Wong et al., 2003). Under normality of such conditional distributions, expression of VaR estimates is $(\mu_t + \sigma_t z_\alpha)$, where μ_t and σ_t are time-varying/conditional mean and standard deviation of return, respectively.

Method Using Tail-Index

The fat tails of unconditional return distribution can also be handled through extreme value theory using, say, tail index, which measures the amount of tail fatness. One can therefore estimate the tail index and measure VaR based on the underlying distribution. The basic premise of this idea stems from the result that the tails of every fat-tailed distribution converge to the tails of Pareto distribution. In a simple case, upper tail of such a distribution can be modeled as:

$$\text{Prob}[X > x] \approx C^\alpha |x|^{-\alpha} \text{ (i.e. Prob}[X \le x] \approx 1 - C^\alpha |x^{-\alpha}; x > C \qquad (3)$$

where C is a threshold above which the Pareto law holds, and the parameter α is the tail-index. Similarly, lower tail of a fat-tailed distribution can be modeled as:

$$\text{Prob}[X > x] \approx 1 - C^\alpha x^{-\alpha} \text{ (i.e. Prob}[X \le x] \approx C^\alpha x^{-\alpha}); \; x < C \qquad (4)$$

where C is a threshold below which the Pareto law holds, and the parameter α, measures the tail fatness.

In practice, observations in the upper tail of the return distribution are generally positive and those in the lower tail are negative. Also, both equations (3) and (4) have importance in VaR measurement.

The holder of a short financial position suffers a loss when return on underlying assets is positive and therefore concentrates on the upper tail of the distribution (i.e., equation (3)) while calculating his or her VaR (Tsay, 2002, p. 258). Similarly, the holder of a long financial position would model the lower tail of return distribution (i.e., use equation (4)), as a negative return on underlying assets makes him or her suffer a loss.

From equations (3) and (4), it is clear that the estimation of VaR is crucially dependent on the estimation of tail index α. There are several methods of estimating tail index, such as Hill's (1975) estimator and the estimator under ordinary least square (OLS) framework suggested by van den Goorbergh (1999). We consider here Hill's widely used estimator of tail index. We consider tail-index-based VaR estimation using Hill's estimator.

Hill's Estimator

For given threshold C in the right tail, Hill (1975) introduced a Maximum Likelihood estimator of $\gamma = 1/\alpha$, which is known as Hill's estimator and given by:

$$\hat{\gamma} = \frac{1}{n}\sum_{i=1}^{n}\log\left(\frac{X_i}{C}\right) \tag{5}$$

where X_i's, i=1,2, …..,n are n observations (exceeding C) from the right tail of the distribution.

To estimate the parameters for the left tail, we simply multiply the observations by –1 and repeat the calculations applicable to the right tail of the distribution.

In practice, however, C is unknown and needs to be estimated. If T sample observations come from Pareto distribution, then C would be estimated by the minimum observed value, the minimum order statistic. However, here we are not modeling a complete portion of Pareto distribution. We are only dealing with a fat-tailed distribution that has right tail that is approximated by the tail of a Pareto distribution. As a consequence, one has to select a threshold level, say C, above which the Pareto law holds. In practice, equation (5) can be evaluated based on order statistics in the right tail, and thus the selection of the order statistics truncation number assumes importance. In other words, one needs to select the number of extreme observations n when using equation (3). Mills (1999, p. 186) discusses a number of available strategies for selecting n. The method adopted in this chapter is due to Phillips, McFarland, and McMahon (1996). They suggest that optimal value of n should be one, which minimizes the Mean-Square-Error (MSE) of the limiting distribution of $\hat{\gamma}$. To implement this strategy, we need estimates of γ for truncation numbers $T_1 = N^{\delta}$ and $T_2=N^{\tau}$, where $0 < \delta < 2/3 < \tau < 1$. Let $\hat{\gamma}_j$ be the estimate of γ for $n = n_j$, j=1,2. Then the optimal choice for truncation number is $n = [\lambda T^{2/3}]$, where λ is estimated as $\hat{\lambda} = |(\hat{\gamma}_1/\sqrt{2})(T/n_2)(\hat{\gamma}_1 - \hat{\gamma}_2)|^{2/3}$. Phillips et al. (1996) recommended setting δ =0.6 and τ = 0.9 (see Mills, 1999, p. 186).

Estimating VaR Using Tail Index

Once estimate of tail-index α becomes available, VaR can be estimated as follows (van den Goorbergh & Vlaar, 1999). Let p and q (p < q) be two tail probabilities and x_p and x_q be corresponding percentiles. Then $p \approx C^{\alpha} (x_p)^{-\alpha}$ and $q \approx C^{\alpha} (x_q)^{-\alpha}$, indicating that $x_p \approx x_q (q/p)^{1/\alpha}$. Assuming that the threshold in the tail of the return (in percent) distribution corresponds to the m-th order statistics (in ascending order), the estimate of x_q is:

$$\hat{x}_p = R\left(\frac{m}{np}\right)^{\hat{\gamma}} \tag{6}$$

where R is the order statistics (in ascending order), giving n observations in the right tail of the underlying distribution, p is the given probability level for which VaR is being estimated, and $\hat{\gamma}$ is the estimate of γ. Knowing the estimated percentile $\hat{x}_p$, one can easily calculate the VaR.

As stated above, the methodology described above estimates tail index and VaR for the right tail of a distribution. To estimate the parameters for the left tail, we simply multiply the observations by –1 and repeat the calculations.

STRAGIES TO EVALUATE VaR MODELS

The accuracy of VaR estimates obtained from a VaR model can be assessed under several frameworks, such as: (1) regulators' backtesting (henceforth simply called as backtesting), (2) Kupiec's test, and (3) loss-function based evaluation criteria. Under each framework, there would be several techniques, and what follows is the summary of some of the widely used techniques.

Backtesting

As recommended by the Basle Committee, central banks do not specify any VaR model that should be used by their supervised banks. Rather, 'internal model approach' is suggested wherein banks are allowed to adopt their own VaR model. There is an interesting issue here. As known, VaR is being used for determining the capital charge—the larger the value of VaR, the larger the capital charge. Because larger capital charge implies less profit, banks may have an inclination towards adopting a model that produces lower VaR estimate since that helps to reduce their capital charge. In order to eliminate such inertia of supervised banks, the Basle Committee has set out certain requirements on VaR models used by banks to ensure their reliability (Basel Committee, 1996a, 1996b) as follows:

1. One-day and 10-day VaRs must be estimated based on the daily data of at least one year.
2. Capital charge is equal to three times the 60-day moving average of 1% 10-day VaRs, or 1% 10-day VaR on the current day, which ever is higher. The multiplying factor (here 3) is also known as 'capital multiplier'.

Further, the Basle Committee (1996b) provides the following backtesting criteria for an internal VaR model (see van den Goorbergh & Vlaar, 1999; Wong et al., 2003):

1. One-day VaRs are compared with actual one-day trading outcomes.
2. One-day VaRs are required to be correct on 99% of backtesting days. There should be at least 250 days (around one year) for backtesting.

If a bank provides a VaR model than fails in backtesting, it will have its capital multiplier adjusted upward, thus increasing the amount of capital charges. For carrying out the backtesting of a VaR model, realized day-to-day returns of the portfolio are compared to the VaR of the portfolio. The number of days when actual portfolio loss was higher that VaR provides an idea about the accuracy of the VaR model. For a good VaR model, this number would approximately be equal to 1% (i.e., 100 times of VaR probability) of backtest trading days. If the number of VaR exceptions or failures (i.e., number of days when loss exceeds VaR) is too high, a penalty is imposed by raising the multiplying factor (which is at least 3), resulting in an extra capital charge. The penalty directives provided by the Basle Committee for 250 backtesting trading days is as follows: multiplying factor remains at minimum (i.e., 3) for number of exceptions up to 4, increases to 3.4 for 5 exceptions, 3.5 for 6 exceptions, 3.65 for 7 exceptions, 3.75 for 8 exceptions, 3.85 for 9 exceptions, and reaches 4.00 for exceptions above 9, in which case the bank is likely to be obliged to revise its internal model for risk management (van den Goorbergh & Vlaar, 1999).

Statistical Tests of VaR Accuracy

The accuracy of a VaR model can also be assessed statistically by applying Kupiec's (1995) test (for an example of an application of the technique, see van den Goorbergh & Vlaar, 1999). The idea behind this test is that frequency of VaR exception should be statistically consistent with the probability level for which VaR is estimated. Kupiec (1995) proposed to use likelihood ratio statistics for testing the said hypothesis.

If *z* denotes the number of times the portfolio loss is worse than the true VaR in the sample (of size T, say), then *z* follows a Binomial distribution with parameters (T, p), where p is the probability level of VaR. Ideally, the more *z*/T closes to p, the more accurate estimated VaR is. Thus the null hypothesis *z*/T = p may be tested against the alternative hypothesis *z*/T ≠ p. The Likelihood Ratio (LR) statistic for testing the null hypothesis against the alternative hypothesis is

$$LR = 2 \left[\log\left(\left(\frac{z}{T}\right)^{z} \left(1-\frac{z}{T}\right)^{T-z} \right) - \log(p^{z}(1-p)^{T-z}) \right] \quad (7)$$

Under the null hypothesis, LR-statistic follows an χ^2-distribution with 1-degree of freedom.

The VaR estimates are also interval forecasts, which thus can be evaluated conditionally or unconditionally. While the conditional evaluation considers information available at each time point, the unconditional assessment is made without reference to it. The test proposed by Kupiec provides only an unconditional assessment, as it simply counts exceptions over the entire backtesting period (Lopez, 1998). In the presence of time-varying volatility, the conditional accuracy of VaR estimates assumes importance. Any interval forecast ignoring such volatility dynamics may have correct unconditional coverage, but at any given time may have incorrect conditional coverage. In such cases, Kupiec's test has limited use as it may classify inaccurate VaR as acceptably accurate.

A three-step testing procedure developed by Christoffersen (1998) involves a test for correct unconditional coverage (as Kupiec's test), a test for 'independence', and a test for correct 'conditional coverage' (Christoffersen, 1998; Berkowitz & O'Brien, 2002; Sarma, et al., 2003). All these tests use Likelihood Ratio (LR) statistics.

Evaluation of VaR Models Using Loss-Function

All the tests mentioned above ultimately deal with the frequency of the occurrence of VaR exceptions, either conditional or unconditional, during the backtesting trading days. These tests, however, do not look at the severity/magnitude of additional loss (excess of estimated VaR) at the time of VaR exceptions. However, a portfolio manager may prefer the case of more frequent but little additional loss than the case of less frequent but huge additional loss. The underlying VaR model in the former case may fail in backtesting, but still the total amount of loss (after adjusting for penalty on multiplying factor if any) during the backtesting trading days may be less than that in the latter case. So long as this condition persists with a VaR model, a portfolio manager, particularly non-banks who are not required to comply with any regulatory requirement, may prefer to accept the VaR model even if it fails in backtesting. This means that the objective function of a portfolio manager is not necessarily the same as that provided by the backtesting. Each manager may set his or her own objective function and try to optimize that while managing market risk. But loss-functions of individual portfolio managers are not available in public domain, and thus it would be impossible to select a VaR model appropriate for all managers. However, discussion on a systematic VaR selection framework by considering a few specific forms of loss-function would provide insight into the issue so as to help the individual manager select a VaR model on the basis of his or her own loss-function. On this perception, it would be interesting to illustrate the VaR selection framework with the help of some specific forms of loss-function.

The idea of using loss-function for selecting VaR model, is proposed first by Lopez (1998). He shows that the binomial distribution-based test is actually minimizing a typical loss-function—it gives a score 1 for a VaR exception and a score 0 otherwise. In other words, the implied loss-function in backtesting would be an indicator function I_t which assumes a value 1 at time t if the loss at t exceeds corresponding VaR estimate and assumes a value zero otherwise. However, it is hard to imagine an economic agent who has such a utility function: one that is neutral to all times with no VaR exception and abruptly shifts to a score of 1 in the slightest failure and penalizes all failures equally (Sarma et al., 2003). Lopez (1998) also considers a more generalized loss-function which can incorporate the regulatory concerns expressed in the multiplying factor and thus is analogous to the adjustment schedule for the multiplying factor for determining required capital. But he himself sees that, like the simple binomial distribution-based loss-function, this loss-function is also based on only the number of exceptions in backtesting observations—paying no attention to other concerns, the magnitudes of loss at the time of failures. In order to handle this situation, Lopez (1998) also proposes a different loss-function addressing the magnitude of exception as follows:

$$L_t = \begin{cases} 1 + (Loss_t - VaR_{t|t-1})^2 & if \;\; Loss_t > VaR_{t|t-1} \\ 0 & otherwise \end{cases} \tag{8}$$

where L_t denotes a score at time t, $Loss_t$ is the magnitude/amount of loss at time t, and $VaR_{t|t-1}$ is the estimated value-at-risk made for time t at time (t-1).

The overall score (i.e., value of the loss-function) is the summation of all scores (L_t) over all backtesting days. One chose a VaR model that gives the minimum overall score.

In the spirit of Lopez (1998), Sarma et al. (2003) consider two loss-functions—regulatory loss-function and the firm's loss-function—which assign scores on t-th backtesting day as follows.

Regulatory Loss-Function

$$L_t = \begin{cases} (Loss_t - VaR_{t|t-1})^2 & if \;\; Loss_t > VaR_{t|t-1} \\ 0 & otherwise \end{cases} \tag{9}$$

Firm's Loss-Function

$$L_t = \begin{cases} (Loss_t - VaR_{t|t-1})^2 & if \;\; Loss_t > VaR_{t|t-1} \\ \rho \; VaR_{t|t-1} & otherwise \end{cases} \tag{10}$$

where ρ represents the opportunity cost of capital, and the meaning of other symbols and variables are as above.

THE NEW TRANSFORMATION-BASED APPROACH TO MEASURING VaR

As seen in the previous section, a major hurdle in estimating VaR has been the non-normality of return distribution. We also have discussed existing literature to handle the problem. In a recent study Samanta (2003) proposed a transformation-based approach for the purpose. The basic features of the transformation-based approach are presented below:

Basic Premises

If the underlying variable (say, change in portfolio value or return) r_t is not normally distributed, let there exist a one-to-one continuous function of r_t, say $g(r_t,\theta)$, θ being a constant parameter, which follows a normal distribution. The function g(.) would take various different forms, as available in the literature on transformations to normality/ symmetry. Because $g(r_t,\theta)$ is a normal variable, its mean and standard deviation can be estimated easily based on the sample observations, provided θ is given. In reality, however, θ is unknown and thus needs to be estimated from the observed data. Let μ_g and σ_g represent the estimated mean and standard deviation of g, respectively. As g(.) represents a one-to-one continuous function, for any real valued number γ we have the events $\{ g(r_t,\theta) < \gamma \}$ and $\{ r_t < g^{-1}(\gamma, \theta) \}$ equivalent in the sense of probability. In other words, the following identity with respect to probability measure holds:

$$\text{Prob}[g(r_t,\theta) < \gamma] = \text{Prob}[r_t < g^{-1}(\gamma,\theta)] \qquad (11)$$

where Prob(.) denotes the probability measure.

By replacing γ in equation (11) with the p-th percentile of the distribution of $g(r_t,\theta)$, say ν_p, we get the p-th percentile of the unknown distribution of r_t as $\xi_p=g^{-1}(\nu_p,\theta)]$. As $g(r_t,\theta)$ follows a normal distribution, its percentiles are simply $\{\mu_g + \tau_p \sigma_g\}$, where τ_p is the p-th percentile of standard normal distribution. We know that $\tau_{0.01} = -2.33$ and $\tau_{0.05} = -1.65$. As the standard normal distribution is symmetric about zero, the values of $\tau_{0.99}$ and $\tau_{0.95}$ are 2.33 and 1.65, respectively. Now, given the market value of the portfolio and estimated percentiles of underlying return distribution, VaR can be estimated easily.

The idea stated above is intuitively appealing and also easy to understand. But we need to know the functional form of g(.) and also to estimate the unknown transformation parameter θ. The literature on the families of transformations to normality/symmetry comes to the rescue.

Transformations of a Random Variable to Normality

The attempt towards transforming a random variable X to improve normality and some other features of a random variable dates back at least to the work of Box and Cox (1964). Thereafter, several other families/classes of transformations have been proposed in the literature.[4] Some of the useful transformations for our purpose would be the signed power transformation (e.g., Bickel & Doksum, 1981), the modulus power transformation of John and Draper (1980), and the more recent transformation class offered by Yeo and Johnson (2000).

The signed power transformation to convert a random variable to a normal one has the following general form:

$$g^{SP}(x,\nu) = \text{sign}(x) \{|x|^{\nu} -1 \} /\nu, \ \nu > 0 \qquad (12)$$

where sign(x) and |x| are sign and absolute value of x, respectively, and ν is the transformation parameter, which can be estimated from the data on x using Maximum Likelihood (ML) technique.

For transforming a symmetric distribution to near normality, John and Draper (1980) suggested the transformation:

$$g^{JD}(x,\delta) = \begin{cases} sign(x)\{(1+|x|)^{\delta} - 1\}/\delta & \text{if}\ \delta \neq 0 \\ sign(x)\log(1+|x|) & \text{if}\ \delta = 0 \end{cases} \qquad (13)$$

The transformation parameter δ in $g^{JD}(x,\delta)$ can be estimated using ML techniques. As per the existing literature, it appears that both, $g^{SP}(x,\nu)$ and $g^{JD}(x,\delta)$ are quite useful to handle the kurtosis problem, but suffer from a serious drawback when applied to skewed distribution. Particularly, if the distribution of x is a mixture of standard normal and gamma densities, then both $g^{SP}(x,\nu)$

and $g^{JD}(x,\delta)$ tend to follow bimodal distributions and look far away from normal. An additional difficulty with $g^{SP}(x,\nu)$ is that the likelihood function is undefined when some observations of x are zero (Burbidge, Magee, & Robb, 1988). To circumvent the problem, Yeo and Johnson (2000) proposed the following new family of transformations:

$$g^{YJ}(x,\lambda) = \begin{cases} \{(1+x)^{\lambda}-1\}/\lambda & \text{if} \quad x \geq 0, \lambda \neq 0 \\ \log(1+x) & \text{if} \quad x \geq 0, \lambda = 0 \\ -\{(1-x)^{2-\lambda}-1\}/(2-\lambda) & \text{if} \quad x < 0, \lambda \neq 2 \\ -\log(1-x) & \text{if} \quad x < 0, \lambda = 2 \end{cases} \tag{14}$$

The parameter λ of $g^{YJ}(x,\lambda)$ can be estimated by ML technique (Yeo & Johnson, 2000). It is seen that this transformation works well in reducing/eliminating asymmetry (i.e., skewness) in distribution.

Selection of Transformation to Normality

We come across several alternative families of transformations to convert a non-normal variable to a near-normal variable. Thus, any exercise on application of normality transformation faces the problem of selecting the appropriate family of transformation from various competing classes. Though theoretical answer to this issue is not very clear, the basic features of each family of transformation discussed above definitely provide certain useful clues. Particularly, three important points are noticed from above:

1. To convert a symmetric (or near symmetric) distribution to normality, family of transformation $g^{JD}(x,\delta)$) is useful. The transformation $g^{SP}(x,\nu)$ is not of much use in our case mainly for its limitation in handling zero returns in likelihood function.
2. To convert a skewed distribution to symmetry, transformation $g^{YJ}(x,\lambda)$ may be used.
3. If a distribution is non-normal due to both skewness and kurtosis problems, the theory on appropriate choice of power transformation is not clear.

In such a scenario, a heuristic approach would suggest to use first $g^{YJ}(x,\lambda)$ to achieve symmetry and then to apply $g^{JD}(x,\lambda)$ on the already transformed near-symmetric distribution. One, however, need to study the properties of parameter estimates under such a case.

On Implementing the Transformation-Based Approach

While implementing the transformation-based approach of VaR estimation, we first need to know whether the underlying distribution is normal or not. If the actual distribution is normal, estimation of VaR would be done by simple normality-based techniques. Thus, a test for normality should precede any attempt to adopting a transformation-based approach. It is also known that a departure from normality may take place due to: (1) non-zero measure of skewness, (2) deviation of measure of kurtosis from 3 (i.e., excess-kurtosis is zero), or (3) both non-zero measure of skewness and deviation of measure of kurtosis from 3. Denoting β_1 and β_2 as measures of skewness and excess-kurtosis[5], respectively, we have following three hypotheses in this regard:

H_{01}: $(\beta_1,\beta_2)=(0,0)$, which will be tested against the alternative hypothesis H_{11}: $(\beta_1,\beta_2)\neq(0,0)$

H_{02}: $\beta_1=0$, which will be tested against the alternative hypothesis H_{12}: $\beta_1\neq 0$

H_{03}: $\beta_2=0$, which will be tested against the alternative hypothesis H_{13}: $\beta_2\neq 0$

In our study, we tested the null hypothesis H_{01} by using the Jarque and Bera (1987) test statistics $Q = n[(b_1)^2/6 + (b_2)^2/24]$, where b_1 and b_2 are sample estimates of β_1 and β_2, respectively, and n is the number of observations used to derive the said estimates. Under normality, Q is asymptotically χ^2 variable with 2 degrees of freedom. Also note that under normality, each of b_1 and b_2 is also asymptotically normally distributed with mean zero and respective variances 6/n and 24/n implying that each of $[n (b_1)^2/6]$ and $[n (b_2)^2/24]$ is asymptotically χ^2 variable with 1 degree of freedom (for a discussion on the Jarque-Bera test (1987) of normality and related issues, see Gujarati, 1995).

With this background, the proposed transformation-based VaR modeling approach can be implemented through the following steps:

- **Step 1:** Test the return series for normality. If normality is accepted, the estimation of VaR will depend upon the percentiles of normal distribution. Otherwise, normality may be rejected for any of the three possible cases of measures of skewness (β_1) and excess-kurtosis (β_2), namely, Case (1) $\beta_1 \neq 0$ and $\beta_2 = 0$, Case (2) $\beta_1 = 0$ and $\beta_2 \neq 0$, and Case (3) $\beta_1 \neq 0$ and $\beta_2 \neq 0$.
- **Step 2:** If normality is rejected for Case (1) of Step 1, then apply $g^{YJ}(x,\lambda)$ transformation for suitably chosen λ. A standard practice is to estimate λ via a grid-search method by maximizing log-likelihood function over a set of potential alternatives of λ. One may also select λ by minimizing the magnitude of measure of skewness. If normality is rejected for Case (2) of Step 1, then apply $g^{JD}(x,\delta)$ transformation. The parameter δ may be estimated either by maximizing log-likelihood function or by minimizing extent of excess-kurtosis over a set of potential alternative. If normality is rejected for Case (3), we may proceed via two phases: first apply $g^{YJ}(x,\lambda)$ on the original variable and then pass the transformed variable so obtained through $g^{JD}(x,\delta)$ transformation.
- **Step 3:** Estimate the mean and standard deviation of the near-normal transformed variable in Step 2. Using these statistics and the known percentiles of the standard normal distribution, percentiles of the transformed near-normal distribution are estimated.
- **Step 4:** Apply inverse transformation on these percentiles to derive the percentiles of the underlying return distribution.
- **Step 5:** Derive VaR using current portfolio value and estimates of percentiles of return distribution.

AN APPLICATION TO STOCK MARKET DATA IN INDIA

In order to demonstrate the possible gain from the new transformation-based VaR modeling approach, it is proposed to assess the performance of the approach vis-à-vis select other available VaR models. As stated earlier, the proposed empirical study focuses on the stock market in India.

Data

The data used in this study are the daily stock price indices. For VaR calculated at portfolio level, it would be interesting to examine the accuracy of a different VaR model with respect to a certain stock portfolio. However, the composition/components of portfolios differ from investor to investor, and it is extremely difficult to suggest any portfolio that is optimal to all investors. But at the same time, it is neither practical nor manageable to consider all possible stock portfolios, as there would be a large number of individual securities and the possible number of portfolios would be astronomically large. A somewhat useful strategy, as adopted by many other researchers also (Bauer, 2000; Christoffersen, Hahn, & Inoue, 2001; Sarma et al., 2003), would be to examine the VaR models with respect to certain stock indices, which by construction represent a well-diversified stock portfolio. Data on these indices are also easily available in the public domain, thus the results based on such a portfolio would be easily verifiable/replicable by the researchers. With this in mind, we consider daily data on three stock price indices (closing price) published by the National Stock Exchange of India Limited (NSEIL)—(1) S & P CNX Nifty, (2) CNX Nifty Junior, and (3) S & P CNX Defty—for the period from April 1, 1999, to March 31, 2005 (which gives 1,509 daily observations on each stock price index considered[6]). The features of chosen indices are available easily from NSEIL's Web site and we choose not to repeat the discussion on the same for the sake of brevity.[7]

Competing VaR Models

We assess the performance of the transformation-based VaR model vis-à-vis a couple of widely used techniques, such as the Normal (variance-covariance) method and the extreme-value approach using Hill's (1975) estimator. All these methods are applied for univariate series on portfolio returns. Also the models we considered are static in a sense that we do not model conditional variance of returns. As known, observed leptokurtosis (excess-kurtosis) behavior of unconditional returns could be due to presence of changing conditional volatility which could be modeled under suitable simple conditional heteroscedastic models. Alternatively, one could directly fit unconditional distribution with suitable non-normal forms of distribution. In our empirical exercise we follow the later approach, and the three competing VaR models/approaches considered in our empirical exercise are: (1) normal (unconditional) method, (2) tail index-based method using Hill's estimator, and (3) the new transformation-based method.

Empirical Results

The returns we consider are continuously compounded, calculated as:

$$R_t=100 *[\log_e(P_t) - \log_e(P_{t-1})] \qquad (15)$$

where P_t represents stock price index for t-th day in the database and R_t denotes corresponding daily continuously compounded return.

We consider VaR in percentage form, which means that VaR number will reflect the maximum percentage loss with given probability and holding period. In other words, estimated VaR corresponds to the possible loss for a portfolio of value 100 units. We shall estimate, on the t-th day, the VaR for the (t+1)-th and future dates. Also we consider only the cases of lower-tail VaRs. As discussed earlier, the task ultimately boils down to estimation of 1st percentile (for VaR with 99% confidence level or equivalently with probability level p=0.01) or 5th percentile (for VaR with probability level p=0.05) of the return distribution. The potential difficulty would arise if the returns do not follow normal distribution.

Empirical Return Distributions and Transformations to Normality

We first examine whether return distributions could be considered normal. For a normal distribution, measures of skewness (β_1) and excess-kurtosis (β_2) are all zero. We performed the null hypotheses H_{01}, H_{02}, and H_{03} against the alternative hypotheses discussed earlier. Results of these tests for chosen stock indices are presented in Table 1. The observed values of chi-square test statistics and corresponding probability value, denoted by 'p-value', are also reported. A null hypothesis would be accepted at a conventional 1% (or 5%) level of significance if the p-value of corresponding test statistics exceeds 0.01 (or

0.05). In the cases of all original return series, p-values are substantially lower than 0.01, strongly rejecting null hypotheses at 1% significance level (hence at 5% significance level also). We therefore could not accept the normality of original returns and decided to pass each original return series through the normality transformation so as to obtain transformation of returns, which follow (approximately) normal distribution.

A simple two-step transformation strategy is followed irrespective of whether the underlying return series is skewed or leptokurtotic (when excess-kurtosis turns out to be significantly different than zero). In the first step, we apply the $g^{YJ}(.,\lambda)$ transformation proposed by Yeo and Johnson (2000) on return, so that the transformed variable have near-symmetric distribution. The transformation parameter λ is estimated through a grid-search over the set of potential alternatives {0, 0.001, 0.002, 0.003, …., 1.999, 2}. The criteria used to choose optimal λ from the grid-search would be 'Maximum Likelihood function' (Yeo & Johnson, 2000) or, heuristically, 'minimum absolute value of skewness measure'.

In the second step, we handle the problem of excess-kurtosis. Thus the transformed series (which are near-symmetric) are passed through the $g^{JD}(.,\delta)$ transformation proposed by John and Draper (1980). The parameter δ is estimated via a grid-search over {-2, -1.999, -1.998, ……., 1.999, 2}. As earlier, the criteria for selecting optimal δ would be 'Maximum Likelihood function' (John & Draper, 1980) or, heuristically, 'minimum absolute value of excess-kurtosis measure'. Based on experimentation on our database, we found that absolute skewness/excess-kurtosis-based estimates of λ and δ work relatively better for our database. The optimal estimates of λ and δ for a return series are chosen accordingly. We hope that the final transformation $y = g^{JD}\{g^{YJ}(r, \hat{\lambda}), \hat{\delta}\}$, where $\hat{\lambda}$ and $\hat{\delta}$ are estimates of λ and δ respectively for the return r, is a (near) normal variable. In order to verify this position, we test the hypotheses H_{01}, H_{02}, and H_{03} (against corresponding alternative hypotheses) for all transformed variables/returns. Corresponding empirical results are given in Table 2. As can be seen from this table, application of the transformation induced normality for all returns considered—the Jarque-Bera statistics and other statistics for normality are statistically insignificant at any conventional level.

Estimation of VaR

In Table 3, we present estimated one-day VaRs at the last day of our database (i.e., March 31, 2005). Also given are the average one-day VaRs in last 60 days of the database. These VaRs could be used for determining capital charge for the next day (i.e., April 1, 2005). All VaR estimations

Table 1. Testing normality of returns in stock market

Asset/ Portfolio	**Measure Of Skewness**	χ^2_1 **For Skewness (Testing H_{02})**	**Excess-kurtosis**	χ^2_1 **For Excess-kurtosis (Testing H_{03})**	**Jarque-bera Statistics (Testing H_{01})**
Nifty	-0.5706	81.7359** (0.0000)	5.6519	2004.4556** (0.0000)	2086.1915** (0.0000)
Nifty Junior	-0.7894	156.3937** (0.0000)	3.8565	933.2669** (0.0000)	1089.6606** (0.0000)
Defty	-0.6331	100.6082** (0.0000)	6.3081	2496.9364** (0.0000)	1503.2489** (0.0000)

*Figures Within ( ) indicate significance level (I.e., P-value). '**' Indicates significant at 1% level of significance.*

Table 2. Testing normality of transformation of returns

Asset/ Portfolio	**Transformation Parameters**	**Measure of Skewness**	**χ_1^2 for Skewness (Testing H_{02})**	**Excess-Kurtosis**	**χ_1^2 for Excess-Kurtosis (Testing H_{03})**	**Jarque-Bera Statistics (Testing H_{01})**
Nifty	$\hat{\lambda} = 1.088$ $\hat{\delta} = 0.306$	-0.0639	1.0638 (0.3116)	0.0002	0.0000 (0.9986)	1.0239 (0.5993)
Nifty Junior	$\hat{\lambda} = 1.136$ $\hat{\delta} = 0.382$	-0.1116	3.1272 (0.0770)	-0.0001	0.0000 (0.9998)	3.1272 (0.2095)
Defty	$\hat{\lambda} = 1.094$ $\hat{\delta} = 0.308$	-0.0572	0.8221 (0.3645)	-0.0013	0.0000 (0.9921)	0.8223 (0.6623)

Figures within ( ) indicate significance level (i.e., p-value). The symbol '^' indicates estimates. All test statistics presented in this table are statistically insignificant at 5% level of significance.

Table 3. VaR estimation (lower/left tail)

Asset/ Portfolio	**p=0.05**			**p=0.01**		
	Normal	**Tail Index**	**Trans. Based**	**Normal**	**Tail Index**	**Trans. Based**
Nifty	2.683 (2.679)	2.301 (2.369)	2.526 (2.501)	3.799 (3.810)	4.736 (4.755)	4.966 (4.975)
Nifty Junior	2.996 (2.957)	2.724 (2.574)	2.587 (2.488)	4.253 (4.226)	7.824 (7.684)	5.493 (5.353)
Defty	2.802 (2.766)	2.360 (2.328)	2.675 (2.592)	3.964 (3.938)	4.795 (4.832)	5.223 (5.125)

Figures within ( ) indicates average of one-day VaR in last 60 days in the database.

pertain to the lower tails of return distributions and are estimated using a rolling window of size 300 days.[8] In other words, VaR for time (t+1) has been calculated at time t based on daily observations for the period from (t-299)-th day to t-th day in the database. For given h-days holding period, the h-days VaR can be calculated approximately as a function of h and one-day VaR. As per the Basle Accord, capital charge for market risk in a day would be the maximum of: (1) average of 10-day 99% VaRs in previous 60 days multiplied by a prescribed number k, known as multiplying factor; and (2) the 10-day 99% VaR of a previous day. From Table 3, it is clear that the estimated VaR numbers vary substantial across the models indicating the sensitiveness of capital charge on choice of VaR model.

Empirical Evaluation of VaR Estimates/Models

We now assess the accuracy of competing VaR models by passing those through the different validation criteria discussed earlier. This assessment will also help us to compare the relative

Table 4. Percentage of VaR exceptions by competing models

Asset/ Portfolio	p=0.05			p=0.01		
	Normal	Tail Index	Trans. Based	Normal	Tail Index	Trans. Based
Nifty	4.7	5.3	4.6	1.7	1.3	1.3
Nifty Junior	4.6	4.9	4.6	2.0	0.8	1.1
Defty	4.7	5.4	4.5	1.8	1.3	1.1

Table 5. Kupiec's tests

Asset/ Portfolio	p=0.05			p=0.01		
	Normal	Tail Index	Trans. Based	Normal	Tail Index	Trans. Based
Nifty	0.1932 (0.6603)	0.1860 (0.6663)	0.3457 (0.5566)	4.0910* (0.0431)	0.8306 (0.3621)	0.8306 (0.3621)
Nifty Junior	0.3457 (0.5566)	0.0212 (0.8843)	0.3457 (0.5566)	7.8272** (0.0052)	0.4337 (0.5102)	0.0978 (0.7544)
Defty	0.1932 (0.6603)	0.3287 (0.5664)	0.5438 (0.4608)	5.2251* (0.0223)	0.8366 (0.3621)	0.8306 (0.3621)

Figures within ( ) denote significance level (i.e., p-value); '' and '**' denote significant at 5% and 1% level of significance, respectively.*

performance of competing VaR models. For any such validation and comparison, the strategy adopted is similar to that of Bauer (2000); we keep the latest 1,000 days in our database for validating VaR models. The validation begins with the estimation of VaRs at the (T-1000)-th day in our database, where T represents the total number of data/days in the database for underlying return series/portfolio. A rolling sample of 300 days is used for estimating VaR numbers. After estimation, we count how often in the following 10 days actual portfolio loss (i.e., negative of return series) exceeds estimated VaR. The task is done for two alternative probability levels, 0.01 and 0.05. (i.e., confidence levels of 99% and 95%, respectively). We then shift the estimation period by 10 days into the future and so on. The process of estimation and comparing loss with VaR in the following 10 days was repeated 100 times so as to cover all 1,000 days in the validation period.

We first present the results of backtesting. Table 4 reports the percentage of VaR failures. As can be seen, though all VaR models perform reasonably well for 95% VaR, the VaR exception for 99% VaR varies considerably across competing models—a finding similar to Bauer (2000), who compared two competing VaR methods, hyperbolic distribution-based method and normal method.

Kupiec's test further establishes the superiority of the transformation-based method over both normal and tail-index methods. It is interesting to note from Table 5 that in the case of stock price data, this test identifies all three competing VaR models statistically accurate for 95% confidence level (i.e., when the probability level is fixed at p=0.05). This was also expected from earlier findings on VaR exceptions. But we see dramatic improvement for transformation-based method when probability level for VaR is fixed at p =0.01. Now, Kupiec's test rejects the accuracy of VaR estimates using the normal method for all three stock price indices considered. The estimates of VaR using tail index and transformation-based methods are now statistically accurate but better for the latter (as the p-value of the LR test statistics is higher or equal to those for tail-index method).

We now discuss the values of Regulators' loss-function (given in equation (9)) over the validation dataset. Relevant results, given in Table 6, show that the transformation-based VaR model outperforms the other two competing models. As known, this loss' function penalizes a model depending upon the extent of loss excess of estimated VaR—leaving the very fact of instances of VaR exception contributing to the penalty/loss-function.

Lopez's loss-function (equation (8)) on the other hand imposes penalty on a model depending upon the frequency of VaR exception and also on the extent of excess loss (excess over VaR). From this point of view, this loss-function appears more general than the regulators' loss-function.

Table 7 presents estimated values of Lopez's loss-function over validation period. Based on these results, it is reestablished that the transformation-based VaR model outperforms the other two competing models. Thus, the transformation-based method is at least a sensible alternative for VaR modeling.

CONCLUSION

We consider a case of estimating VaR when an adequately long history of returns from a portfolio is available. If returns were normally distributed, estimation of VaR would be made simply by using the first two moments of the distribution and the tabulated values of standard normal distribution. But the experience from empirical literature shows that the task is potentially difficult because of the fact that the financial market returns seldom follow normal distribution. It is observed that empirical return distributions have thicker tails than normal and at times are skewed. In order to handle the non-normality, a number of techniques have been proposed in the literature. Recently, Samanta (2003) proposed a new approach based on transformations to normality. He argues that

Table 6. Values of regulator's loss-function

Asset/ Portfolio	p=0.05			p=0.01		
	Normal	Tail Index	Trans. Based	Normal	Tail Index	Trans. Based
Nifty	219.31	215.44	213.69	140.84	117.07	100.51
Nifty Junior	310.13	299.97	302.99	203.26	150.04	146.61
Defty	246.68	239.43	239.39	164.94	131.89	119.98

Table 7. Values of Lopez's loss-function

Asset/ Portfolio	p=0.05			p=0.01		
	Normal	Tail Index	Trans. Based	Normal	Tail Index	Trans. Based
Nifty	266.31	268.44	259.69	157.84	130.07	113.51
Nifty Junior	356.13	348.97	348.99	223.26	158.04	157.61
Defty	293.68	293.43	284.39	182.94	144.89	131.98

a return series (which possibly does not follow normal distribution) may first of all be transformed to a (near-) normal variable by applying suitable transformations to normality/symmetry; required percentiles of this near-normal transformed distribution would be estimated, and finally the value of the inverse function of normality transformation at the estimated percentiles would produce required percentiles for the original return and hence VaR for actual portfolio. Logically, the performance of the proposed approach depends upon the efficiency of the applied transformation to convert a non-normal distribution to a (near-) normal distribution. Unlike this, the efficiency of conventional strategies lies in their capability in approximating unknown (true) distribution of portfolio return. The performance of the new VaR modeling approach has been assessed with respect to select stock price indices in India. The empirical results are quite encouraging and support the usefulness of the new VaR modeling approach.

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ENDNOTES

1 Note that $\Delta W_t(k)$ is the change in value of the assets in the financial position from time point t to (t+k) and the k-period return would be measured by $[100*\{\Delta W_t(k)/W_t\}]$. Another widely used form of k-period return, known as log-return, is defined by $[100\{\log_e(W_{t+k}) - \log_e(W_t)\}]$. Throughout the chapter, the base of logarithmic transformation is 'e' and therefore, anti-log (i.e., the inverse of log-transformation) of a real number x is anti-log(x) = e^x, sometimes denoted by anti-log(x) = exp(x).

2 As stated earlier, exp[.] functions in the expressions of VaR are due to the base 'e' chosen for log-transformation.

3 For a summary of select approaches, one may also refer to Samanta and Nath (2003).

4 As stated, the power transformation proposed by Box and Cox (1964) and many other transformations available in related literature are concerned with several purposes, one of which is to improve normality or symmetry. In this chapter, transformations are discussed only in the context of improving normality/symmetry of return distribution.

5 The measure of skewness $\beta_1 = \mu_3/\mu_2^{(3/2)}$ and measure of kurtosis = μ_4/μ_2^2 indicating that the excess-kurtosis $\beta_2 = \mu_4/\mu_2^2 - 3$, where μ_j denotes the j-th order central moment, $j \geq 2$. For normal distribution, $\beta_1 = \beta_2 = 0$.

6 Data on stock price indices are collected from the Web site of the National Stock Exchange of India Limited (*www.nse-india.com*).

7 Besides, for our empirical exercise, we need some series of portfolio returns and we consider stock price indices for the purpose as they represent some easily verifiable well-diversified portfolio. For our analysis, we consider these portfolios are given and no analysis on understanding their behavior is attempted here. So, we could safely skip the discussion on the features of the chosen indices.

8 As per the guidelines one should calculate one-day VaR based on at least one-year daily data—that is, about 250-260 days' data there are 5 trading-days in a week.

Chapter XVIII
Data Mining and the Banking Sector:
Managing Risk in Lending and Credit Card Activities

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ABSTRACT

Banking has changed rapidly over the last decades due to the ability to capture massive data sets easily and the availability of new tools for analysis. The new, commonly used expressions to describe these phenomena are data warehousing and data mining. The changes have transformed traditional banking activities such as extending loans and given birth to new businesses. For example, the credit card business would simply not exist today, or not in today's form, without the use of high powered computers and new statistical methods. In this chapter, we will discuss a few areas of this vast and important phenomenon, following the outline below. We will be focusing on corporate lending, although data mining permeates all aspects of today's banking. We will discuss corporate lending based on Citigroup's own practices, and the rest of the subject will be based on practices generic to the industry.

INTRODUCTION TO RISK ASSESEMENT

One of the key areas in banking is corporate lending, in which a bank loans money to a company for a set period of time at a given interest rate. The decision to make a loan is not easy. All companies are exposed to various situations, such as rising and falling interest rates, economic/business cycles, industry cycles, and so forth, which will affect the likelihood that the company may not repay the loan at the agreed upon terms. Traditionally, banks have focused their analysis on assessing this risk of non-repayment—or default—on the loan. Increasingly, however, banks are realizing (and trying to measure) a second, yet equally important part of the credit risk that the bank takes on when lending to a variety of obligors—the losses incurred if there is a default.

The importance of measuring and understanding credit risk—both the likelihood of default and loss incurred if there is a default—is vital to the banks' decision-making processes. Credit risk factors into a variety of aspects of the banks' business, such as how they identify their risk appetite and choose their customer base, how they market different loan products to different customers, and finally, how they price loans. The better a bank is at identifying and assessing the credit risks it takes on from its lending activities, the better it can maximize its return on those risks taken. The ideal situation is not necessarily for the bank to identify all possible customers that are the least risky and only do business with those customers. It could, instead, choose to identify the risk profile it would like to maintain as best as possible. Once identified, the bank would strive to price products according to the risk taken on each customer and thereby maximize the return, given the risk taken. By assessing and pricing for the risk appropriately, banks can, theoretically, widen their target markets to encompass a broader risk spectrum.

Predicting the risk profile, or default likelihood, of a prospective customer is difficult, as we are predicting an event—default—with a low probability of occurring. Even in 2001 and 2002, when there were a record numbers of defaults, the overall risk of default among corporations is a rare event.

Not identifying a defaulting or deteriorating company, or "getting it wrong", has a high penalty for the bank in terms of credit losses. For example, lending in Argentina or to Kmart recently resulted in severe credit losses for many institutions. One can also recall Bank of New England's foray into real estate lending, which contributed to that bank's insolvency in January 1991. Identifying a company that does not default as a likely defaulter (a "false positive") also translates into a costly proposition, because there is a loss of business and opportunity. As a result, there is a strong incentive to "get it right": that is, to accurately identify companies that will default, while minimizing the mistaken identification of non-defaulters as companies likely to default. There is no benefit in erring on the conservative side, since business opportunities may be lost to institutions that are more accurate in assessing credit risk. Rather, there is always a benefit in trying to minimize any errors on both sides. The key here is the collection of data and utilizing those data to create models that will help identify companies with weak or declining credit worthiness.

Finally, success in risk management is a difficult and time-consuming concept to measure. The relationship a bank has with its customers is not a second-by-second relationship. It is a relationship that is built over time and it takes observation and data collection over the lifetime of a loan in order to determine whether the prediction of default or deterioration was accurate.

RISK ASSESSMENT TODAY

Data Warehousing and Credit Risk Modeling

Prior to the real estate collapse and leveraged buyouts of the late 1980s and the economic recession of the early 1990s, very little statistically based risk assessment was done. Most banks, and other arbiters of risk analysis (including rating agencies Moody's and Standard and Poor's) relied on the expert opinion of loan officers, credit officers and analysts, rather than any objective, statistical analysis.

After the crisis, banks became interested in how they could understand and manage the credit risk they were taking as part of their business on a more consistent basis. For example, Citigroup began an initiative to warehouse data that would be used to assist in risk assessment and utilize new data mining methods to analyze them. This effort involves the collection, storage and maintenance of large amounts of data, application of advanced modeling techniques, and constant monitoring and validation of the models that are in use.

A wide variety of data are necessary to analyze credit risk. Information on a company's financial position is one of the key pieces of data necessary, which is generally acquired via its annual financial statements. In the United States, for instance, financial statement data are readily available for companies that trade on one of the exchanges, as they are required to submit financial statements in a timely fashion to the Securities and Exchange Commission (SEC). An interested party can buy large data sets of company financials from a vendor or download statements from the SEC's EDGAR Website.

A side note to warehousing data and modeling in the United States is that approximately 1800 public U.S. companies are rated by one of the public rating agencies. For some institutions, ratings available from the agencies have mitigated the need for internal credit risk models, although larger institutions clearly need better coverage of companies that are not rated. There are clear risks to sole reliance on agency ratings. Since 2001, there has been a record number of "fallen angels" documented by the agencies. A fallen angel is a company rated investment grade that is downgraded to non-investment grade (or "junk" status). In some cases, the deterioration may have, in fact, been quite sudden. In others, it was clear that the agencies resisted downgrading the companies until the brink of default. While the key rating agencies have publicly committed to more timely downgrades, they are also concerned about volatile ratings, and some would charge, have a conflict of interest in rating companies that pay for those ratings.

Moving outside the United States data are not as easy to buy and timely reporting requirements are not necessarily as stringent. Because Citigroup has been doing business in over 100 countries on all continents (excluding Antarctica) for many years, we have access to both data and expertise across a wide population of corporations. As such, Citigroup requires effective credit assessment tools that produce ratings that are not only accurate but globally consistent.

Regardless of where a company is domiciled, a key aspect of data collection behind the development of credit tools focuses on defaulted companies: both the identification of "default" and also collection of financial information prior to default on this set of companies. Building a warehouse of financial statements of defaulted companies, with statements at least one-year prior to default, is essential if we are to build models to predict the one-year probability of default (which is an accepted time horizon in risk assessment). In effect, the only means of "validating" a model's accuracy against defaults is to be able to test it against actual defaults. If we can actively test the models against current or recent defaulted companies, we can make a judgment about the quality of the model today. A true benefit for credit risk modeling at Citigroup is that we have over 30 years of history on internal defaults across all businesses and regions. Those internal data, combined with research into non-customer defaults to build a global default database, have greatly enhanced our credit risk modeling efforts and allowed us to move toward models that directly measure default, rather than a rating category.

Internally, we also have access to a wealth of history on non-financial characteristics of companies, as well as industry segmentation. Generally, industrial data are gathered from outside vendors, as well as internal sources. Industrial data include general data on the industries with which we are working and information about a particular company's position relative to its peers in the industry. The existence of models and a rating-based credit process for over 13 years at Citigroup has allowed us to collect a variety of data regarding a company's market position, management quality, the risk appetite of management, quality of audited statements, time in business and time as a customer.

The next critical phase after data collection is data cleaning. No matter how much data we have, inconsistencies or inaccuracies can seriously jeopardize the quality of any modeling effort. Data quality is a concern whether we are working with our own internal data or data from a vendor. And unlike market data, credit risk data (such as financial statements) are "low frequency" (annual data in most instances). As such, almost every data point is valuable and serious effort is made to ensure that the data are accurate, while we discard as little data as possible. Many elements of the data will be checked, both through automated and manual processes. For instance, does the balance sheet balance, does the income statement flow properly to the reported net income, and can we confirm the default date?

Finally, this large warehouse of data, both customer and non-customer, which spans many years and many countries, will be used in modeling different aspects of credit risk that the bank will use in assessing the credit quality of a client.

VARIOUS MODELS OF RISK ASSESSMENT

Basic Models to Measure Credit Risk

As a starting point, lenders need basic credit risk calculators to assess the credit worthiness of their customers. At Citigroup, those calculators are called credit risk models. The large amount of financial and ratings data that the bank has actively collected and accumulated over the last 13 years, along with the extensive default database, allow researchers to build a variety of models that measure credit risk and associate that risk with a given probability of default. In line with the rating agencies, the bank utilizes a 10-category rating system with notching around each category (similar to S&P's system of letters such as AA+, AA, AA-, etc.). Unlike the agency ratings, each category is associated with a range of probabilities of default at Citigroup. There are models covering Citigroup's commercial and industrial customers (i.e., manufacturing, wholesale, retail, and service businesses) and commercial bank customers. Generally, the models cover a specific geographic region, while some models, such those for North America and Western Europe, have underlying industry-based modules.

The models use a variety of data elements that have been warehoused to accurately predict default probability directly or a rating that reflects a range of default probabilities. These include fundamental financial/credit analysis, company size and qualitative assessments. By taking the balance sheet and income statement of the company and boiling them down to a set of financial ratios that are common in credit analysis – such as the interest coverage ratio, the leverage ratio and the cash flow to debt ratio – we can use this information to help determine the credit worthiness or default likelihood of the customer. Ratios and inputs will vary from region to region and from industry to industry depending on factors such as accounting rules, local practices and, importantly, statistical significance.

Another key factor in determining default likelihood is the size of the company, which we have found to be correlated with credit quality: larger companies tend to have more financial flexibility (access to funding from many sources), more diverse revenue streams, customer base and geographic reach, and so forth. Depending on the specific model, the measure of size will be selected on a basis similar to the process for selecting the financial ratios. To the extent that we have history on more "qualitative" aspects of firms, such as market position, quality of management and infrastructure, and so forth, these data elements allow the modeler to "fine tune" the model for qualitative factors.

The first generation of models took the form of a model that tried to predict a given risk category and back out the probability of default utilizing simple linear regression. Currently, we still build and utilize models of this kind in which insufficient history does not allow direct modeling of default probability. But more and more, as we gather data and financial information on defaulted companies, we are able to model the probability of default directly. The key to building precise and statistically significant models is to gather both financial and qualitative data on defaulted companies—data such as the date of default, an understanding of why the default occurred and most importantly, the statement of accounts in the years preceding the default. This provides a more precise measure of risk assessment, as you are directly identifying the probability of default.

Originally, the models were delivered as a desktop application, and relied on an MS Access back end to warehouse all the data. Users were asked to input a limited balance sheet and income statement into the application, answer a selection of qualitative questions and then calculate the risk rating category. This method had severe limitations in terms of being a catalyst for data collection and warehousing. For the credit analyst using the model to make a credit decision, the inability to easily and electronically share data was a limitation. For the modeler, the database that stored the data input was not centralized. This meant that whenever any new analysis or model validation was required, the modeler had to solicit the data from a variety of locations.

At Citigroup, we have model coverage for our portfolio across the globe, with as many as 3,000 users, so any kind of data collection effort became a tedious, time consuming process for a large amount of people. Identifying all users, soliciting their databases and having them sent to the modelers took considerable time, yet was a supported venture by all involved because the value of the data and the models that it would create was recognized.

The credit risk models are generally re-estimated every three to five years, depending on performance and the volatility of the businesses covered. Every new release of the credit models includes increased sophistication with regard to the statistical analysis used to create the algorithm and with regard to the software. A key focus of new software development is how to simplify and improve the data warehousing. Finally, after much time and effort, a new credit risk model application was launched last year over a Citigroup-wide global network. One database will warehouse all the data that users from all over the globe enter into the model. This is the first step in building a real time data warehouse. The next step is implementing the models on an Internet-based platform, where the users would input information via a Web page, all relevant data are warehoused and a risk category is provided. Introducing a new global application is not a simple process and depends heavily on the information technology environment in all countries where Citigroup does business. So, an application, either server- or Web-based, that works seamlessly in New York, may be unusable in Kinshasa or Kuala Lumpur due to existing technological obstacles. Thus, the application must be designed with these variances in mind and tested extensively prior to implementation.

Not only does the data collected in real time allow modelers to build new models, it allows modelers to validate existing models – certainly a requirement of the new Basel II Accord (reviewed later in this chapter), which will allow qualifying banks to use internal ratings to set regulatory capital. With access to the data on an ongoing basis, we should be able to more quickly answer the question of whether or not the models are assigning the appropriate risk category to companies with declining credit worthiness. This aspect of validation is key to providing the risk managers, analysts and other users with tools that they can use to manage the risk of the portfolio and to identify problem customers. The most important validation of a credit model is via the collection of data on defaulted companies – this will let us see that the model is correctly assigning a more risky category to a weak credit. Ideally, you always want to observe a positive relationship between a more risky category and the incidence of default. This kind of validation allows us to adjust the model when appropriate, bearing in mind that the data used are yearly in frequency.

Early Warning Models

In addition to these fundamental models that measure credit risk, there are other kinds of models that can be built using the data that have been warehoused – models that provide early warning signals regarding default and deteriorating credit worthiness. They can fall into many categories, but we will discuss two:

1. Models that measure default likelihood.
2. Models that measure changes in credit risk.

These models are not used to assign risk categories to customers, but allow banks to monitor customers carefully and, generally, on a more frequent basis than fundamental credit risk models. Most importantly, they can provide an early signal that a credit is facing default or deterioration.

Default likelihood early warning models generate default likelihood estimates as output and can be built using company financial information, stock market information or a combination of the two. Because they mainly rely on stock market information as a data input, we can provide more up-to-date monitoring of the credit. Additionally, thousands of companies are listed on the U.S. exchanges, so a huge number of companies can be reviewed at one time.

Reliance on stock market data perhaps implies that the results will be less accurate than if the analysis was done on a company-by-company basis – as in the fundamental credit risk models discussed earlier. The stock market provides rich data that have significant information content regarding a company's health and welfare, but there is also much "irrational exuberance" embedded in the data, as well as other "noise" that may not speak directly to credit risk. Nonetheless, these models provide an efficient way to monitor both problem credits, as well as credits which may begin to deteriorate over time, for both the customer base and the non-customer base.

The second kind of early warning model focuses on change in credit quality. This "credit quality trend" model provides an estimate of the likelihood that the company's risk category or rating will be downgraded (i.e., the risk increases). This model is also built utilizing market information, so it has the same positive and negative issues with regard to using equity data to predict credit phenomena as the probability of default early warning models.

These models can be used for informational monitoring on a monthly basis and can be used to trigger reviews and investigation based on the results. As their use becomes more accepted and widespread, they can be used to trigger actual, policy-driven actions regarding the customer – such as limits on how much the bank can lend to the customer, required rating reviews and discussions with management of the customer.

The models are monitored on a monthly basis and accuracy and goodness-of-fit are objectively measured. Any changes that are deemed necessary because of the testing can be made as often as needed—this would generally be done on a monthly basis, since that is the frequency of the data being used in the testing. The default probability model is tested against new defaults that are identified to see if we have captured the defaults with a sufficiently high default likelihood. The credit quality trend model is also being objectively tested against publicly rated companies that have experienced significant degradation in their credit worthiness.

Measuring Loss

The second component of credit risk is the loss given default (LGD) for the portfolio of the bank. This does not represent a significant connection to data mining, but it is integral to risk assessment and goes hand-in-hand with the other true data mining activities described above. Generally, the loss given default refers to the loss the bank will incur from its exposure to a given customer in the event that the customer defaults. If a bank, for example, has an LGD of 40%, the bank, on average, can expect to lose 40 cents for every dollar of exposure to a defaulting customer. It is this piece of information, along with the credit risk category, that will enable the bank to calculate the amount of regulatory capital it will be required to hold—we will discuss this in the next section.

There is a tremendous problem here with capturing the data necessary to perform this calculation. A large amount of detail is required on the specifics of the actual lending to calculate an accurate LGD, as well as a long history of defaults and the concurrent information about the lending.

Use of Information

2002 was a year when market watchers saw the credit worthiness of the corporate world at a low point. Countries defaulted, there were widespread defaults in various industries, like the telecom industry, and fraud-related defaults plagued the international markets. Now, uncertainty of the international political scene continues to have the financial markets in disarray and the hope for an end to the U.S. recession is further away.

Even so, in this high default rate environment, the organizations suffering the most are not necessarily the banks, as one would expect. In this current credit cycle, the banks have finally been able to use the information and analysis that they have been doing in a fruitful way. As banks have begun to understand the credit risk of their portfolios, they are creating new products, like credit derivatives, bundling the credit risk and selling it. As a result, the credit risk is no longer concentrated on the books of the banks, but rather, has been voluntarily spread amongst many insurance companies and pension funds, as they have purchased the derivitive as an investment.

FUTURE OF RISK ASSESSMENT

One of the important aspects of data warehousing and model building is, as we have discussed, that the banks can make more informed decisions regarding the risk they hold on their balance sheets. They can identify the customers with which they want to do business, the level of risk they want to incur and make decisions regarding the management of the risk they are carrying. Other important factors that the banks will have to address are the fundamental reforms that are sweeping through the banking industry.

Currently, banks are required to keep a fixed amount of regulatory capital set aside for a credit event. This amount is regulated by the 1988 Basel Capital Accord of the Bank for International Settlements. The Basel Committee on Banking Supervision announced in June 1999 a proposal to replace the 1988 Capital Accord with a more risk-sensitive framework, the Basel II Accord. A second proposal was released in January 2001 that incorporated comments on the original proposal. The proposal is based on "three pillars" that would allow banks and regulators to evaluate various aspects of banking risk, including market, credit and operational risk. These include: minimum capital requirements, supervisory review and market discipline. The existing accord focuses on coming up with the total amount of bank capital, an amount that is important in preventing a bank from insolvency during a credit event. It uses an approach that does not benefit a bank that has any active risk management. For instance, a bank that actively seeks out very low risk customers will be required to hold the same amount of regulatory capital as a bank that does not manage its risk profile.

The new proposal seeks to expand this approach to include a variety of measures of risk, including a bank's own internal methodologies. For credit risk, there are two approaches: the Standardized approach and the Internal Ratings Based, or IRB,approach. The Standard approach is very similar to the existing Accord, but where the existing Accord only provides one risk weight, the Standard approach will provide four. The IRB approach is where banks who have been warehousing data and using them to build better credit risk models will benefit tremendously. This approach will allow banks to use their credit risk models in determining what amount of capital will need to be held. The approach is broken into two segments: foundation and advanced. In the foundation approach, a bank will be able to use the output of its credit risk models—the rating—which is associated with a likelihood of default, and the banking supervisor will provide the other inputs to calculate the capital requirement. In the advanced approach, a bank will use the output of its credit risk models and will be able to supply the other inputs as well. In addition to the probability of default, these inputs include loss given default, exposure at default and maturity.

Ideally, if a bank is managing its risk, it can reduce the amount of regulatory capital that it is required to hold. Because this approach provides significant benefit to banks that can prove the validity of their risk management system to their regulators, via detailed testing results and disclosure on the data and modeling used, there is much incentive to continue to warehouse data in the most efficient fashion and continue to build better, more precise credit risk models that utilize newer statistical techniques.

CONSUMER LENDING

Consumer lending traditionally included house mortgages, car loans, personal loans, and so forth managed at the local branch. The risk evaluation was very crude; there was little specificity in the risk assessment. Usually, the loans were treated alike and a common risk was assigned to them. With the help of the computer, the data collection started, which paved the way for tailored risk decisions. The decisions of extending a loan and then pricing it moved beyond the previous crude means and now were based on statistical models using the massive data sets compiled.

Nowadays, the newest methods, neural networks, may be utilized to evaluate the risk of customer lending. The models are constantly validated and updated by each loan activity—approved or rejected and defaulted or non-defaulted. These techniques can easily place the model building and updating into the hands of the banker, who only has to feed the key parameters of the next loan and those of the borrower into the neural network. The technique presents the accepted/rejected decision, which the banker is free to modify. The final decision about the approval is fed back into the system, where this extra information prompts the neural network to adjust and fine tune its decision-making process. The parameters of the defaulted loans are also fed into the system, which causes the decision-making process to adjust itself. Besides the widely used so-called score-card, this flexible neural network approach has been gaining importance and it may provide a tailored decision-making process for each branch.

The revolution in consumer banking can also be seen in the widespread use of the automated teller machines (or ATMs). Behind those "money machines" there are high-powered databases, linking all accounts of a customer instantaneously with artificial intelligence.

The newest way of banking is the online banking, which provides access to almost all services we used to obtain at a branch. Barring a few activities (e.g., withdrawing cash, getting a certified check), we can perform all banking transactions on our personnel computer. The online banking is not only a service to the customers, but it acts as a regular Website, equipped with all marketing and artificial intelligence power.

CREDIT CARD

Credit Card (which is a special, proliferated loan business) belongs to consumer banking, but it has become so large a business that we discuss it independently. The lucrative credit card business, in today's form, owes its existence solely to data warehousing and data mining. The business is only a few decades old (e.g., the predecessor of the Visa card was born in 1958), but it has grown into one of the most important segments of banking. A credit card is a revolving credit, where the customer pays an annual fee (which is waived at many institutions in today's competitive market) and interest on the borrowed amount, and the merchant pays a certain percentage on the purchase. The primary activity of the company that issues the credit card is information storage (recording each purchase of each credit card account), purchase authorization, billing and fee collection.

The amount of information gathered and stored is tremendous. Let us take a modest portfolio of 1 million credit card accounts and assume 30 purchases a month per each account. The portfolio will accumulate data on 360 million purchases within a short year, and each purchase will be described by many attributes (e.g., amount and time of purchase, type and location of store). Without any investment, adding all available internal data on the customers (e.g., activities of other bank accounts) can further enrich this precious data set. The data set is also enriched by adding information from external sources, as well. Such data can be individual lifestyle and demographics information (e.g., buying preferences, various magazine subscriptions, residential information, etc.), or census data at the lowest possible level.

The ability to warehouse, link, and mine this information can lead to profitable and powerful business opportunities, and the possibilities are enormous. Accordingly, these colossal databases are useless unless we can extract the necessary knowledge from them. The various statistical techniques offered by data mining allow us to probe these huge files and create models for any kind of marketing activity. Let us review some of the main activities in the credit card operation. These activities are synchronized efforts between marketing and data analysis. The two sides affect each other by constant interaction and feedback. For example, marketing plans to solicit certain merchandise. Data mining can not only discover segments of the population receptive to that solicitation, but can describe various hidden attributes of those segments, which, in turn, can help marketing to position its product more effectively.

- **Acquisition:** Acquisition is the most fundamental activity that builds up the portfolios. Even though the local markets might be saturated, there is still opportunity by offering second or third cards, and the local portfolios can be expanded into global ones. Acquisition may target current customers or people from external sources. The successful acquisition campaigns target the potential customers with the help of statistical modeling, which predicts the highest possible rate of acceptance and conversion.
- **Retention:** Retaining existing customers is the cheapest way of acquisition and it gains importance as the market gets saturated. In a

way, it complements acquisition. It analyzes the characteristics of those customers who cancelled their credit card accounts, and in the next wave of acquisitions, those types of customers can be identified in advance and special programs can be designed and directed at them to keep them active customers. For example, credit cards with special promotions (such as purchase reimbursement) can be offered.

- **Default management:** Managing risk in the credit card portfolio is as fundamental as in the corporate loan portfolio described in the first section of the chapter. Similar to the practices there, the collection and full analysis of the defaulting credit card accounts is the centerpiece of building statistical models to predict, minimize or avoid defaults. The knowledge learned from the defaulting accounts influence almost all activities in the portfolio.
- **Cross-selling:** A principal rule of marketing is, "Your own customers are your best customers". It is much more cost effective to sell a product to a current customer than to a non-customer. We collect huge amounts of high quality information on our own customers. The knowledge gained from mining this vast set of data provides many possible ways to offer our next product. But more importantly, our customers have already demonstrated loyalty, which increases our chances for success. Cross-selling involves the bank's various financial products (e.g., investment), but the bank can team up with other financial (e.g., insurance) and non-financial (e.g., travel) companies to solicit products of a different nature. Besides generating outright profit, cross-selling is also an opportunity to add more information to the customer database, making it more valuable for the next marketing campaign.
- **Boosting long-term value:** After maintaining a long relationship with the credit card customers, the bank possesses so much information that a statistical model can be developed to model the long-term value of the customer—as a credit card holder and as a general bank customer. The former may only rely on the credit card purchase history of the customer; the latter takes into consideration the activities in all accounts of the customer. The long-term value model should influence the cross-selling practices, since that value is the combination of all accounts and the optimum may be achieved, while the profit in one account is not the largest possible. The bank performs delicate research by linking all available data of a customer and sometimes learns information not directly translatable into profit, in order to boost customer loyalty. The virtue of restraining marketing efforts should also be exercised (e.g., let us not bombard the customer with solicitations of a low-profit product, when the customer may purchase a high-profit product).
- **Fraud detection:** Fraud detection protects both the bank itself and the customer. Credit card and identity theft is an increasing danger, which can be fought with the help of data mining. Utilizing various statistical methods, we can recognize unusual purchase patterns and act immediately. The purchase pattern recognition is based on some common rules applied to all customers utilizing *individual* purchase history data. The model is individually built, at least in the sense that a common framework takes the parameters or trigger values specific to a credit card account. Of course, the longer the credit card account has been active, the more reliable the fraud detection.
- **Selling customer data:** Data warehousing, data mining and capturing high quality information on long credit card usage gave birth to a new business within the credit card

sector: information commerce or selling information on customers. First, we have to state that customers' privacy must be protected and selling information must be done within the legal and *ethical* constraints. Prudence has a selfish reason, too: companies protect their best customers. Two types of activities can be differentiated based on the level of information sold: individual and summarized.

- Selling mailing listsof defined properties (e.g., list of new parents, which could be compiled by identifying accounts of twenty- and thirtysomethings with sudden disappearance of restaurant use and concurrent appearance of pharmacy use, especially diaper purchases). Companies can easily find the segments of desired attributes in the databases.
- The databases can be researched for buyer's behavior, specific purchase patterns, merchandise preference, linking of merchandise, and so forth. This market research results in summarized information found in the database, not individual customer data as before. Other companies perform similar market research (let us think only of supermarket chains, which offer various discount cards not only to boost customer loyalty, but equally importantly, to gather precious data to facilitate market research).

- **Customer service, online account information:** Data warehousing makes flexible, multifaceted customer service possible. Besides providing a basic billing and account information service, it opens a new channel of marketing and selling various products. After the customer initiates the contact and obtains the necessary service, the system instantaneously directs the customer service representative to offer products in which the customer is likely to be interested.

Notes:

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EDITOR'S NOTES

As you can see, the evolution of data, storage and analytic techniques has helped transform and augment a number of strategic functional activities within the banking sector. The effective utilization of quantitative and statistical methods incorporated in data mining can often lead to more effecient organizational operations. The past chapter clearly illustrated this concept by describing the benefits data mining and quantitative analytic techniques add to risk management activities in the world of lending. The next chapter will further address the topic of enhancing operational efficiency in lending practices and will focus more on activities in lending to small buinsesses. The concepts in the next section provide a more detailed illustration of managing risk in lending to small businesses through data mining and also extends to such topics as increasing market shart (e.g., new customer acquisition) and overall profitability.

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Chapter XIX
Data Mining for Credit Scoring

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ABSTRACT

Credit scoring is one of the most popular uses of data mining in the financial industry. Credit scoring can be defined as a technique that helps creditors decide whether to grant credit to customers. With the use of credit scoring, decisions about granting of loans can be made in an automated and faster way in order to assist the creditors in managing credit risk. This chapter begins with an explanation of the need for credit scoring followed by the history of credit scoring. Then it discusses the relationship between credit scoring and data mining. The major applications of credit scoring in three areas, which include credit card, mortgage, and small business lending, are introduced. This is followed by a discussion of the models used for credit scoring and evaluation of seven major data mining techniques for credit scoring. A study of default probability estimation is also presented. Finally the chapter investigates the benefits and limitations of credit scoring as well as the future developments in this area.

INTRODUCTION

Data mining has been widely applied in the financial industry to predict stock prices, forecast interest rates, assess credit ratings of bonds, and manage portfolios. Among all applications of data mining in the financial industry, credit scoring, which is prediction and management of risk, is one of the most popular applications with a long history. This chapter will describe the history, applications, models evaluation, benefits, and limitations of credit scoring.

Credit Scoring

Credit scoring refers to the "techniques that help lenders decide whether or not to approve loan applications" (Lyn, 2006). It is a procedure in which every single piece of information obtained from a customer's credit application is assigned points that are consequently aggregated to form a numeric figure called credit score (Mays, 2004). To determine these points, a "scorecard" is used. Credit scoring grew in response to a surging demand for offering more credits in a quicker, fairer, and more consistent way in the expanding financial markets. Lenders are turning to this decision-making system because lending to consumers represents chances of default, and they seek ways to minimize the default risk and increase debt repayment (Limsombunchai, Gan, & Lee, 2005).

The classification of an applicant as a good or a bad payer is determined by the characteristics noted on the credit application and creditworthiness behavior of the person. Various factors are considered that include data from the application form (e.g., occupation, income, address, age, marital status, etc.) and behavioral data activities (credit history, average balance, etc.) (Thomas, Ho, & Scherer, 2001; Thomas, Edelman, & Crook, 2002). There are two types of decisions that lenders need to make. The first decision is whether to grant credit to a new applicant, and the second decision is how to deal with existing applicants and whether to increase their credit limits or not. The former is called application scoring and it applies the technique of credit scoring and is performed for credit risk determination, loan amount approval, and limit setting on the grounds of statistical analysis. The latter is known as behavioral scoring or a statistical approach to forecast future performance of customers by utilizing their current and recent behavioral data. Credit restriction or marketing efforts directed towards a current customer are adjusted after recalculation of score to capture the risk level over a timeline. Decisions on authorizations, limitation of overdraft applications, renewal reviews, and collection strategies are made based on behavioral scoring. In both cases, the essence lies in the fact that a large sample of customers with their application details and subsequent credit history are available. Both scoring techniques use the sample to identify relationships between the characteristics of the consumers and how 'good' or 'bad' their subsequent history is. Thus, it can be said that both application and behavioral scoring techniques are focused on predicting how the borrower will behave in the future given how they have behaved in the past.

BACKGROUND

Manual assessments of credits by analysts in the early days before the Second World War were error-prone and inconsistent as firms depended on the credit analysts' rules of thumb to decide to whom to give loans. Automation of credit decisions and the classification techniques developed in statistics were linked together to give rise to a systematic practice in making lending decisions. The forerunner roles were taken up by Bill Fair and Earl Isaac in the United States in 1958 to develop the first commercial scorecard system. The initial adoption of FICO scores proved to be a successful move, as delinquencies were reduced by 20-30% while maintaining similar volumes of lending, or lending volume increased by 20-30% when delinquency was maintained at the same level (Fishelson-Holstine, 2004).

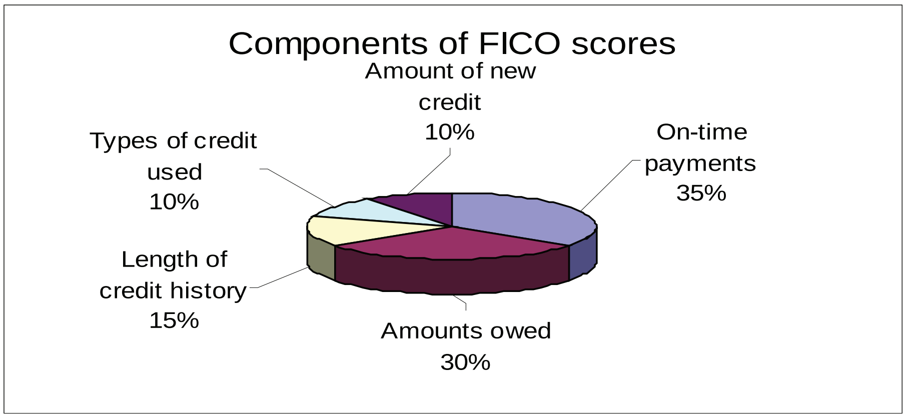
Credit scoring was not widely embraced until the arrival of credit cards in the late 1960s. The large number of people applying for credit cards everyday made it impossible in manpower terms to process these applications without an automated lending decision mechanism. Because of that, banks and other card issuers finally realized the utility brought by credit scoring. Meanwhile, Fair Isaac had developed the first bank scorecard system for Connecticut Bank and Trust. With the growing popularity of credit scoring, 60% of the nation's largest banks, 70% of finance companies, major credit card issuers, and all the travel-and-entertainment cards implemented a quantifiable scoring system by the end of 1970s. The passage of the Equal Credit Opportunity Act and its amendments in the U.S. in 1975-1976 guaranteed a general acceptance of credit scoring. The technique then spread from the U.S. to the UK in a short period of time.

The use of credit scoring in handling applications for credit cards demonstrated that banks could use scoring for other financial services like personal loans, mortgage loans, small business loans, and so forth. The trend was accompanied by technological advancements in the exploration of more sophisticated techniques for building the most preferable scorecard. For instance, logistic regression and linear programming that were introduced in the early 1980s and artificial intelligence techniques such as neural networks that were introduced in the 1990s became a part of credit scoring systems. Nowadays, the focus of attention in scoring has switched from trying to minimize the default rates of a customer on specific products to emphasizing how the firm can maximize profits that it can generate from the customer. A variety of scorecards that can estimate response, usage, retention, attrition, debt management, and fraud detection have been augmented to the original intention of predicting default risks in classic models. More scoring systems have been introduced for different types of consumer lending products by many different types of lending organizations all over the world throughout the decades, and this trend is believed to be proliferating. In fact, it has been reported that an average person in the U.S. or UK undergoes credit scoring at least once a week (Thomas, 2000). This goes on to show the importance of credit scoring.

Fair Isaac Corporation (FICO) Score

Nearly all large banks build and use their own models for credit scoring purposes, but the most commonly adopted one is the Fair Isaac Corporation (FICO) score. The FICO score is calculated using mathematical formulae developed by Fair Isaac, a well-known credit scoring consultancy

Figure 1. Components of the FICO score for credit scoring



firm in the United States. The three major credit reporting agencies in the U.S. calculate their own versions of the FICO score: Beacon at Equifax, Empirica at TransUnion, and Fair Isaac Risk Score at Experian. These versions, developed by Fair Isaac using the same method and testing procedures, differ slightly. Although the exact formula for calculating the FICO score is a closely guarded secret, Fair Isaac has disclosed the components and the approximate weighted contribution of each component, as illustrated in Figure 1.

Credit Scoring and Data Mining

Credit scoring and data mining are closely related. Credit scoring models always involve the successful use of data mining techniques. It is undeniable that the commercial advantage found in the credit industry has aroused corporate attention in the emerging technology of data mining. With the advent of electronic money transfers at point of sale and various loyalty cards, lending organizations are able to gather information on all customer transactions. Significance of the customer information is highly treasured, as the firms think it is essential to understand and target their customers. Advanced computing and the presence of the Internet have allowed the firms to analyze large volumes of data collected on a real-time basis. At the same time the Web has introduced new competitors and substitute products, and encouraged easy communication channels that promote customer churn. To combat this situation, organizations are willing to set aside a considerable budget for the development of data warehouses that record all customer data and apply data mining techniques for analyzing them. Processing and exploration of the large volume of data resident in the data warehouse while discovering meaningful patterns and relationships makes data mining a powerful analytical tool. Data mining techniques such as data summary, variables reduction, observation clustering, and prediction and explanation are useful for credit scoring, as those are derived from standard statistical techniques.

TYPES OF CREDIT SCORING AND ASSOCIATED MODELS

The following sections will introduce and discuss three major credit scoring applications in credit card, mortgage, and small business lending, respectively. Credit scoring was first developed in order to be used for credit card approval, and later on it was also applied for mortgage applications and small business lending.

Credit Scoring for Credit Cards

A credit card issuer would like to grant credit cards to candidates with a good risk profile and no previous history of unsettled debts or unpaid loans. There are two procedures used for this, namely credit checking and credit scoring. The lenders will check the customer's credit history, which records the past borrowing and repayment patterns (late payments or bankruptcy information) from credit reference agencies such as Experian, Equifax, or TransUnion. Factual personal information like name and address, past Country Court Judgments, or defaults about him or her are included as part of the relevant credit reference.

After capturing the credit reference for the customer, the lenders will score the customer by allocating various points to the answers given in the application form according to its own scoring system (Hurlston, 2005). The points received by the customer's application are then summed up to give a final credit score, which determines the success or failure of the application of the customer. It is a common and well-known practice to assign higher points if the customer can provide a home telephone number, and can demonstrate a considerable tenure with the current job and the same for residence location. At the same time the customer needs to show evidence of maintaining a satisfactory relationship with banks. Nonetheless, the application is usually affected if there are any signs suggesting there is a repayment problem or if any inconsistencies are observed between the address provided in the application form with that which appears on the Electoral Roll.

Credit Scoring for Mortgages

A mortgage is a method of using property as security for the payment of a debt. Scoring for mortgages is quite different from scoring for a personal loan or credit card because of the collateral involved in the loan and the schedule of interest rates. It is easier to do mortgage credit scoring because lenders are less concerned about how the borrowers are going to pay the mortgage. However, the calculation of mortgage rate is complex, as interest rate has a great influence on the period of the loan and the customer's credit history plays a role in deciding on the interest rate.

Automated underwriting systems use score-based loss forecasting models to determine the likelihood of a borrower defaulting on his or her mortgage loan obligation (Financial Services Roundtable, 2001). The models are based on data available for each loan at the time of origin. They compare payment histories from literally millions of similar loans coupled with the credit score of the applicant, and then estimate probability of each loan's lifetime default and the likely amount of the loss if there is a default. The expected lifetime loss for a loan is input to the models to calculate a risk-based interest rate and prices for loan pools. The estimated future portfolio losses at every point in the life of the portfolio are also used to evaluate the adequacy of loan loss reserves.

Equifax, Experian, and TransUnion are the three major repositories of credit and background information. The monthly credit report of the payment history of a consumer is provided by the creditor when the consumer obtains credit. The five key factors analyzed by the credit scoring systems to generate a single score are the borrower's record of paying their debts, collection accounts, and public records like bankruptcies and lawsuit judgments; inquiries to a borrower's credit report; ratio of outstanding balances to available credit limits; and length of time since the opening of the credit account (Chisholm, 1998).

Credit Scoring for Small Business Lending

In the past, the way to make loans to small businesses was similar to that for large corporations where the borrower and the lender negotiated loan terms uniquely. The small businesses needed to provide detailed information about business plans and the firm's financial statements while the lenders carefully review the data using analytics. Therefore, the loan approval process highly depended on the relationship between the company and the bank, as well as the information of the company held by the bank (Frame, Srinivasan, & Woosley, 2001).

Due to the increasing amount of small business lending, the Small Business Scoring Service (SBSS) consisting of 11 credit scoring models was developed by Fair Isaac and adopted by Wells Fargo in 1993. These models are designed for evaluating companies with sales under US$5 million that are applying for loans up to US$250,000. The following are the four major types of small business credit scoring models from which to choose, or to combine, depending on the needs of the business:

- A generic model that predicts the likelihood of a company paying in a severely delinquent manner based on a sample of businesses from across all industry segments and utilizing a wide range of commercial information.
- An industry-specific model that predicts the probability of delinquent payments based on a sample of firms within a given industry.

- A model that predicts the likelihood of a small business's payment performance based on the owner's payment behavior.
- A scoring model developed from a sample of businesses that most resemble the bank's actual borrowers.

Data Mining Techniques for Credit Scoring

The following section presents seven common data mining techniques for credit scoring. According to a white paper published by Fair Isaac in May 2003, the first three of these techniques, namely neural network, support vector machine, and discriminant analysis, are very commonly used.

A *neural network (NN)* is an information processing structure that transforms a set of inputs into a set of outputs. More specifically an NN is a collection of simple processing units linked via directed and weighted interconnections. Each processing unit receives a number of inputs, weights these inputs based on the weights of the corresponding interconnections, combines these weighted inputs, produces an output based on this combined input, and passes this output to other processing units via the appropriate weighted interconnections. Mathematically, this process can be represented by a non-linear mapping function that maps the set of inputs to a set of outputs (West, 2000). NNs have commonly been adopted in credit scoring. They have demonstrated good capability and robustness in dealing with bad applicants in consumer lending (Sarlija, Bensic, & Zekic-Susac, 2006). According to a study conducted in Maine, USA, NN models exhibited 92% accuracy in predicting disposition of small business loans, as compared to 86% accuracy exhibited by a regression model (Yegorova, Andrews, Jensen, Smoluk, & Walczak, 2001).

A *support vector machine (SVM)* is a new technology for solving the classification problem. This is described in terms of three elements. The first element is the score formula, which is a linear combination of the features selected for the classification problem. The second element is the objective function, which takes into account both training samples and test samples to optimize the classification of new data. The third element is the optimization algorithm for finding the parameters that optimize the training sample objective function.

Discriminant analysis (DA) classifies a set of elements into two or more predefined classes based on a set of variables (predictors). Unlike regression analysis, the dependent variable in DA must be categorical. There are two ways to describe DA. If the method classifies according to the ways of processing the predictors, then this is known as the direct method. This method involves estimation of the discriminant function so that all predictors are assessed simultaneously. There is also the stepwise method which allows the predictors to enter the model sequentially. If the classification is done according to the number of categories for the dependent variable, then the two-group method allows the dependent variable to have two categories and the multiple-group method allows three or more categories.

A *decision tree (DT)* is a predictive technique with a tree structure, where the branches represent different possible values of input variables, and the leaves refer to the final classification (i.e., output). A decision tree can be developed by starting from the root node and asking questions related to the input variables, so as to split the next level into two or more branches. In other words, each path from the root to a leaf essentially refers to exactly one classification rule. A number of credit scoring models have been developed using decision trees. For instance classification and regression trees (CARTs) were used to classify commercial loans (Marais, Patell, & Wolfson, 1985). In a study carried out in China, it was found that the decision tree gave a smaller error rate than logistic regression in classifying customers at a commercial bank (Li, Ying, Tuo, Li, & Liu, 2004).

Survival analysis (SA) is a new type of model used for credit scoring. The conventional customer credit scoring methods distinguish good borrowers from bad ones at the time of loan application in terms of the ability for repayment. In addition to varying the price and interest rates charged to customers with different perceived risks, there is a growing interest to investigate when the customer can be expected to fail to reimburse. SA is beneficial because it can provide financial institutions with the ability to compute the profitability of the customer over the customer's lifetime and further perform profit scoring (Baesens, Van Gestel, Stepanova, & Vanthienen, 2004). Instead of predicting the likelihood that an event will occur, SA predicts the time until the event will occur (Mays, 2004). In an SA approach, a probability that the stated event will happen in each future time period will be derived. For loan application, the major interests are borrowers' default and other profit impacting events such as early repayments. Data sets of applicants accepted for loans will be analyzed using different modeling techniques such as the Kaplan-Meier method, proportional hazards model, or NN (Baesens et al., 2004), and the corresponding probabilities of borrowers' default or early prepayment are determined in each future time period of the loan's life. By incorporating such information, banks can monitor their debt provisioning and repayment behaviors demonstrated by customers. SA also allows the incorporation of the effect of changes in the economy over the loan duration which makes it an important tool for behavioral scoring.

A *fuzzy rule-based system (FRBS)* closely models human knowledge and experience (Weber, 1999). While most of the credit scoring models focus on providing an accurate score without explaining how the results are produced, recent developments in FRBS allow credit experts to design rules that accurately derive the credit score with explanation (Hoffmann, Baesens, Martens, Put, & Vanthienen, 2002). A key component in developing an FRBS is to convert the numeric inputs into categorical measures. For example, quality of management is judged to be poor, fair, or good, and debt burdens are described as low, moderate, or high. As a means to model the concept of partial truth, FRBS is specifically designed to deal with imprecise concepts in natural languages like 'slightly', 'quite', and 'very'.

When rating the credit of a bond, Moody's Investors Service, Standard & Poor's, and Fitch all claim that economic, fiscal, debt, and administrative factors should be considered, and about 10 to 20 core variables should be used. However, it is said that the rating agencies themselves have been ambiguous about the key inputs affecting their rating decisions. According to Lovescek and Crowley (1996): "Rating agencies have never publicly revealed either what variables are, on average, the prime determinants of bond ratings, or the weights to assign each variable."

FRBSs are particularly well suited for the rating process because the fuzzy rules are specifically designed to enable contextual use of information. They can handle both quantitative and qualitative factors. Therefore, the use of fuzzy rules for a large set of inputs leads to scoring results that are less sensitive to small measurement errors. An FRBS to evaluate financial performance of governments shows that in rating bond credit, the correlation between FRBS summary score and Moody's score is 0.85 (Ammar, Duncombe, Hou, Jump, & Wright, 2001).

A *hybrid model (HM)* is a general term used to describe credit scoring models developed by combining two or more existing models. Research has noted that the weaknesses in the existing models are a reflection of the failure of the model's architecture rather than a failure of the model itself (Hsieh, 2005). The following paragraphs describe two hybrid models that have been developed for application in credit scoring.

The structural default-risk model was extended from the Merton model by combining the traditional models with the contingent claim analysis structural models. This model is particularly useful for estimating default probabilities of firms and for valuing corporate liabilities. It is based on the idea that "corporate liabilities (debt and equity) can be valued as contingent claims on the firm's assets" (Benos & Papanastasopoulos, 2005). It takes in data about a firm's current financial information (including accounting variables and financial ratios), which reveals the future prospects of the underlying firm. Unlike traditional models, it does not take into account credit risk factors such as liquidity, profitability, efficiency, and viability.

The second hybrid model is known as generic hybrid genetic algorithm–artificial immune system (GA–AIS). As its name suggests the model was developed by combining the Genetic Algorithm and Artificial Immune Systems. It is expected that the model can be applied to a wide range of areas including consumer, corporate business, and country credit. The model is based on the algorithm called artificial immune recognition system (AIS), which has "proved to be among the best classifiers" (Leung, 2006). The model was trained using historical data, the results were compared with those generated from standard credit scoring statistical techniques, and it was shown that AIS has better performance than existing methods.

Table 1. Comparison of data mining techniques for credit scoring

	Strengths	Weaknesses
Neural network	◆ Captures non-linear, non-additive relationships in data ◆ Handles both continuous and categorical predictors and outcomes ◆ Handles multiple outcomes in a single model ◆ Technology readily available in the form of popular software	◆ Provides few insights about data ◆ Results are difficult to interpret ◆ The solution may be sensitive to starting point due to multiple locally optimal solutions
Support vector machine	◆ Captures non-linear, non-additive relationships in data ◆ Handles both continuous and categorical predictors ◆ No data structure assumptions in the non-parametric case	◆ Difficult to interpret unless the features are interpretable ◆ Standard formulations do not include specification of business constraints
Discriminant analysis	◆ Can separate and classify individuals into multiple groups ◆ Handles multiple outcomes	◆ Predictor must be categorical ◆ Assumes predictor variables are distributed as multivariate normal
Decision tree	◆ Easy to use and understand ◆ No processing of data is required ◆ Handles both continuous and categorical predictors	◆ Output must be categorical ◆ Limited to one output attribute
Survival analysis	◆ Provides time-varying credit information ◆ Offers estimation for the whole loan period (instead of just before loan application)	◆ Needs to give unambiguous definition of "death" (e.g., customer's default)
Fuzzy rule-based system	◆ Provides more specific results with explanation ◆ Identifies real-world ambiguity	◆ Difficult to formulate due to its informal interpretation of data
Hybrid models	◆ Higher accuracy given by combining advantages of two or more models	◆ More difficult to formulate and implement than ordinary models

Alternative hybrid credit scoring models include neural discriminant models (Lee, Chiu, Lu, & Chen, 2002), neural networks and adaptive multivariate regression splines (Lee & Chen, 2005), and two-stage genetic programming (Huang, Tzeng, & Ong, 2006). It has been shown that most hybrid models have better predictability than models based on individual methods (Wang, Wang, & Lai, 2005) and allow easy interpretation of classified results (Hsieh, 2005). Table 1 compares the seven data mining techniques in terms of their strengths and weaknesses.

Model Development

The following describes how credit scoring models are developed. Experian's (2003) Commercial Intelliscore model is provided as an example to illustrate each step:

- **Define the objective:** The whole process of model development is initiated by a specific objective. In general, each model is developed for the need to predict the possibility of a certain outcome based on specific information. For instance, the objective of the Commercial Intelliscore model is to predict the likelihood of a business becoming greater than 90 days delinquent (i.e., delayed repayment) within a six-month period.
- **Collect data:** Once the objective has been defined, the next step is to gather sample data related to the objective. A common practice is to gather as much data as possible so that a better model can be obtained. In the Commercial Intelliscore model, data on 3.4 million businesses, including commercial credit information, business demographic information, and public record information, are obtained.
- **Analyze data and create a model:** The step that follows data collection is data analysis using data mining techniques. The data mining process looks for significant relationships between what the model wants to predict (dependent variable) and all the possible variables that can influence the predicted variable. The variables that have a relationship with the dependent variable are called independent variables. Once the process identifies all significant relationships between the dependent variable and the independent variables, an equation of the model is generated. Given the values of the independent variables, the equation can be used to predict the value of the dependent variable. The model can be fine-tuned by a process called segmentation, which involves division of the sample data into homogeneous groups (also called segments or scorecards). In the case of the Commercial Intelliscore model, regression of the sample data is used as the first step to generate six segments with more than 50 independent variables. The six segments are based on prior trade experience, amount of trade activity, presence of public record information, and size of business.
- **Validate the model:** After a model is created, it needs to be validated. When a model is being developed, a small set of data is randomly selected from the original sample data. This data is not used to develop the model and is called the holdout sample. The dependent variable value predicted using the model is compared with the actual value of the holdout sample. The closer the predicted value is to the actual value, the better the performance of the model. The Commercial Intelliscore model continues to be validated regularly by Experian and its clients that use the model to score portfolios of accounts.

A Study in Default Probability Estimation for Business Lending

Default is a failure to meet financial obligations (Davydenko, 2005). Before a financial institution issues a loan to a business, whether large or small, a major concern is how likely is the debtor to pay back the loan. In other words, estimating the probability of default (PD) of a business is a very basic step to business lending. In the following section, we will present a number of models for estimating PD, which are categorized into two types: economy-based models and accounting-based models. The former considers parameters that are related to the economy of a particular business sector, while the latter focuses on data of the concerned business (Chakrabarti & Varadachari, 2003).

Economy-Based Models

A basic assumption of economy-based models is that within a specific business sector, all firms will have similar financial performance in a particular period of the business cycle. Chan-Lau (2006) suggested the following framework for estimating PD:

$$p_t = h(X_t, V_t),$$

where p_t is the sector-specific PD over a given time horizon t, X_t is a set of economic variables (such as GDP, interest rates, and unemployment rate), and V_t is a random economic shock.

In particular, the following equation has been developed to estimate macroeconomic effects in PD based on default rates in various industries (including construction, agriculture, manufacturing, etc.) in Finland (Virolainen, 2004):

$$p_{j,t} = \frac{1}{1 + \exp(y_{i,t})}$$

where $y_{i,t}$ is an increasing function of a number of macroeconomic variables. In other words, a set of more favorable economic indexes result in a lower PD, which holds for most economy-based models.

Accounting-Based Models

Accounting-based models rely on accounting data from a business for estimating firm-specific PD. The common accounting data used include profitability ratios, leverage ratios, growth variables, liquidity ratios, activity ratios, and size variables. These variables are selected in such a way that they have a higher discriminating power for predicting cases of default (Chan-Lau, 2006).

One of the most well-known accounting-based models is Altman's Z-score, which was developed by Edward Altman in the early 1960s using Multiple Discriminant Analysis (Altman, 1968). A total of eight variables from accounting statements are used to predict a firm's PD.

From these eight variables, the following five ratios can be evaluated:

X_1 = (current assets - current liabilities) / total assets
X_2 = retained earnings / total assets
X_3 = EBIT / total assets
X_4 = market value of equity / total liabilities
X_5 = net sales / total assets

There are two versions of the Z-score (Altman, 2000):

For public business: $Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$

Table 2. Variables used in Altman's score

Variables in Altman's Z-score
◆ total assets
◆ total liabilities
◆ current assets
◆ current liabilities
◆ market value of equity
◆ retained earnings
◆ earnings before interest and taxes (EBIT)
◆ net sales

For private business: $Z = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$

Table 3 gives a rough interpretation of Altman's Z-score (Aiyabei, 2002).

Evaluation

In principle, accounting-based models rely on financial information that reveals the past performance of a firm, which may not be a good indicator of the future due to the potential volatility of business performance, and yet reliable volatility is difficult to measure. In contrast, economy-based models can be used to produce reliable forecast of projected behavior of economy. In terms of accuracy, accounting-based models use firm-specific accounting figures for evaluation, instead of sector-wide economic data used in economy-based models, allowing PD to be reported more accurately. As for ease of application, accounting figures used in accounting-based models are often easily available in the firm's financial statements. On the other hand, it is necessary but difficult to obtain economic variables of a complete business cycle to make the results of economy-based models reliable.

BENEFITS AND LIMITATIONS OF CREDIT SCORING

Today's credit executives need to make fast and accurate decisions about high-value and high-volume credit transactions. Credit scoring helps companies avoid unnecessary credit risk by performing a detailed and consistent credit analysis.

Some of the major benefits of credit scoring include the following:

- **Quicker approval process:** Credit scoring greatly reduces the time needed in the loan approval process. For instance, automated data feeds can speed up data entry of credit information including personal details, financial ratings, and account status. An automated software system can generate credit scores for customers immediately and approve customer orders without any delay. Thus the operating efficiency is greatly increased by credit scoring.
- **Consistent and accurate analysis:** When approving new customers, all of the necessary factors involved in the credit granting decision process are received and scored. Since credit scores build up rules that are applied to every customer, all factors involved in the scoring are considered and analyzed in the same way. There is consistency in the evaluation process, and accuracy is increased as human error is eliminated.
- **Reduced bad debt losses and operating costs:** Credit scoring reduces bad debt losses and personnel costs. By quickly identifying existing customers that require immediate attention, companies can hold orders that otherwise may have been approved and take legal action while assets are still available to be attached. A typical financial firm like a bank has several thousand customers. With

Table 3. Interpretation of Altman's Z-score

Range of Z-score	Interpretation
Z<1.10	Business in a financial distress zone
1.10< Z< 2.60	Business in a gray zone
Z>2.60	Non-bankruptcy

the use of an automated software system, credit scoring can significantly reduce personnel costs as fewer people are required to research customers, check references, and make decisions about them.

- **Quantifiable risk:** It is difficult for management executives to set up effective strategies without having a score to understand what risk is being taken at the portfolio level. Credit scoring allows credit executives to fine tune credit risk guidelines over time and enables management to plan for different strategies for low-risk, medium-risk, and high-risk customers. Collection activity is prioritized as credit risk scores can be coupled with amounts of loans.
- **Objective judgment:** Since the score is calculated by the credit scoring system based on the same set of rules, human manipulation in the approval process is minimized. People who have traditionally suffered from mortgage discrimination benefit from a system that is objective and impartial.
- **Management reports:** Historically most credit executives used the days sales outstanding (DSO) figure to measure the quality of their accounts receivable. Now many firms have recognized that how a customer pays for the loan is often a poor indicator of risk. A credit score that uses various types of credit information to evaluate a customer's risk is a better measure than that which uses only a single factor. Credit scoring enables the credit executives to prepare management reports that accurately reflect the quality of the whole portfolio and reveal groups of customers who carry more risk. Credit scoring also allows audit trail by keeping track of how data is evaluated and how decisions are made. In this way the decisions become more reliable and supportable for financial reporting.

Limitations of Credit Scoring

- **Privacy concerns:** Some information in credit reports may cause breaches of consumers' privacy. Unnecessary private information about customers, such as their medical details and the treatment they receive, is disclosed to many companies. The ability to discern from a credit report that a customer may be suffering from some diseases like a mental problem or AIDS may potentially lead to discriminatory treatment. Many people also complain that reporting collection accounts without indicating the original creditor makes it difficult for consumers to decipher their own reports (Consumer Federation of America, 2002).
- **Accuracy of the score:** Accuracy is one of the most important considerations in the application of credit scoring. High-risk customers may appear to be able to pay promptly and some low-risk customers may not be well represented in the credit data. According to a survey conducted by the Consumer Federation of America, tens of millions of consumers are at risk of being penalized in the form of increased costs or decreased access to credit and vital services for incorrect information in their credit report. About 10% of consumers run the risk of being excluded from the credit marketplace altogether because of incomplete records, duplicate reports, and mixed files.
- **Limitations when there is a small customer base or large loan amount:** Large firms with a very high number of customers are likely to benefit from credit scoring due to increased efficiency, higher accuracy, and reduced cost in the approval process. For firms with fewer customers, the score obtained is less precise as the information is more difficult to validate and analyze.

Usually a mortgage that involves a large dollar amount will have a large impact on revenue, and it requires extra care in its evaluation by credit executives.

FUTURE TRENDS

In the past, credit scoring mainly focused on minimizing the risk of a default loan. However, in the past few years, creditors have expressed interest in making use of credit scoring for maximizing profits resulting from the lending activities. Risk-based pricing is a good example that can illustrate the use of credit scoring for maximization of profits.

Risk-based pricing is where the creditors adjust the price or interest rate offered to the customers according to the perceived risk. In general, most credit products within the same product category have a fixed price across the credit market which is the charged interest rate. This resembles consumer goods that have a fixed price in the market. Due to the fixed price, the products lack flexibility. There are always groups of people who fall outside the bands of products available in the market and so it becomes hard for them to get the credit they want. In addition to that, those who are not likely to default are actually subsidizing those with a high chance of default with the fixed credit product price. The concept of risk-based pricing is to vary the credit product price according to the potential risk of default to increase the flexibility of the credit products and to cater to a larger customer base.

CONCLUSION

The objective of the chapter is to study the application of credit scoring in three areas—credit card approval, mortgage, and small business lending. We have explained in general terms how credit scoring models are developed and have compared the pros and cons of some of the commonly used data mining techniques for developing these models. This chapter has stressed how data mining as a major field of academic research can be applied to improve the process of credit scoring. Although powerful and useful as a method, credit scoring gives rise to a number of concerns that have been listed in this chapter. Finally, the use of risk-based pricing as a future trend has been presented.

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