Expert Systems with Applications 36 (2009) 2592–2602

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Review

Application of data mining techniques in customer relationship management: A literature review and classification

E.W.T. Ngai [a,*], Li Xiu [b], D.C.K. Chau [a]

[a] Department of Management and Marketing, The Hong Kong Polytechnic University, Hong Kong, PR China
[b] Department of Automation, Tsinghua University, Beijing, PR China

ARTICLE INFO

Keywords:
Data mining
Customer relationship management
Literature review
Classification

ABSTRACT

Despite the importance of data mining techniques to customer relationship management (CRM), there is a lack of a comprehensive literature review and a classification scheme for it. This is the first identifiable academic literature review of the application of data mining techniques to CRM. It provides an academic database of literature between the period of 2000–2006 covering 24 journals and proposes a classification scheme to classify the articles. Nine hundred articles were identified and reviewed for their direct relevance to applying data mining techniques to CRM. Eighty-seven articles were subsequently selected, reviewed and classified. Each of the 87 selected papers was categorized on four CRM dimensions (Customer Identification, Customer Attraction, Customer Retention and Customer Development) and seven data mining functions (Association, Classification, Clustering, Forecasting, Regression, Sequence Discovery and Visualization). Papers were further classified into nine sub-categories of CRM elements under different data mining techniques based on the major focus of each paper. The review and classification process was independently verified. Findings of this paper indicate that the research area of customer retention received most research attention. Of these, most are related to one-to-one marketing and loyalty programs respectively. On the other hand, classification and association models are the two commonly used models for data mining in CRM. Our analysis provides a roadmap to guide future research and facilitate knowledge accumulation and creation concerning the application of data mining techniques in CRM.

1. Introduction

Customer relationship management (CRM) comprises a set of processes and enabling systems supporting a business strategy to build long term, profitable relationships with specific customers (Ling & Yen, 2001). Customer data and information technology (IT) tools form the foundation upon which any successful CRM strategy is built. In addition, the rapid growth of the Internet and its associated technologies has greatly increased the opportunities for marketing and has transformed the way relationships between companies and their customers are managed (Ngai, 2005).

Although CRM has become widely recognized as an important business approach, there is no universally accepted definition of CRM (Ling & Yen, 2001; Ngai, 2005). Swift (2001, p. 12) defined CRM as an "enterprise approach to understanding and influencing customer behaviour through meaningful communications in order to improve customer acquisition, customer retention, customer loyalty, and customer profitability". Kincaid (2003, p. 41) viewed CRM as "the strategic use of information, processes, technology, and people to manage the customer's relationship with your company (Marketing, Sales, Services, and Support) across the whole customer life cycle". Parvatiyar and Sheth (2001, p. 5) defined CRM as "a comprehensive strategy and process of acquiring, retaining, and partnering with selective customers to create superior value for the company and the customer. It involves the integration of marketing, sales, customer service, and the supply chain functions of the organization to achieve greater efficiencies and effectiveness in delivering customer value". These definitions emphasize the importance of viewing CRM as a comprehensive process of acquiring and retaining customers, with the help of business intelligence, to maximize the customer value to the organization.

From the architecture point of view, the CRM framework can be classified into operational and analytical (Berson, Smith, & Thearling, 2000; He, Xu, Huang, & Deng, 2004; Teo, Devadoss, & Pan, 2006). Operational CRM refers to the automation of business processes, whereas analytical CRM refers to the analysis of customer characteristics and behaviours so as to support the organization's customer management strategies. As such, analytical CRM could help an organization to better discriminate and more effectively allocate resources to the most profitable group of customers. Data

* Corresponding author. Tel.: +852 2766 7296; fax: +852 2774 3679.
E-mail address: mswtngai@polyu.edu.hk (E.W.T. Ngai).

0957-4174/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2008.02.021

mining tools are a popular means of analyzing customer data within the analytical CRM framework. Many organizations have collected and stored a wealth of data about their current customers, potential customers, suppliers and business partners. However, the inability to discover valuable information hidden in the data prevents the organizations from transforming these data into valuable and useful knowledge (Berson et al., 2000). Data mining tools could help these organizations to discover the hidden knowledge in the enormous amount of data.

Turban, Aronson, Liang, and Sharda (2007, p.305) defines data mining as "the process that uses statistical, mathematical, artificial intelligence and machine-learning techniques to extract and identify useful information and subsequently gain knowledge from large databases". Berson et al. (2000), Lejeune (2001), Ahmed (2004) and Berry and Linoff (2004) also provide a similar definition regarding data mining as being the process of extracting or detecting hidden patterns or information from large databases. With comprehensive customer data, data mining technology can provide business intelligence to generate new opportunities (Bortiz & Kennedy, 1995; Fletcher & Goss, 1993; Langley & Simon, 1995; Lau, Wong, Hui, & Pun, 2003; Salchenberger, Cinar, & Lash, 1992; Su, Hsu, & Tsai, 2002; Tam & Kiang, 1992; Zhang, Hu, Patuwo, & Indro, 1999).

The application of data mining tools in CRM is an emerging trend in the global economy. Analyzing and understanding customer behaviours and characteristics is the foundation of the development of a competitive CRM strategy, so as to acquire and retain potential customers and maximize customer value. Appropriate data mining tools, which are good at extracting and identifying useful information and knowledge from enormous customer databases, are one of the best supporting tools for making different CRM decisions (Berson et al., 2000). As such, the application of data mining techniques in CRM is worth pursuing in a customer-centric economy.

This paper presents a comprehensive review of literature related to application of data mining techniques in CRM published in academic journals between 2000 and 2006. A classification of framework is also presented. The paper is organized as follows: first, the research methodology used in the study is described; second, the method for classifying data mining articles in CRM is presented; third, articles about data mining in CRM are analysed and the results of the classification are reported; and finally, the conclusions, limitations and implications of the study are discussed.

2. Research methodology

As the nature of research in CRM and data mining are difficult to confine to specific disciplines, the relevant materials are scattered across various journals. Business intelligence and knowledge discovery are the most common academic discipline for data mining research in CRM. Consequently, the following online journal databases were searched to provide a comprehensive bibliography of the academic literature on CRM and Data Mining:

- ABI/INFORM Database;
- Academic Search Premier;
- Business Source Premier;
- Emerald Fulltext;
- Ingenta Journals;
- Science Direct; and
- IEEE Transaction.

The literature search was based on the descriptor, "customer relationship management" and "data mining", which originally produced approximately 900 articles. The full text of each article was reviewed to eliminate those that were not actually related to application of data mining techniques in CRM. The selection criteria were as follows:

- Only those articles that had been published in business intelligence, knowledge discovery or customer management related journals were selected, as these were the most appropriate outlets for data mining in CRM research and the focus of this review.
- Only those articles which clearly described how the mentioned data mining technique(s) could be applied and assisted in CRM strategies were selected.
- Conference papers, masters and doctoral dissertations, textbooks and unpublished working papers were excluded, as academics and practitioners alike most often use journals to acquire information and disseminate new findings. Thus, journals represent the highest level of research (Nord & Nord, 1995).

Each article was carefully reviewed and separately classified according to the four categories of CRM dimensions and seven categories of data mining models, as shown in Fig. 1. Although this search was not exhaustive, it serves as a comprehensive base for an understanding of data mining research in CRM.

3. Classification method

According to Swift (2001, p. 12), Parvatiyar and Sheth (2001, p. 5) and Kracklauer, Mills, and Seifert (2004, p. 4), CRM consists of four dimensions:

(1) Customer Identification;
(2) Customer Attraction;
(3) Customer Retention;
(4) Customer Development.

These four dimensions can be seen as a closed cycle of a customer management system (Au & Chan, 2003; Kracklauer et al., 2004; Ling & Yen, 2001). They share the common goal of creating a deeper understanding of customers to maximize customer value to the organization in the long term. Data mining techniques, therefore, can help to accomplish such a goal by extracting or detecting hidden customer characteristics and behaviours from large databases. The generative aspect of data mining consists of the building of a model from data (Carrier & Povel, 2003). Each data mining technique can perform one or more of the following types of data modelling:

(1) Association;
(2) Classification;
(3) Clustering;
(4) Forecasting;
(5) Regression;
(6) Sequence discovery;
(7) Visualization.

The above seven models cover the generally mentioned data mining models in various articles (Ahmed, 2004; Carrier & Povel, 2003; Mitra, Pal, & Mitra, 2002; Shaw, Subramaniam, Tan, & Welge, 2001; Turban et al., 2007). There are numerous machine learning techniques available for each type of data mining model. Choices of data mining techniques should be based on the data characteristics and business requirements (Carrier & Povel, 2003). Here are some examples of some widely used data mining algorithms:

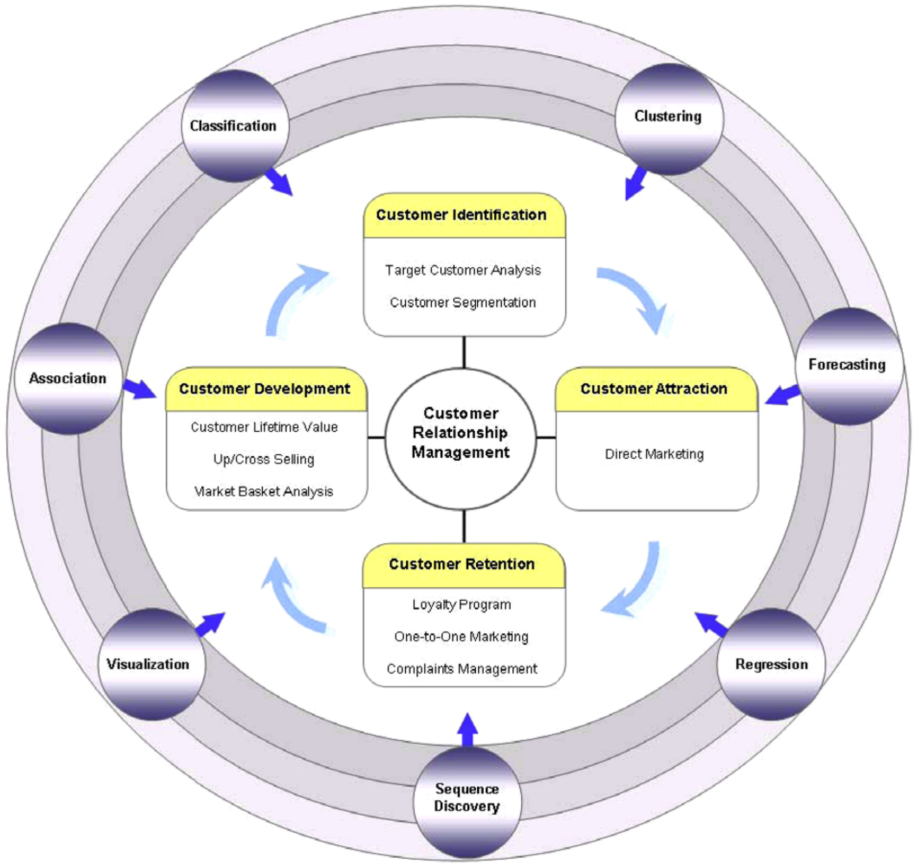

Fig. 1. Classification framework for data mining techniques in CRM.

(1) Association rule;
(2) Decision tree;
(3) Genetic algorithm;
(4) Neural networks;
(5) *K*-Nearest neighbour;
(6) Linear/logistic regression.

A graphical classification framework on data mining techniques in CRM is proposed and shown in Fig. 1; it is based on a review of the literature on data mining techniques in CRM. Critically reviewing the literature on data mining in CRM helped to identify the major CRM dimensions and data mining techniques for the application of data mining techniques in CRM. This framework is also based on the research conducted by Swift (2001), Parvatiyar and Sheth (2001) and Kracklauer et al. (2004). They described CRM dimensions as: Customer Identification, Customer Attraction, Customer Retention and Customer Development. In addition, Ahmed, 2004; Carrier and Povel, 2003; Mitra et al., 2002; Shaw et al., 2001 described the types of data mining model as Association, Classification, Clustering, Forecasting, Regression, Sequence Discovery and Visualization. We provide a brief description of these four dimensions and some references for further details, and each of them is discussed in the following sections.

3.1. Classification framework – CRM dimensions

In this study, CRM is defined as helping organizations to better discriminate and more effectively allocate resources to the most profitable group of customers through the cycle of customer identification, customer attraction, customer retention and customer development. Detailed knowledge must be built up systematically so as to obtain a deeper understanding of each customer's behaviours, characteristics and needs. The four dimensions of the CRM cycle are essential efforts to gain customer insight (Ling & Yen, 2001).

(i) *Customer identification:* CRM begins with customer identification, which is referred to as customer acquisition in some articles. This phase involves targeting the population who are most likely to become customers or most profitable to the company. Moreover, it involves analyzing customers who are being lost to the competition and how they can be won back (Kracklauer et al., 2004). Elements for customer identification include target customer analysis and customer segmentation. Target customer analysis involves seeking the profitable segments of customers through analysis of customers' underlying characteristics, whereas customer segmentation involves the subdivision of an entire customer base into smaller customer groups or segments, consisting of customers who are relatively similar within each specific segment (Woo, Bae, & Park, 2005).

(ii) *Customer attraction:* This is the phase following customer identification. After identifying the segments of potential customers, organizations can direct effort and resources into attracting the target customer segments. An element of customer attraction is direct marketing. Direct marketing is a promotion process which motivates customers to place orders through various channels (Cheung, Kwok, Law, & Tsui, 2003; He et al., 2004; Liao & Chen, 2004; Prinzie & Poel, 2005). For instance, direct mail or coupon distribution are typical examples of direct marketing.

(iii) *Customer retention:* This is the central concern for CRM. Customer satisfaction, which refers to the comparison of customers' expectations with his or her perception of being satisfied, is the essential condition for retaining customers (Kracklauer et al., 2004). As such, elements of customer retention include one-to-one marketing, loyalty programs and complaints management. One-to-one marketing refers to personalized marketing campaigns which are supported by analysing, detecting and predicting changes in customer behaviours (Chen, Chiu, & Chang, 2005; Jiang & Tuzhilin, 2006; Kim & Moon, 2006). Thus, customer profiling, recommender systems or replenishment systems are related to one-to-one marketing. Loyalty programs involve campaigns or supporting activities which aim at maintaining a long term relationship with customers. Specifically, churn analysis, credit scoring, service quality or satisfaction form part of loyalty programs.

(iv) *Customer development:* This involves consistent expansion of transaction intensity, transaction value and individual customer profitability. Elements of customer development include customer lifetime value analysis, up/cross selling and market basket analysis. Customer lifetime value analysis is defined as the prediction of the total net income a company can expect from a customer (Drew, Mani, Betz, & Datta, 2001; Etzion, Fisher, & Wasserkrug, 2005; Rosset, Neumann, Eick, & Vatnik, 2003). Up/Cross selling refers to promotion activities which aim at augmenting the number of associated or closely related services that a customer uses within a firm (Prinzie & Poel, 2006). Market basket analysis aims at maximizing the customer transaction intensity and value by revealing regularities in the purchase behaviour of customers (Aggarval & Yu, 2002; Brijs, Swinnen, Vanhoof, & Wets, 2004; Carrier & Povel, 2003; Chen, Tang, Shen, & Hu, 2005; Giudici & Passerone, 2002; Kubat, Hafez, Raghavan, Lekkala, & Chen, 2003).

3.2. Classification framework – data mining models

Within the context of CRM, data mining can be seen as a business driven process aimed at the discovery and consistent use of profitable knowledge from organizational data (Ling & Yen, 2001). It can be used to guide decision making and forecast the effects of decisions. For instance, data mining can increase the response rates of the marketing campaign by segmenting customers into groups with different characteristics and needs; it can predict how likely an existing customer is to take his/her business to a competitor (Carrier & Povel, 2003). Each of the CRM elements can be supported by different data mining models, which generally include association, classification, clustering, forecasting, regression, sequence discovery and visualization.

(i) *Association:* Association aims to establishing relationships between items which exist together in a given record (Ahmed, 2004; Jiao, Zhang, & Helander, 2006; Mitra et al., 2002). Market basket analysis and cross selling programs are typical examples for which association modelling is usually adopted. Common tools for association modelling are statistics and apriori algorithms.

(ii) *Classification:* Classification is one of the most common learning models in data mining (Ahmed, 2004; Berry & Linoff, 2004; Carrier & Povel, 2003). It aims at building a model to predict future customer behaviours through classifying database records into a number of predefined classes based on certain criteria (Ahmed, 2004; Berson et al., 2000; Chen, Hsu, & Chou, 2003; Mitra et al., 2002). Common tools used for classification are neural networks, decision trees and if-then-else rules.

(iii) *Clustering:* Clustering is the task of segmenting a heterogeneous population into a number of more homogenous clusters (Ahmed, 2004; Berry & Linoff, 2004; Carrier & Povel, 2003; Mitra et al., 2002). It is different to classification in that clusters are unknown at the time the algorithm starts. In other words, there are no predefined clusters. Common tools for clustering include neural networks and discrimination analysis.

(iv) *Forecasting:* Forecasting estimates the future value based on a record's patterns. It deals with continuously valued outcomes (Ahmed, 2004; Berry & Linoff, 2004). It relates to modelling and the logical relationships of the model at some time in the future. Demand forecast is a typical example of a forecasting model. Common tools for forecasting include neural networks and survival analysis.

(v) *Regression:* Regression is a kind of statistical estimation technique used to map each data object to a real value provide prediction value (Carrier & Povel, 2003; Mitra et al., 2002). Uses of regression include curve fitting, prediction (including forecasting), modeling of causal relationships, and testing scientific hypotheses about relationships between variables. Common tools for regression include linear regression and logistic regression.

(vi) *Sequence discovery:* Sequence discovery is the identification of associations or patterns over time (Berson et al., 2000; Carrier & Povel, 2003; Mitra et al., 2002). Its goal is to model the states of the process generating the sequence or to extract and report deviation and trends over time (Mitra et al., 2002). Common tools for sequence discovery are statistics and set theory.

(vii) *Visualization:* Visualization refers to the presentation of data so that users can view complex patterns (Shaw et al., 2001). It is used in conjunction with other data mining models to provide a clearer understanding of the discovered patterns or relationships (Turban et al., 2007). Examples of visualization model are 3D graphs, "Hygraphs" and "SeeNet" (Shaw et al., 2001).

A combination of data mining models is often required to support or forecast the effects of a CRM strategy. In such a situation, the classification of data mining models mentioned in the article will be based on the major CRM issues that the article would like to address. For instance, in the case of up/cross selling programs, customers can be segmented into clusters before an association model is applied to each cluster. In such cases, the up/cross selling program would be classified as being supported by an association model because relationships between products are the major concern; in the case of direct marketing, a certain portion of customers may be segmented into clusters to form the initial classes of the classification model. The direct marketing program would be classified as being supported by classification as prediction of customers' behaviour is the major concern.

3.3. Classification process

Each of the selected articles was reviewed and classified according to the proposed classification framework by three independent researchers. The classification process consisted of four phases:

(1) Online database search.
(2) Initial classification by first researcher.
(3) Independent verification of classification results by second researcher; and
(4) Final verification of classification results by third researcher.

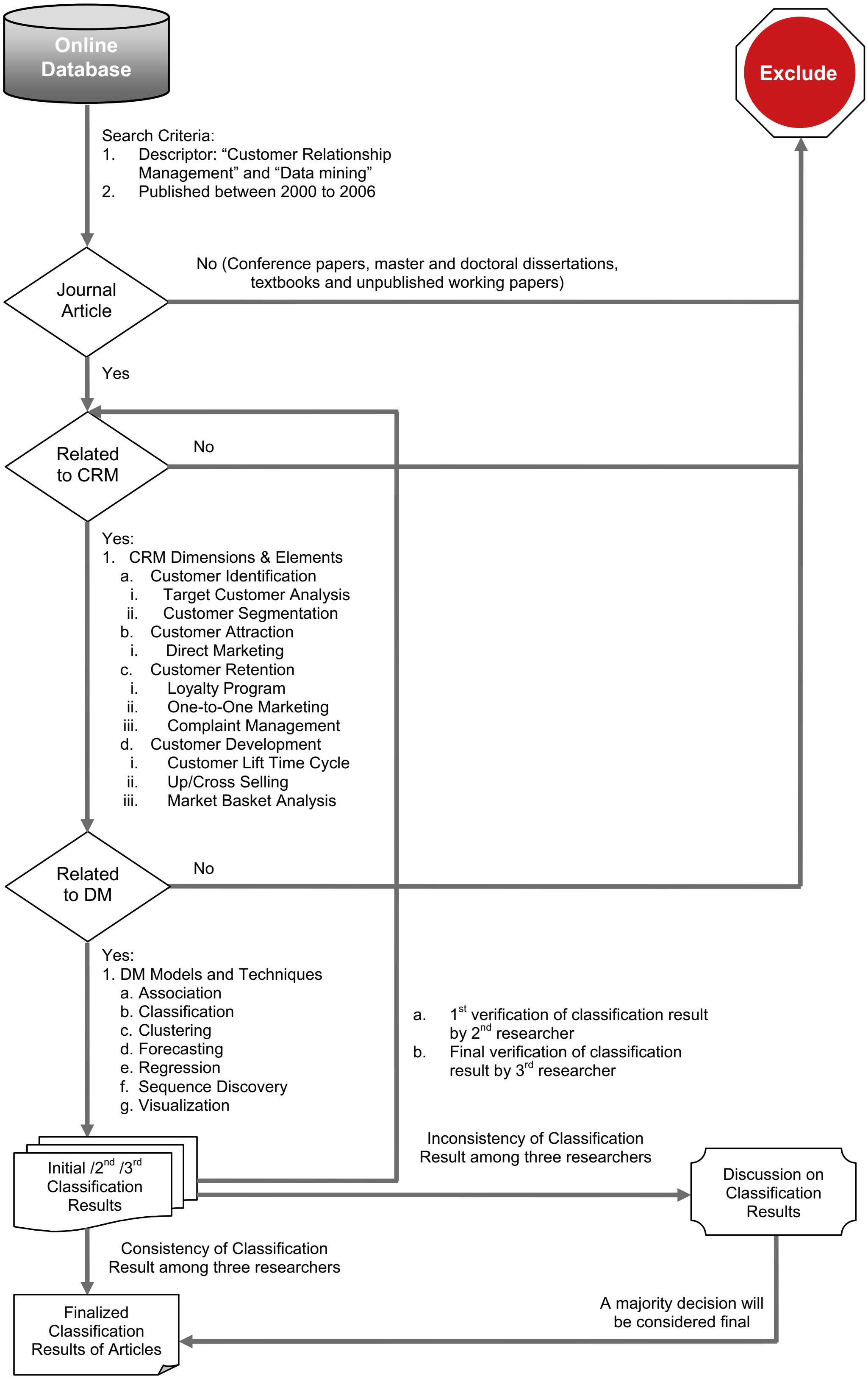

Fig. 2. Selection criteria and evaluation framework.

If there was a discrepancy in classification, each of these articles was then discussed until there was agreement on how the article should be classified from the final set in the proposed classification framework. The selection criteria and evaluation framework is shown in Fig. 2. The collection of articles was analyzed in accordance with CRM elements and data mining models, by year of publication and according to the journal in which the article was published.

4. Classification of the articles

A detailed distribution of the 87 articles classified by the proposed classification framework is shown in Table 1.

4.1. Distribution of articles by CRM dimensions and data mining models

The distribution of articles classified by the proposed classification model is shown in Table 2. Among the four CRM dimensions, customer retention (54 out of 87 articles, 62.1%) is the most common dimension for which data mining is used to support decision making. There were 13 articles for each of customer identification and customer development covering various aspects of CRM.

Of the 54 customer retention articles, 51.9% (28 articles) and 44.4% (24 articles) are related to one-to-one marketing and loyalty programs respectively. One-to-one marketing and loyalty programs also rank first (28 articles out of 87 articles, 32.2%) and second (24 articles out of 87 articles, 27.6%) in terms of subject matter dealt with data mining and CRM. However, there were relatively few articles covering "up/cross selling" (2 articles, 2.3%), "complaint management" (2 articles, 2.3%), "target customer analysis" (5 articles, 5.7%) and "customer lifetime value analysis" (5 articles, 5.7%).

In one-to-one marketing, 46.4% (13 out of 28 articles) used association models to analyze the customer data, followed by 25.0% (7 out of 28 articles) which used classification models. With regard to loyalty programs, 83.3% (20 out of 24 articles) used classification models to assist in decision making.

Table 3 shows the distribution of articles by data mining techniques. Among 34 data mining techniques which have been applied in CRM, neural networks is the most commonly used technique. It has been described in 30 (34.5%) out of 87 articles in total. Following are decision tree and association rules which have been described in 21 (24.1%) and 20 (23.0%) articles respectively. We provide a brief description of the three most used techniques and some references as follows:

Neural networks: In the artificial intelligence field, neural network techniques have been applied successfully to speech recognition, image analysis, and adaptive control. Most of the currently employed neural network systems simulate the human brain, and are readily applied to areas involving classification, clustering and prediction (Berry & Linoff, 2004; Turban et al., 2007). Of the 30 articles which applied neural network techniques, 16 (53.3%) adopt self-organizing map subtypes, which entails mapping structured, high-dimensional data onto a much lower-dimensional array of neurons in an orderly fashion through the training process (Song, Kim, Cho, & Kim, 2004).

Decision trees: This technique can be used to extract models describing sequences of interrelated decisions or predicting future data trends (Berry & Linoff, 2004; Chen et al., 2003; Kim, Song, Kim, & Kim, 2005). It classifies specific entities into particular classes based upon the features of the entities: a root is followed by internal nodes, each node is labeled with a question, and an arc associated with each node covers all possible responses (Buckinx, Moons, Poel, & Wets, 2004; Chen et al., 2003). Some of the most well-known algorithms are ID3, C4.5 and classification and regression trees.

Association rules: These are concerned with the discovery of interesting association relationships, which are above an interesting threshold, hidden in databases (Berry & Linoff, 2004; Brijs et al., 2004; Wang, Zhou, Yang, & Yeung, 2005). The threshold tells how strong the pattern is and how likely the rule is to occur again (Berson et al., 2000). Selected association rules can be used to build a model for predicting the value of a future customer (Wang et al., 2005).

4.2. Distribution of articles by year of publication

The distribution of articles by year of publication is shown in Fig. 3. It is obvious that publications which are related to application of data mining techniques in CRM have increased significantly from 2000 to 2005. In 2006, the amount of publication decreased by 30% when compared with 2005.

4.3. Distribution of articles by journal in which the articles were published

Table 4 shows the distribution of articles by journal. Articles related to application of data mining techniques in CRM are distributed across 24 journals. Of these, "Expert Systems with Applications", which focuses on the knowledge of the application

Table 1
Distribution of articles according to the proposed classification model

CRM dimensions	CRM elements	Data mining functions	Data mining techniques	References
Customer identification	Segmentation	Classification	Decision tree	Kim, Jung, Suh, and Hwang (2006)
			Self-organizing map, decision tree and Markov chain model	Ha, Bae, and Park (2002)
		Clustering	*K*-means	Dennis, Marsland, and Cockett (2001)
			Data envelopment analysis, self organizing map & decision tree	Lee and Park (2005)
			Pattern based cluster	Yang and Padmanabhan (2005)
			Self-organizing map	Bae, Park, and Ha (2003), Verdú, García, Senabre, Marín, and Franco (2006)
		Regression	Logistic regression	Hwang, Jung, and Suh (2004)
	Target customer analysis	Classification	Decision tree	Chen et al. (2003), Wu, Kao, Su, and Wu (2005), Yu, Ou, Zhang, and Zhang (2005)
		Clustering	Self-organizing map	Lee, Suh, Kim, and Lee (2004)
		Visualization	Customer map	Woo et al. (2005)
Customer attraction	Direct marketing	Regression	Logistic regression	Prinzie and Poel (2005)
		Classification	Bayesian network classifier	Baesens et al. (2002)
			Decision tree	Buckinx et al. (2004)
			Genetic algorithm	Ahn et al. (2006), Chiu (2002)
			Neural network and genetic algorithm	Kim and Street (2004)
		Clustering	Outlier detection	He et al. (2004)

(*continued on next page*)

Table 1 (*continued*)

CRM dimensions	CRM elements	Data mining functions	Data mining techniques	References
Customer retention	Complaints management	Clustering	Self-organizing map	Bae et al. (2005)
		Sequence discovery	Survival analysis	LariviÈRe and Poel (2005)
	Loyalty program	Classification	Decision tree 20	Cox (2002), Douglas et al. (2005), Larivie'Re and Poel (2005)
			Genetic algorithm	Kim et al. (2003)
			Logical analysis of data	Lejeune (2001)
			Neural network, *K*-nearest neighbor and decision tree	Datta et al. (2000)
			Classification and regression tree and multivariate adaptive regression splines	Lee et al. (2006)
			Logistic regression and neural network	Kim (2006)
			Logistic regression, neural network and random forest	Buckinx and Poel (2005)
			Neural network and decision tree	Hung et al. (2006)
			Self-organizing map and Markov chain	Kim et al. (2005)
			Logistic regression, neural network and decision tree	Koh and Chan (2002), Mozer et al. (2000), Smith et al. (2000)
			Self-organizing map and decision tree	Chu, Isai, and Ho (2007)
			Data mining by evolutionary learning	Au et al. (2003)
			Multi-classifier class combiner approach	Wei and Chiu (2002)
			Self-organizing map	Song et al. (2004)
			Survival analysis	Larivie'Re and Poel (2004), Poel and Larivière (2004)
		Clustering	Attribute oriented induction	Li et al. (2006)
		Regression	Logistic regression	Cassab and Maclachlan (2006), Poel and Buckinx (2005)
		Sequence discovery	Goal oriented sequential pattern	Chiang et al. (2003)
	One to one marketing	Association	Association rules	Adomavicius and Tuzhilin (2001), Au and Chan (2003), Chen, Chiu, and Chang (2005), Demiriz (2004), Jiao et al. (2006), Lee et al. (2001), Wang et al. (2004)
			Set theory and self-organizing map	Changchien and Lu (2001)
			Association rules and self-organizing map	Ha (2002), Ha et al. (2006), Hsieh (2004)
			Association rules and *K*-means	Liu and Shih (2005)
			MARFS1/S2	He et al. (2005)
		Classification	Decision tree	Kim, Song, Kim, and Kim (2005), Min et al. (2002)
			If-then-else	Leung et al. (2003)
			Support vector machine and latent class model	Cheung et al. (2003)
			Decision tree, naive Bayes, rule based RIPPER, *K*-nearest network, S-means, S-means mod, farther first, expectation Max & Expectation Max Mod	Jiang and Tuzhilin (2006)
			Constructive assignment algorithm	Kim and Moon (2006)
			Self-organizing map	Lee and Park (2003)
		Clustering	Association rules	Liao and Chen (2004)
			K-nearest neighbor	Cho and Kim (2004)
			Neural network and genetic algorithm	Kuo et al. (2005)
			Self-organizing map	Cho et al. (2005), Min and Han (2005)
			Association rules	Song et al. (2001)
			Association rules and online	Kwan et al. (2005)
			Analytical mining neural network	Chang et al. (2006)
Customer development	Lifetime value	Classification	Bayesian network classifier	Baesens et al. (2004)
		Clustering	Neural network	Drew et al. (2001)
			Survival analysis	Rosset et al. (2003)
		Forecasting	Markov chain model	Etzion et al. (2005)
		Regression	Linear regression	Verhoef and Donkers (2001)
	Market basket analysis	Association	Association rules	Aggarval and Yu (2002), Brijs et al. (2004), Jukic and Nestorov (2006)
			Markov chain model	Giudici and Passerone (2002)
		Sequence discovery	Association rules	Chen, Tang, Shen, and Hu (2005), Kubat et al. (2003)
	Up/cross selling	Association	Neural network and association rule	Changchien et al. (2004)
		Sequence discovery	Mixture transition distribution	Prinzie and Poel (2006)

of expert and intelligent systems in industry, government and university worldwide, contains more than 40% (38 of 87 articles) of the total number of articles published.

5. Conclusion, research implications and limitations

Application of data mining techniques in CRM is an emerging trend in the industry. It has attracted the attention of practitioners and academics. This paper has identified eighty seven articles related to application of data mining techniques in CRM, and published between 2000 and 2006. It aims to give a research summary on the application of data mining in the CRM domain and techniques which are most often used. Although this review cannot claim to be exhaustive, it does provide reasonable insights and shows the incidence of research on this subject. The results presented in this paper have several important implications:

- Research on the application of data mining in CRM will increase significantly in the future based on past publication rates and the increasing interest in the area.
- The majority of the reviewed articles relate to customer retention. Of these, 51.9% (28 articles) and 44.4% (24 articles) are related to one-to-one marketing and loyalty programs respectively. These articles could provide insight to organization policy makers on the common data mining practices used in retaining customers.

Table 2
Distribution of articles by CRM and data mining model

CRM dimensions	CRM elements	Data mining model	Amount		
Customer identification	Customer segmentation		8		
		Classification		2	
		Clustering		5	
		Regression		1	
	Target customer analysis		5		
		Classification		3	
		Clustering		1	
		Visualization		1	
					13
Customer attraction	Direct marketing		7		
		Regression		1	
		Classification		5	
		Clustering		1	
					7
Customer retention	Complaints management		2		
		Clustering		1	
		Sequence Discovery		1	
	Loyalty program		24		
		Classification		20	
		Clustering		1	
		Regression		2	
		Sequence discovery		1	
	One to one marketing		28		
		Association		13	
		Classification		7	
		Clustering	5		
		Sequence discovery		3	
					54
Customer development	Customer lifetime value		5		
		Classification		1	
		Clustering		2	
		Forecasting		1	
		Regression		1	
	Market basket analysis		6		
		Association		4	
		Sequence discovery		2	
	Up/cross selling		2		
		Association		1	
		Sequence discovery		1	
					13
Total			87	87	87

Table 3
Distribution of articles by data mining techniques

Data mining techniques	Amount
Neural network	30
Decision tree	23
Association rules	18
Regression	10
Genetic algorithm	4
Markov chain	4
Survival analysis	4
K means	3
K nearest neighbour	3
Bayesian network classifier	2
If-then-else	1
Set theory	1
Support vector machine	1
Attribute oriented induction	1
Constructive assignment	1
Customer map	1
Data envelopment analysis	1
Data mining by evolutionary learning	1
Expectation Max	1
Expectation Max Mod	1
Farthest first	1
Goal oriented sequential pattern	1
Latent class model	1
Logical analysis of data	1
MARFS1/S2	1
Mixture transition distribution	1
Multi-classifier class combiner	1
Multivariate adaptive regression splines	1
Online analytical mining	1
Outlier detection	1
Pattern based cluster	1
Rule-based RIPPER	1
S-means	1
S-means Mod	1
Total[a]	125

[a] Remark: Each article may have used more that one data mining techniques.

- Of the 54 articles related to customer retention, only two of them discuss complaints management. Complaints management is a crucial requirement for successful businesses when managing customers' needs and changes in behavior. Data mining techniques could be applied to discover unseen patterns of complaints from a company's database. The root of the problems may also be uncovered by investigating the association between complaints from different customers. Therefore, more research could be conducted on the application of data mining techniques in complaints management.
- There are relatively fewer articles discussing target customer analysis. Data mining techniques, such as neural networks and decision trees, could be used to seek the profitable segments of customers through analysis of customers' underlying characteristics. Despite the fewer number of articles related to target customer analysis, it does not mean the application of data mining in this aspect is less mature than in the others. Applications of data mining in other CRM domains, such as in one-to-one marketing, may also be applied in target customer analysis if they possess the same goal of analysing the characteristics of customers.

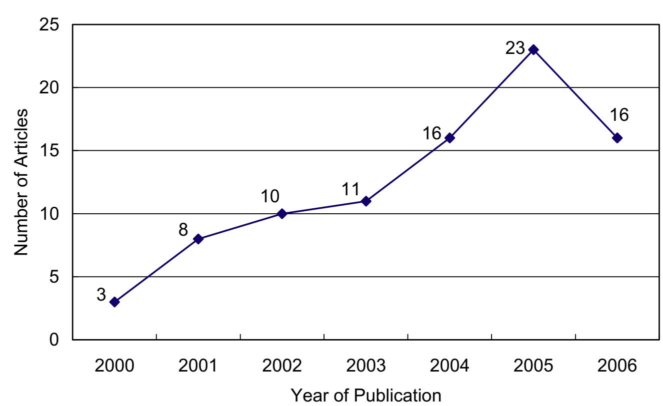

Fig. 3. Distribution of articles by year of publication.

- The classification model is the most commonly applied model in CRM for predicting future customer behaviors. This is not surprising as classification modeling could be used to predict the effectiveness or profitability of a CRM strategy through the prediction of customer behaviors.
- Only one article discussed the visualization of data mining results within the context of CRM. One can view visualization as a complement to other data mining models as it is concerned with the presentation of discovered patterns or relationships. Therefore, good visualization systems could magnify the merit of data mining techniques in CRM. More research could be done on this issue.

Table 4
Distribution of articles by journal

Journal title	Amount	Percentage (%)
Expert Systems with Applications	*38*	43.70
Decision Support Systems	9	10.30
European Journal of Operational Research	5	6.90
IEEE Transaction on Knowledge and Data Engineering	5	5.70
Data Mining and Knowledge Discovery	4	4.60
IEEE Intelligent Systems	4	4.60
Artificial Intelligence Review	2	2.30
Computational Statistics and Data Analysis	2	2.30
IEEE Transactions on Power Systems	2	2.30
Computers and Industrial Engineering	1	1.10
Electronic Networking Applications and Policy	1	1.10
Evolutionary Computation	1	1.10
IEEE Transactions on Fuzzy Systems	1	1.10
IEEE Transactions on speech and audio processing	1	1.10
Information and Management	1	1.10
Information Systems Frontiers	1	1.10
International Journal of Contemporary Hospitality Management	1	1.10
International Journal of Productivity and Performance Management	1	1.10
Journal of knowledge management	1	1.10
Journal of Service Research	1	1.10
Journal of the Operational Research Society	1	1.10
Knowledge-Based Systems	1	1.10
Singapore Management Review	1	1.10
Telecommunication Systems	1	1.10
Total	*87*	*100.00*

- Among the 87 articles, 30 described neural networks in the CRM domain. Neural networks can be applied in classification, clustering and prediction. Thus, it is not surprising that neural networks were used in a wide range of CRM domains.
- Decision trees and association rules techniques rank after neural networks in popularity of application in CRM. The logic of both techniques can be followed more easily by business people than neural networks. Therefore, the two techniques should be a good choice for non-experts in data mining.
- With respect to the research findings, we suggest more research can be conducted in the customer development domain. In order to maximize an organization's profits through CRM, policy makers have to both retain valuable customers and increase the lifetime value of the customer. As such, customer retention and development are both important to maintaining a long term and pleasant relationship with customers.

This study might have some limitations. Firstly, this study only surveyed articles published between 2000 and 2006, which were extracted based on a keyword search of "customer relationship management" and "data mining". Articles which mentioned the application of data mining techniques in CRM but without a keyword index could not be extracted. Secondly, this study limited the search for articles to 7 online databases. There might be other academic journals which may be able to provide a more comprehensive picture of the articles related to the application of data mining in CRM. Lastly, non-English publications were excluded in this study. We believe research regarding the application of data mining techniques in CRM have also been discussed and published in other languages.

Acknowledgements

This research was partly supported by The Hong Kong Polytechnic University (Project no.: G-YF20) and National Natural Science Foundation of China (NSFC, Project no.: 70671059).

References

Adomavicius, G., & Tuzhilin, A. (2001). Expert-driven validation of rule-based user models in personalization applications. *Data Mining and Knowledge Discovery, 5*, 33–58.

Aggarval, C. C., & Yu, P. S. (2002). Finding localized associations in market basket data. *IEEE Transactions on Knowledge and Data Engineering, 14*, 51–62.

Ahmed, S. R. (2004). Applications of data mining in retail business. *Information Technology: Coding and Computing, 2*, 455–459.

Ahn, H., Kim, K. J., & Han, I. (2006). Hybrid genetic algorithms and case-based reasoning systems for customer classification. *Expert Systems with Applications, 23*, 127–144.

Au, W. H., & Chan, K. C. C. (2003). Mining fuzzy association rules in a bank-account database. *IEEE Transactions on Fuzzy Systems, 11*, 238–248.

Au, W. H., Chan, K. C. C., & Yao, X. (2003). A novel evolutionary data mining algorithm with applications to churn prediction. *IEEE Transactions on Evolutionary Computation, 7*, 532–545.

Bae, S. M., Ha, S. H., & Park, S. C. (2005). A web-based system for analyzing the voices of call center customers in the service industry. *Expert Systems with Applications, 28*, 29–41.

Bae, S. M., Park, S. C., & Ha, S. H. (2003). Fuzzy web ad selector based on web usage mining. *IEEE Intelligent Systems*, 62–69.

Baesens, B., Verstraeten, G., Dirk, V. D. P., Michael, E. P., Kenhove, V. K., & Vanthienen, J. (2004). Bayesian network classifiers for identifying the slope of the customer-lifecycle of long-life customers. *European Journal of Operational Research, 156*, 508–523.

Baesens, B., Viaene, S., Poel, D. V. D., Vanthienen, J., & Dedene, G. (2002). Bayesian neural network learning for repeat purchase modelling in direct marketing. *European Journal of Operational Research, 138*, 191–211.

Berry, M. J. A., & Linoff, G. S. (2004). *Data mining techniques second edition - for marketing, sales, and customer relationship management*. Wiley.

Berson, A., Smith, S., & Thearling, K. (2000). *Building data mining applications for CRM*. McGraw-Hill.

Bortiz, J. E., & Kennedy, D. B. (1995). Effectiveness of neural network types for prediction of business failure. *Expert Systems with Applications, 9*, 503–512.

Brijs, T., Swinnen, G., Vanhoof, K., & Wets, G. (2004). Building an association rules framework to improve product assortment decisions. *Data Mining and Knowledge Discovery, 8*, 7–23.

Buckinx, W., Moons, E., Poel, D. V. D., & Wets, G. (2004). Customer-adapted coupon targeting using feature selection. *Expert Systems with Applications, 26*, 509–518.

Buckinx, W., & Poel, D. V. D. (2005). Customer base analysis: Partial defection of behaviorally-loyal clients in a non-contractual FMCG retail setting. *European Journal of Operational Research, 164*, 252–268.

Carrier, C. G., & Povel, O. (2003). Characterising data mining software. *Intelligent Data Analysis, 7*, 181–192.

Cassab, H., & Maclachlan, D. L. (2006). Interaction fluency: A customer performance measure of multichannel service. *International Journal of Productivity and Performance Management, 55*, 555–568.

Chang, S. E., Changchien, S. W., & Huang, R. H. (2006). Assessing users' product-specific knowledge for personalization in electronic commerce. *Expert Systems with Applications, 30*, 682–693.

Changchien, S. W., Lee, C. F., & Hsu, Y. J. (2004). On-line personalized sales promotion in electronic commerce. *Expert Systems with Applications, 27*, 35–52.

Changchien, S. W., & Lu, T. C. (2001). Mining association rules procedure to support on-line recommendation by customers and products fragmentation. *Expert Systems with Applications, 20*, 325–335.

Chen, M. C., Chiu, A. L., & Chang, H. H. (2005). Mining changes in customer behavior in retail marketing. *Expert Systems with Applications, 28*, 773–781.

Chen, Y. L., Hsu, C. L., & Chou, S. C. (2003). Constructing a multi-valued and multi-labeled decision tree. *Expert Systems with Applications, 25*, 199–209.

Chen, Y. L., Tang, K., Shen, R. J., & Hu, Y. H. (2005). Market basket analysis in a multiple store environment. *Decision Support Systems, 40*, 339–354.

Cheung, K. W., Kwok, J. T., Law, M. H., & Tsui, K. C. (2003). Mining customer product ratings for personalized marketing. *Decision Support Systems, 35*, 231–243.

Chiang, D. A., Wang, Y. F., Lee, S. L., & Lin, C. J. (2003). Goal-oriented sequential pattern for network banking churn analysis. *Expert Systems with Applications, 25*, 293–302.

Chiu, C. (2002). A case-based customer classification approach for direct marketing. *Expert Systems with Applications, 22*, 163–168.

Cho, Y. B., Cho, Y. H., & Kim, S. H. (2005). Mining changes in customer buying behavior for collaborative recommendations. *Expert Systems with Applications, 28*, 359–369.

Cho, Y. H., & Kim, J. K. (2004). Application of web usage mining and product taxonomy to collaborative recommendations in e-commerce. *Expert Systems with Applications, 26*, 233–246.

Chu, B. H., Tsai, M. S., & Ho, C. S. (2007). Toward a hybrid data mining model for customer retention. *Knowledge-Based Systems, 20*, 703–718.

Cox, L. A. (2002). Data mining and causal modeling of customer behaviors. *Telecommunication Systems, 21*, 349–381.

Datta, P., Masand, B., Mani, D. R., & Li, B. (2000). Automated cellular modeling and prediction on a large scale. *Artificial Intelligence Review, 14*, 485–502.

Demiriz, A. (2004). Enhancing product recommender systems on sparse binary data. *Data Mining and Knowledge Discovery, 9*, 147–170.

Dennis, C., Marsland, D., & Cockett, T. (2001). Data mining for shopping centres-customer knowledge management framework. *Journal of Knowledge Management, 5*, 368–374.

Douglas, S., Agarwal, D., & Alonso, T. (2005). Mining customer care dialogs for "daily news". *IEEE Transactions on Speech and Audio Processing, 13*, 652–660.

Drew, J. H., Mani, D. R., Betz, A. L., & Datta, P. (2001). Targeting customers with statistical and data-mining techniques. *Journal of Service Research, 3*, 205–220.

Etzion, O., Fisher, A., & Wasserkrug, S. (2005). E-CLV: A modeling approach for customer lifetime evaluation in e-commerce domains, with an application and case study for online auction. *Information Systems Frontiers, 7*, 421–434.

Fletcher, D., & Goss, E. (1993). Forecasting with neural networks: An application using bankruptcy data. *Information and Management, 3*.

Giudici, P., & Passerone, G. (2002). Data mining of association structures to model consumer behaviour. *Computational Statistics and Data Analysis, 38*, 533–541.

Ha, S. H. (2002). Helping online customers decide through web personalization. *IEEE Intelligent Systems, 17*, 34–43.

Ha, S. H., Bae, S. M., & Park, S. C. (2002). Customer's time-variant purchase behavior and corresponding marketing strategies: An online retailer's case. *Computers and Industrial Engineering, 43*, 801–820.

Ha, S. H., Bae, S. M., & Park, S. C. (2006). Digital content recommender on the internet. *IEEE Intelligent Systems, 21*, 70–77.

He, Z., Xu, X., Deng, S., & Ma, R. (2005). Mining action rules from scratch. *Expert Systems with Applications, 29*, 691–699.

He, Z., Xu, X., Huang, J. Z., & Deng, S. (2004). Mining class outliers: Concepts, algorithms and applications in CRM. *Expert Systems with Applications, 27*, 681–697.

Hsieh, N. C. (2004). An integrated data mining and behavioral scoring model for analyzing bank customers. *Expert Systems with Applications, 27*, 623–633.

Hung, S. Y., Yen, D. C., & Wang, H. Y. (2006). Applying data mining to telecom churn management. *Expert Systems with Applications, 31*, 515–524.

Hwang, H., Jung, T., & Suh, E. (2004). An LTV model and customer segmentation based on customer value: A case study on the wireless telecommunication industry. *Expert Systems with Applications, 26*, 181–188.

Jiang, T., & Tuzhilin, A. (2006). Segmenting customers from population to individuals: Does 1-to-1 keep your customers forever. *IEEE Transactions on Knowledge and Data Engineering, 18*, 1297–1311.

Jiao, J. R., Zhang, Y., & Helander, M. (2006). A Kansei mining system for affective design. *Expert Systems with Applications, 30*, 658–673.

Jukic, N., & Nestorov, S. (2006). Comprehensive data warehouse exploration with qualified association-rule mining. *Decision Support Systems, 42*, 859–878.

Kim, E., Kim, W., & Lee, Y. (2003). Combination of multiple classifiers for the customer's purchase behavior prediction. *Decision Support Systems, 34*, 167–175.

Kim, J. K., Song, H. S., Kim, T. S., & Kim, H. K. (2005). Detecting the change of customer behavior based on decision tree analysis. *Expert Systems with Applications, 22*, 193–205.

Kim, S. Y., Jung, T. S., Suh, E. H., & Hwang, H. S. (2006). Customer segmentation and strategy development based on customer lifetime value: A case study. *Expert Systems with Applications, 31*, 101–107.

Kim, Y. A., Song, H. S., & Kim, S. H. (2005). Strategies for preventing defection based on the mean time to defection and their implementations on a self-organizing map. *Expert Systems with Applications, 22*, 265–278.

Kim, Y. H., & Moon, B. R. (2006). Multicampaign assignment problem. *IEEE Transactions on Knowledge and Data Engineering, 18*, 405–414.

Kim, Y. S. (2006). Toward a successful CRM: Variable selection, sampling, and ensemble. *Decision Support Systems, 41*, 542–553.

Kim, Y. S., & Street, W. N. (2004). An intelligent system for customer targeting: A data mining approach. *Decision Support Systems, 37*, 215–228.

Kincaid, J. W. (2003). Customer relationship management: Getting it right. *Upper saddle river*. N.J.: Prentice Hall PTR.

Koh, H. C., & Chan, K. L. G. (2002). Data mining and customer relationship marketing in the banking industry. *Singapore Management Review, 24*, 1–28.

Kracklauer, A. H., Mills, D. Q., & Seifert, D. (2004). Customer management as the origin of collaborative customer relationship management. *Collaborative Customer Relationship Management - taking CRM to the next level*, 3–6.

Kubat, M., Hafez, A., Raghavan, V. V., Lekkala, J. R., & Chen, W. K. (2003). Item set trees for targeted association querying. *IEEE Transaction on Knowledge and Data Engineering, 15*, 1522–1534.

Kuo, R. J., Liao, J. L., & Tu, C. (2005). Integration of art2 neural network and genetic k-means algorithm for analyzing web browsing paths in electronic commerce. *Decision Support Systems, 40*, 355–374.

Kwan, I. S. Y., Fong, J., & Wong, H. K. (2005). An e-customer behavior model with online analytical mining for internet marketing planning. *Decision Support Systems, 41*, 189–204.

Langley, P., & Simon, H. A. (1995). Applications of machine learning and rule induction. *Communication of the ACM, 38*, 55–64.

Larivie'Re, B., & Poel, D. V. D. (2004). Investigating the role of product features in preventing customer churn, by using survival analysis and choice modeling: The case of financial services. *Expert Systems with Applications, 27*, 277–285.

Larivie'Re, B., & Poel, D. V. D. (2005). Predicting customer retention and profitability by using random forests and regression forests techniques. *Expert Systems with Applications, 29*, 472–484.

LarivièRe, B., & Poel, D. V. D. (2005). Investigating the post-complaint period by means of survival analysis. *Expert Systems with Applications, 29*, 667–677.

Lau, H. C. W., Wong, C. W. Y., Hui, I. K., & Pun, K. F. (2003). Design and implementation of an integrated knowledge system. *Knowledge-Based Systems, 16*, 69–76.

Lee, C. H., Kim, Y. H., & Rhee, P. K. (2001). Web personalization expert with combining collaborative filtering and association rule mining technique. *Expert Systems with Applications, 21*, 131–137.

Lee, J. H., & Park, S. C. (2003). Agent and data mining based decision support system and its adaptation to a new customer-centric electronic commerce. *Expert Systems with Applications, 25*, 619–635.

Lee, J. H., & Park, S. C. (2005). Intelligent profitable customers segmentation system based on business intelligence tools. *Expert Systems with Applications, 29*, 145–152.

Lee, S. C., Suh, Y. H., Kim, J. K., & Lee, K. J. (2004). A cross-national market segmentation of online game industry using SOM. *Expert Systems with Applications, 27*, 559–570.

Lee, T. S., Chiu, C. C., Chou, Y. C., & Lu, C. J. (2006). Mining the customer credit using classification and regression tree and multivariate adaptive regression splines. *Computational Statistics and Data Analysis, 50*, 1113–1130.

Lejeune, M. A. P. M. (2001). Measuring the impact of data mining on churn management. *Internet Research: Electronic Networking Applications and Policy, 11*, 375–387.

Leung, R. W. K., Lau, H. C. W., & Kwong, C. K. (2003). On a responsive replenishment system: A fuzzy logic approach. *Expert Systems with Applications, 20*, 20–32.

Li, S. T., Shue, L. Y., & Lee, S. F. (2006). Enabling customer relationship management in ISP services through mining usage patterns. *Expert Systems with Applications, 30*, 621–632.

Liao, S. H., & Chen, Y. J. (2004). Mining customer knowledge for electronic catalog marketing. *Expert Systems with Applications, 27*, 521–532.

Ling, R., & Yen, D. C. (2001). Customer relationship management: An analysis framework and implementation strategies. *Journal of Computer Information Systems, 41*, 82–97.

Liu, D. R., & Shih, Y. Y. (2005). Integrating AHP and data mining for product recommendation based on customer lifetime value. *Information and Management, 42*, 340–387.

Min, H., Min, H., & Eman, A. (2002). A data mining approach to developing the profiles of hotel customers. *International Journal of Contemporary Hospitality Management, 14*, 274–285.

Min, S. H., & Han, I. (2005). Detection of the customer time-variant pattern for improving recommender systems. *Expert Systems with Applications, 28*, 189–199.

Mitra, S., Pal, S. K., & Mitra, P. (2002). Data mining in soft computing framework: A survey. *IEEE Transactions on Neural Networks, 13*, 3–14.

Mozer, M. C., Wolniewicz, R., Grimes, D. B., Johnson, E., & Kaushansky, H. (2000). Predicting subscriber dissatisfaction and improving retention in the wireless telecommunications industry. *IEEE Transactions on Neural Networks, 11*, 690–696.

Ngai, E. W. T. (2005). Customer relationship management research (1992–2002): An academic literature review and classification. *Marketing Intelligence, Planning, 23*, 582–605.

Nord, J. H., & Nord, G. D. (1995). MIS research: Journal status and analysis. *Information & Management, 29*, 29–42.

Parvatiyar, A., & Sheth, J. N. (2001). Customer relationship management: Emerging practice, process, and discipline. *Journal of Economic & Social Research, 3*, 1–34.

Poel, D. V. D., & Buckinx, W. (2005). Predicting online-purchasing behavior. *European Journal of Operational Research, 166*, 557–575.

Poel, D. V. D., & Larivière, B. (2004). Customer attrition analysis for financial services using proportional hazard models. *European Journal of Operational Research, 157*, 196–217.

Prinzie, A., & Poel, D. V. D. (2005). Constrained optimization of data-mining problems to improve model performance: A direct-marketing application. *Expert Systems with Applications, 29*, 630–640.

Prinzie, A., & Poel, D. V. D. (2006). Investigating purchasing-sequence patterns for financial services using Markov, MTD and MTDg models. *European Journal of Operational Research, 170*, 710–734.

Rosset, S., Neumann, E., Eick, U., & Vatnik, N. (2003). Customer lifetime value models for decision support. *Data Mining and Knowledge Discovery, 7*, 321–339.

Salchenberger, L. M., Cinar, E. M., & Lash, N. A. (1992). Neural networks: A new tool for predicting thrift failures. *Decision Sciences, 23*, 899–916.

Shaw, M. J., Subramaniam, C., Tan, G. W., & Welge, M. E. (2001). Knowledge management and data mining for marketing. *Decision Support Systems, 31*, 127–137.

Smith, K. A., Wills, R. J., & Brooks, M. (2000). An analysis of customer retention and insurance claim patterns using data mining: A case study. *Journal of the Operational Research Society, 51*, 532–541.

Song, H. S., Kim, J. K., Cho, Y. B., & Kim, S. H. (2004). A personalized defection detection and prevention procedure based on the self-organizing map and association rule mining: Applied to online game site. *Artificial Intelligence Review, 21*, 161–184.

Song, H. S., Kim, J. K., & Kim, S. H. (2001). Mining the change of customer behavior in an internet shopping mall. *Expert Systems with Applications, 21*, 157–168.

Su, C. T., Hsu, H. H., & Tsai, C. H. (2002). Knowledge mining from trained neural networks. *Journal of Computer Information Systems, 42*, 61–70.

Swift, R. S. (2001). Accelarating customer relationships: Using CRM and relationship technologies. *Upper saddle river*. N.J.: Prentice Hall PTR.

Tam, K. Y., & Kiang, M. Y. (1992). Managerial applications of neural networks: The case of bank failure predictions. *Management Science, 38*, 926–947.

Teo, T. S. H., Devadoss, P., & Pan, S. L. (2006). Towards a holistic perspective of customer relationship management implementation: A case study of the housing and development board, Singapore. *Decision Support Systems, 42*, 1613–1627.

Turban, E., Aronson, J. E., Liang, T. P., & Sharda, R. (2007). *Decision support and business intelligence systems* (Eighth ed.). Pearson Education.

Verdú, S. V., García, M. O., Senabre, C., Marín, A. G., & Franco, F. J. G. (2006). Classification, filtering, and identification of electrical customer load patterns through the use of self-organizing maps. *IEEE Transactions on Power Systems, 21*, 1672–1682.

Verhoef, P. C., & Donkers, B. (2001). Predicting customer potential value an application in the insurance industry. *Decision Support Systems, 32*, 189–199.

Wang, K., Zhou, S., Yang, Q., & Yeung, J. M. S. (2005). Mining customer value: From association rules to direct marketing. *Data Mining and Knowledge Discovery, 11*, 57–79.

Wang, Y. F., Chuang, Y. L., Hsu, M. H., & Keh, H. C. (2004). A personalized recommender system for the cosmetic business. *Expert Systems with Applications, 26*, 427–434.

Wei, C. P., & Chiu, I. T. (2002). Turning telecommunications call details to churn prediction: A data mining approach. *Expert Systems with Applications, 23*, 103–112.

Woo, J. Y., Bae, S. M., & Park, S. C. (2005). Visualization method for customer targeting using customer map. *Expert Systems with Applications, 28*, 763–772.

Wu, C. H., Kao, S. C., Su, Y. Y., & Wu, C. C. (2005). Targeting customers via discovery knowledge for the insurance industry. *Expert Systems with Applications, 29*, 291–299.

Yang, Y., & Padmanabhan, B. (2005). A hierarchical pattern-based clustering algorithm for grouping web transactions. *IEEE Transaction on Knowledge and Data Engineering, 17*, 1300–1304.

Yu, J. X., Ou, Y., Zhang, C., & Zhang, S. (2005). Identifying interesting visitors through web log classification. *IEEE Intelligent Systems, 20*, 55–59.

Zhang, G., Hu, M. Y., Patuwo, B. E., & Indro, D. C. (1999). Artificial neural networks in bankruptcy prediction: General framework and cross validation analysis. *European Journal of Operational Research, 116*, 16–32.