Journal of Global Information Management
Volume 27 • Issue 1 • January-March 2019

Behavior Analysis of Customer Churn for a Customer Relationship System: An Empirical Case Study

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ABSTRACT

This article describes how the bank industry in Taiwan must function in today's tough and fiercely competitive domestic credit card market and subdued global market. Banks are increasingly emphasizing the importance of retaining customers in order to sustain market share and remain profitable. This study proposes a new model which local banks can use to detect potential customer churn and provide an early warning indicator of problems that could lead to loss of customers. The model incorporates a customer relationship management database with a built-in time factor and applied temporal abstraction to represent data for a specific time period as defined by experts. Association rule mining is applied to analyze and detect abnormal customer behavior. The results of this article indicate that the system is relatively effective in detecting customer churn early on and thus helpful at assisting banks to address issues before they escalate. Furthermore, the tested rules are further scrutinized by experts to establish the relationship between the defined rules and management. This study provides an expert system for banks to assess the quality of their marketing campaigns and reestablish faltering customer relationships.

KEYWORDS

Association Rules, Banking Industry, Customer Churn, Customer Relationship Management (CRM), Temporal Abstraction,

1. INTRODUCTION

Recently, with the growth of intense competition in today's business environment, companies are forced to develop effective marketing strategies in order to survive. Marketing managers are forced to focus more attention and resources on customer retention (Tamaddoni, Stakhovych, & Ewing, 2016). The maintenance of good relationships with current customers is more important than the acquisition of new customers (Karakostas, Kardaras, & Papathanassiou, 2005; Navimipour & Soltani, 2016). A small improvement in customer retention can lead to a significant increase in profit (Van den Poel & Lariviere, 2004). In short, retaining the customer base has become a critical issue for managers.

Several studies have shown that acquiring a new customer is usually five to six times more expensive than retaining an existing customer (Athanassopoulos 2000; Slater & Narver 2000). Customer churn management is aimed at minimizing losses caused by customer attrition and at

DOI: 10.4018/JGIM.2019010106

retaining high-value customers, thereby maximizing profit. Recently, companies have become interested in identifying potential churners (Keramati et al., 2016).

According to the credit card and financial information published on the website of the Banking Bureau of the Financial Supervisory Commission, monthly customer churn accounts for approximately 1% of the total number of cards in circulation (annual customer churn is approximately 12%). Clearly, in Taiwan's highly competitive credit card market, ignoring the problem of customer loss can seriously affect business development. Customers may choose to switch to credit cards issued by other banks if they lose out on preferential treatment or value-added services. However, if the issuer can formulate the correct strategies to retain customers, it will enhance customer loyalty and customer contribution. Simply reducing the rate of customer churn can contribute to an enterprise's operating profits and sales.

A customer churn prediction model can be used as an early warning tool for businesses, and extracting critical factors related to customer churn can provide additional useful knowledge that supports decision making (Chu, Tsai, & Ho, 2007). There are many existing studies on the topic of customer churn detection or prediction. However, most of these pay more attention to providing different classifiers to improve the accuracy rate (Coussement, Benoit, & Van den Poel, 2010; De Bock & Van den Poel, 2011; Kisioglu & Topcu, 2011) than proposing a framework which identifies critical factors and generates actionable suggestions. Most of these studies have used only customer demographic data (such as place of residence and age) and billing data (such as average payment amount and average minutes of usage) to predict customer churn. It has been observed however, that customer relationships and satisfaction are often seen as key factors for customer retention, and their effects have been investigated by many (Gustaffsson, Johnson, & Roos, 2006; Hennig-Thurau & Klee, 1997). On the other hand, customer churn occurs gradually over time. The problem is that a gradual reduction in the amount of consumption per card cannot be seen by looking at the average value in the last three months prior to the occurrence of customer churn. If the bank were to become aware of the signs of upcoming customer churn earlier, they might be able to put into place relevant countermeasures to avoid continued decline in the quantity of cards issued.

In order to fill these gaps in the body of research, this study proposes a framework which integrates the techniques of temporal abstraction and association rule mining to observe gradual downward trends in the amount of customer consumption, with the added dimension of customer care. To the best of our knowledge, there have been no studies of customer churn using real transaction data aimed at understanding the temporal variation of behavioral trends and considering the dimension of customer care.

Customer behaviour analysis is a good way for firms to better understand the consumers' intention. Especially, changes in customer behavior over time can offer valuable information from which meaningful implications can be drawn. Data mining tools can be applied to discover interesting patterns from customer databases. Such information can shed much light on the process of customer churn, so that actions can be taken in advance to retain them. This study applies the method of temporal abstraction to collect and transform the data to understand the process of temporal evolution, and association mining is used to filter interesting user behavior rules. The rules established for various types of customer churn can clearly explain changes in customer behavior over time, giving more complete reference information for management to plan relevant strategies, actively care for existing customers and reestablish damaged customer relationships. To the best of our knowledge, there has been no analysis of customer behaviors using association rules extracted from real usage patterns aimed at understanding behavioral differences between churn customers and normal users.

The proposed framework can be used to establish a rule model of customer churn, designed to assist credit card issuing banks with the formulation of marketing strategies as quickly as possible in order to reduce loss. In addition, the experimental results are determined based on rules extracted from a large customer relationship management database generated by the bank. The accuracy of the rules is empirically confirmed and their validity is also verified by consultation with experts.

In the next section, we briefly review previous research studies, then describe the proposed framework in detail. In addition, the proposed procedures are analyzed in a series of experiments. After this discussion some managerial implications for marketing reference are offered. Finally, we state the limitations of this study, and outline potential directions for future research.

2. LITERATURE REVIEW

This study analyzes customer behavior in order to understand the process of customer formation and churn. The technique of "temporal abstraction" is adopted for data preprocessing against the background of temporal variation to understand trends in customer behavior, while association rules are used for classification and to mine the rules for customer churn. A literature review is carried out of work related to customer churn, temporal abstraction and association rule classification.

2.1. Customer Churn

Marketing strategy can increase customer numbers, but timely maintenance activities are necessary to retain them. Past studies have discussed the customer's lifetime value from three dimensions: past contribution, potential value (benefits possibly obtained in future) and customer churn rate (Hwang, Jung, & Suh, 2004). The degree of future customer contribution is equal to the "potential value" multiplied by the "customer retention ratio". Enterprises need to reduce customer churn to retain potential customer value.

Studies adopting customer lifetime value in their discussion of customer churn show that customer churn has a big effect on enterprise profitability. Strategies need to be developed for customer retention that enhance customer loyalty and increase the value of future customer contributions (Karakostas et al., 2005). Previous studies into customer churn have tended to focus on which classification methods should be used to increase the accuracy of statistical techniques. Table 1 shows a summary and comparison of works related to data mining applications for customer churn prediction in terms of the techniques used and problem domains.

Kisioglu et al. (2011) using a dataset comprised of customer data from Turkish telecommunications companies, such as place of residence, age, average payment amount and average minutes of usage, applied Bayesian network technology to establish a customer churn prediction model. In another study, partial least squares (PLS) analysis was applied for the establishment of a churn model with the average minutes of usage per household, average frequency of usage per household, monthly average usage and other selected variables (Lee, Lee, Cho, Im, & Kim, 2011). Bhattacharyya, Jha, Tharakunnel, and Westland (2011) compared three classification methods, namely the logistic regression, random forest and support vector machine methods to find that overall, the random forest method has the best effect. The parameters selected were basic customer information, average payment amount, and so on. Some other studies have compared the effect of multiple kinds of classifiers (Huang, Kechadi, & Buckley, 2012).

The recognition of who are the most profitable customers and how to ensure customer retention are extremely important. In their study, Lin, Tzeng, and Chin (2011) divided customers into survival, potential churn and volunteer churn customers, then used a classification method to establish a churn model. The variables selected were age, gender and other demographic information, annual transaction frequency, annual average payment amount, etc.

Zhang et al. (2012) proposed a novel prediction model based on social network analysis of a mobile telecommunications dataset. The results proved that prediction accuracy could be improved by incorporating interpersonal influence into classification. Neural network and association rule methods were used to establish a two-stage behavioral scoring model, which banks could use to understand the profitability of each group and devise appropriate business strategies (Hwang et al., 2004). The above-mentioned studies conducted explorations into customer behavior using different classification methods which adopted gender attributes and multi-stage behavior scoring models.

Table 1. Summary of related work

Authors (year)	Industry	Variables	Research methodology
Hwang et al. (2004)	Credit card	Installment payment customers, payment in full customers, short-term fund demand customers	Neural network
Lin et al. (2011)	Credit card	Demographic, annual transaction frequency and annual average payment amount	Rough set theory
Kisioglu et al. (2011)	Telecommunications	Age, average payment amount and average minutes of usage	Bayesian belief network
Lee et al. (2011)	CRM	Average household minutes of usage, average household usage frequency, monthly average usage of bill	Partial least squares
Bhattacharyya et al. (2011)	Credit card	Billing information, demographic information	Support vector machine; random forests
Huang et al. (2012)	Telecommunications	Call details, line information, bill and payment information	Logistic regressions; naive bayes; decision trees
Zhang et al. (2012)	Telecommunication	Network attributes, traditional attributes	Logistic regression; decision tree; neural network
Farquad et al. (2014)	Credit card	Socio-demographic, behavioral data	Support vector machine
Chen et al. (2015)	Logistics industry	Recency, frequency, monetary, profit	C4.5; support vector machine; logistic regression
Keramati et al. (2016)	Electronic banking services	Demographic variables, transaction data, customer complaints	Decision tree

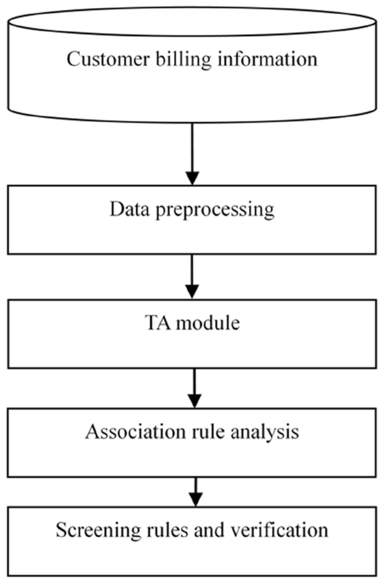
Despite the establishment of a decent classification model, potential information obtained during the process of temporal evolution has not been considered. If the time state information and trend factors can be added into the data mining process, it is believed that more meaningful classification rules can be established.

This study examines credit card customers. However, credit cards expire in 2 to 5 years. Nowadays, for promotional purposes, most banks have cancelled annual fees meaning that customers may hold a credit card but not use it, making them potential churn customers. Unlike in other industries, such customers may be classified in the category of survivors but still have no business contacts.

2.2. Temporal Abstraction

Temporal abstraction (TA) is a kind of structured knowledge derived from the context, external events, and other parameters of the domain. The TA algorithm is applied to summarize temporal data showing the qualitative representation of a specific time period as defined by experts (Stacey & McGregor, 2007). Temporal abstraction includes the time stamp, parameters, events and abstraction aim. The knowledge established can support collection, maintenance, reuse, enjoyment and other functions (Stacey & McGregor, 2007). The technique of TA has mostly been applied for the analysis of medical behavior, to effectively transform the tacit professional knowledge of the clinician into shareable explicit knowledge for disease prevention or enhancement of the quality of medical treatment

Figure 1. Structure of the proposed framework



(Bellazzi, Larizza, Magni, & Bellazzi, 2005; Orphanou, Stassopoulou, & Keravnou, 2014; Shahar, 1997; Su, Ping, Tseng, & Lai, 2014; Yeh, Wu, & Tsao, 2011; Cheng, Hu, Chiou, 2017)).

Stacey et al. (2007) discussed the use of temporal abstraction in intelligent data analysis and its applications. Temporal abstraction is an important step in intelligent data analysis. Incorrect data are detected through a data verification procedure designed to reduce noise and select important characteristic attributes, after which the data are materialized with the transformative technique of temporal abstraction. An inference engine is used to establish a rule model to explain rule implications for further applications. The threshold value for each item used during the process of transformation by temporal abstraction is defined based on the experience of domain experts (Stacey et al., 2007). Temporal abstraction mainly describes the temporal change of an event, and changes or trends of its state, and the time attribute value is added to explore the rules implied in events. Temporal abstraction can be divided into the basic state, basic trend or complex state. Basic temporal abstraction can be divided into two types: state or trend. The state is obtained through the transformation of raw data based on the transformed threshold value suggested by specific domain experts: high (H), higher than normal (N/H), normal (N), lower than normal (N/L), lower (L), etc. The state can be divided into different levels according to the attribute characteristics. There are three types of trends in temporal abstraction: I (increasing), D (decreasing) and S (stable), which can be obtained through transformation in a short time state.

2.3. Association Rules

Association rule analysis, generally called Market-basket Analysis, was first proposed by Agrawal et al, with the apriori algorithm being the most well-known method. Association rule analysis is often used in the field of data mining, as it can uncover the relationship between valuable items extracted from large amounts of data which can be used as a reference for future marketing. For instance, we can apply association rule mining on supermarkets customers' purchase records to classify the customers' purchase behaviors. Next, we can further find the behaviors to improve profitability. For example, one potential rule might show that beer and baby diapers are often purchased at the same time. Thus, the supermarket can adjust the position of goods on the shelf to put baby diapers and beer together to increase sales opportunities.

In this formulation, I is the set of all the items in the database and i is the item, indicated by $I=\{i_1,i_2,i_3,\ldots,i_n\}$; T is a set composed of items in a deal, indicated by $T\subseteq I$; X and Y are both itemsets. If the condition is that X itemsets in deal T correspond to the results of Y itemsets in deal T, the association rule can be defined as X->Y, where X and Y are both subsets of I and can be indicated as X, $Y\subset$I. Furthermore, there is no intersection of the items of X and Y as indicated by $X\cap Y=\varnothing$. Here, X is called the conditional item; Y is called the conclusion item.

3. RESEARCH METHOD AND STRUCTURE

A framework integrating temporal abstraction and association rules is developed. This study uses the customer database of a specified bank to explore the behavioural characteristics of churn customers. The customer relationship management database includes demographic data, customer relationship data and the bank's monthly credit card billing account data. The proposed framework consists of the following modules: screening of the attribute field; data pre-processing; TA module; and association rules analysis, as illustrated in Figure 1.

According to data published by the Banking Bureau of Financial Supervisory Commission in August 2011, approximately 36.7% of credit card customers have not used their card for more than 6 months. In this study, customers who have not paid by credit card for 6 months are considered potential churn customers. Customer attributes are defined into the following 3 categories:

1. **Surviving Customers (Normal Transactions):** these customers hold a valid card for normal consumption and have used it at least once in the last 6 months (as defined by the Banking Bureau of Financial Supervisory Commission).
2. **Potential Churn Customers:** such customers may hold a valid credit card for normal consumption but they have not used it for more than 6 months.
3. **Volunteer Churn Customers:** such customers have cancelled all their credit cards for the specified bank.

3.1. Data Preprocessing

During data preprocessing, to avoid deviation in the data from affecting the results, we first exclude company credit cards not belonging to individuals, because consumption with these cards is related to the needs and regulations of the company rather than determined by the individual user. Secondly, the subjects in this study are customers with normal consumption patterns. Thus, those who have cancelled credit cards during the period of analysis or whose spending frequency is less than 6 times in the following 6 month period after analysis are excluded.

After discussion with experts, we choose fifteen fields which are combined with customer demographic information and data related to consumption and payment status. The demographic data convey important information about the attributes to help categorized the customers. For example, the customer's age will affect their economic conditions, life preferences and credit card usage habits. The details are illustrated in Table 2.

"Customer affiliation" is indicative of the importance of customers to the bank as well as the how much the bank is willing to invest in these customers. The customer's total assets (such as savings and other funds) held by the bank as well as the degree of contribution over the past year are taken into account for affiliation classification. Appropriate strategies are formulated for different customer affiliations in pursuit of maximized profits. Different levels of resources and services are invested in different customer groups. In order to improve relationships and ensure the loyalty of

Table 2. Attributes Selected

Data category	Item	Attributes	Remarks
	1	Customer identification no.	
Demographic data	2	Age	
	3	Gender	1 (male) 2 (female)
	4	Place of residence	Indicated by the area code of the residential phone
	5	Customer affiliation	1 financial customer groups 2 customer groups with development value 3 general customer groups
Customer relationship data	6	Frequency of customer calls to the service center	unit: number of times
	7	Customer satisfaction with their service center calls	H: satisfied N: no interview L: dissatisfied
	8	Frequency of return calls from the customer service center for care (or marketing)	unit: number of times
Spending account data	9	Closing day	date bills are generated; YYYYMMDD (Republic of China date), for the use of time interval
	10	Perpetual credit line	unit: NTD
	11	Credit interest rate per cycle	2 integers and 3 digits after decimal point
	12	Consumption amount in the current period	unit: NTD
	13	Balance of installment	unit: NTD
	14	Balance of cycle credit	unit: NTD
	15	Code showing payment status in the prior period (amount)	1 entirely paid the unpaid balance 2 paid the minimum payment 3 (did not pay the minimum payment 4 X (no unpaid balance)

high-value customers, banks will provide specific services tailored to these customers. The goal is also to increase investment and the purchase of financial commodities. Such customer information is of great assistance in identifying customer churn.

To the best of our knowledge, there has been no previous research study using a customer relationship database to detect customer churn. The database fields include: “frequency of customer calls to the customer service center”, “customer satisfaction with their service center calls” and “frequency of calls from customer service centers to customers (or marketing)”. The customer service center is the main channel for banks to provide service to credit card customers. Services include consultation on the rights and interests of card users, accounting consultation, loss reporting, reissuing of lost cards, and so on. The establishment of good relationships with customers is based on the convenience and safety of the card service.

In order to confirm whether the quality of the service offered by the customer service center conforms to customer expectations, follow up calls are systematically made by banks to conduct customer satisfaction surveys. Objective data are gathered to test internal service quality. It is believed that service quality is important to the customer retention rate.

Outgoing follow-up calls for care (or marketing) are an important tool for banks to encourage credit card users to continue paying by credit. Banks can provide exclusive activities for specific customer groups or notify customers of special offers. Such calls help to build customer relationships. Customer feedback can be collected through the interaction, which can be used as reference for strategy making to conform to customers' requirements.

The customer billing account and consumption data include information about the "perpetual credit line", "consumption amount in the current period", "balance of installments", "consumption amount in the current period" and "amount of interest in the current period". The "perpetual credit line" is used by banks to evaluate the customers' credit rating, assets, wages, income and other factors as well as the maximum payment the customer is willing to bear. A higher credit line is usually indicative of more assets or higher wage income for this customer. Such customers may also be more valuable to the bank. However, a lower credit line does not necessarily represent lower assets or wage income for this customer. The customer might desire a reduction in their credit line to make it safer to use the card. A customer request for an increase or reduction in their credit line indicates continued use of this card which is related to customer churn.

- "Consumption amount in the current period" is greater than 0 if consumption has occurred during the current month, and indicates loyal customers. When the amount of credit interest is greater than 0, it indicates that customers require these funds. Although such customers bring in considerable interest income to the bank, it is necessary to conduct regular audits to avoid loss as a consequence of overdue receivables or bad debts.
- When the "balance of installment" is greater than 0, it indicates that customers have installment payments to meet. They pay what they owe by installments and pay attention to banking activities. Good customer relationships can be maintained through timely promotions and marketing campaigns.
- From "consumption amount in the current period" and "amount of payable interest in the current period" one can estimate the degree of contribution of the customer. "Credit interest rate" refers to the interest rate automatically assigned by the system every month in accordance with the customer's credit standing (inter-bank borrowing amount) and payment status. A higher interest rate means that it is more likely that the customer will sever a contract without payment. Banks may lose customers due to poor credit. The overall status of customer payment can be known from the "billing accounts payable in the current period" and "payment status in the prior period", which is helpful in the analysis of customer churn.

3.2. TA Module

Parts of the numeric fields are processed by temporal abstraction after discussion with experts, to transform them into meaningful information. It is hoped that pattern mining can be used to discover the initial pattern indicative of customer churn. If this is known preferential marketing strategies can be designed in a timely manner aimed at retaining these customers. It is hoped that banks can gain greater benefits by means of this method, rather than spending more manpower and money to retain customers after customer churn has occurred.

The TA model is applied first using the customer relationship management database containing the time series of characteristics. Through discussion with a senior customer service IT supervisor, the important attribute fields required in the experiment are determined and related data are summarized in the same database. The data attribute fields are divided into temporal abstraction attributes and non-temporal abstraction attributes. The trends of changes in the fields over time and the reference values used in practice are selected based on the suggestions given by the customer service supervisor. The class interval parameters for the threshold values used in the temporal abstraction attribute field are defined by means of expert suggestions for transformation of the basic state in temporal abstraction.

In the non-temporal abstraction attribute field, the categories corresponding to the numeric values and frequency count are transformed.

Temporal abstraction is used to understand the correlation between changes in the value of the attribute field for monthly credit card billing accounts and customer churn. The attribute data are transformed, and the class intervals for the attribute are defined according to the defined thresholds for each interval. Most attributes can be classified into five intervals: H (highest), N/H (higher than normal), N (normal), N/L (lower than normal) and L (lowest). However, the changes are not always significant. The experts suggested using only three intervals. Since customer consumption may differ due to overall economic status, this study adopts a dynamic method to calculate the threshold value of each temporal abstraction attribute.

The basic TA process is carried out for the attribute items having the temporal abstraction characteristics and significance according to the definition of the threshold value for each attribute value. This study uses 3 months of billing data as one period, determining the basic temporal abstraction for the earlier period (the 1st to the 3rd month) and for the later period (the 4th to the 6th month). The average value for the billing period is calculated, and then transformed according to the definition of the threshold value. For example, the consumption amount can be transformed into the "basic state of bill consumption amount in the earlier period", "basic state of bill consumption amount in the later period" and "basic state of bill consumption amount".

In complex temporal abstraction, the connection between the basic temporal abstraction state and the trend is symbolized by ">". For instance, the "basic state of bill consumption amount in the earlier period" is "H" and the "trend state of bill consumption amount" is "I", thus the complex temporal abstraction will be indicated by "H>I".

3.3. Association Rule Analysis

The relational data mining technique is used to understand the association between the customers' demographic data and billing data, and customer churn, by establishing itemsets which satisfy the two parameters of minimum support and minimum confidence. We then examine the importance of the rules, so as to understand the association rules for customer churn.

Association rule mining is applied to the customers' transaction data. The set of database attributes are called "itemsets". In this study, there are 3 categories of customers: surviving customers (normal transactions), potential churn customers and voluntary churn customers. The support and confidence are defined as follows:

Support: The portion of customers in itemset X and customer churn category Y among all customers

$$Support = \frac{\left|\mathrm{X} \quad \cup \ \mathrm{Y}\right|}{\text{Total number of customers}}. \tag{1}$$

Confidence: The portion of customers in item set X and customer churn category Y among the customers in itemset X

$$\text{Confidence} = \frac{\left|\mathrm{X} \quad \cup \ \mathrm{Y}\right|}{\text{Total number of customers in X}}. \tag{2}$$

Importance: The proportion of confidence supporting itemset X and customer churn results Y in non-item set X and customer churn result Y. This is used to determine the relative importance of the association rule classification results. If the value is greater than 0, it indicates that this rule has significance, and the greater the value, the more important it is; if the value is smaller than 0, it indicates that this rule has no significance

$$\text{Importance} = \log\left(\frac{P(Y \mid X)}{P(Y \mid NotX)}\right) \tag{3}$$

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1. Experimental Data

This study seeks to determine the marketing value of credit card customer groups for one certain bank in Taiwan. Data mining is conducted on demographic data, customer relationship data and monthly billing account data to find the association rules and managerial implications. In order to prove that the rule found will be applicable in future, we continued to collect data for half a year following the experimental period. Adopting the same methods as in the experimental stage pre-processing is carried out for transformation of the data, which will be used to verify the rules established in the experimental stage.

The samples are taken from customer data from January to June for a period of one year. A total of six months data is used for data mining to find out the churn pattern, with customer data from the latter half of the year (from July to December) used to verify whether these rules will appear in the same threshold. Table 3 shows the data distribution in the experimental stage.

The temporal abstraction attributes are divided into three types in terms of the amount, satisfaction with call service, and frequency of incoming/outgoing calls to/from the service center. The status of the customer is indicated through changes in trends for these three types of attributes. The attributes include the consumption amount, cyclical credit balance, balance of installments and other fields. A gradual reduction in consumption amount may mean upcoming customer churn. The attributes for accounts are classified into 5 class intervals in total. If the attribute value of this category is 0, it represents no consumption or use, which is of great significance. Therefore, if the amount is 0, it is indicated by L (low). The overall economic environment, people's consumption habits, consumption cycle and other factors need to be considered, although they cannot be indicated with a fixed reference value. So as suggested by the experts, customers whose amount of use in each time interval is greater than 0 are selected and divided into 4 class intervals according to the amount of use: H (high), N/H (higher than normal), N (normal), N/L (lower than normal). The threshold value is defined dynamically according to the experimental data which is beneficial to the follow-up transformation and analysis. Other threshold values for non-amount attributes are formulated based on the experts' suggestions. The calculated threshold values of the fields of the amount attributes are shown in Table 4.

Parts of the numeric fields have smaller change intervals, so they can be only divided into 3 states. Specifically, the fields divided into only 3 class intervals during are satisfaction with incoming call service and frequency of incoming and outgoing calls to customer centers. The data are transformed.

Table 3. Experimental Data Result Distribution

Category code	Customer category	Number of transactions	Proportion
1	Surviving customers	95,323	84.82%
2	Potential churn customers	15,179	13.51%
3	Volunteer churn customers	1,875	1.67%

Table 4. Threshold Value for the Amount Attribute Field

Period	Attribute category	Threshold value			
		H_VALUE (high)	NH_VALUE (higher than normal)	NL_VALUE (lower than normal)	L_VALUE (low)
In the first quarter of 2011	FEE_AMT1 (cycle interest)	1,578	721	242	0
	LOAN_AMT1 (cycle balance)	116,304	53,216	15,531	0
	STAGE_AMT1 (balance of installment)	29,979	11,154	3,560	0
	STMT_AMT1 (bill amount)	28,576	10,726	3,644	0
In the second quarter of 2011	FEE_AMT2 (cycle interest)	1,543	679	213	0
	LOAN_AMT2 (cycle balance)	118,643	55,545	18,375	0
	STAGE_AMT2 (balance of installment)	30,540	11,748	3,552	0
	STMT_AMT2 (bill amount)	27,154	10,120	3,500	0

1. **Non-Amount Field of the Temporal Abstraction Attribute:** Based on the description of the class interval code and the threshold value, the basic state transformation of temporal abstraction is conducted.
2. **Amount Field of the Temporal Abstraction Attribute:** Based on the defined threshold value for the amount attribute field, the basic state transformation of temporal abstraction is conducted. For instance, the billing amounts for customers A, B, and C in the first quarter of 2011 (sum of accounts from January to March) are respectively NTD 0, NTD 5,000 and NTD 15,000, respectively indicated by L, N and N/H.
3. **Field of the Non-Temporal Abstraction Attribute:** The numeric value is transformed to the category and frequency count. For instance, customers A, B, and C are respectively 23, 45 and 67 years old so the age categories are transformed into 2, 4 and 6. (age category = age divided by 10 to become an integer)

The basic state and trend are further transformed into complex temporal abstractions. The "basic state of temporal abstraction", "basic trend of temporal abstraction", "complex state of temporal abstraction", "attribute value of frequency count" and "basic attribute value" (such as customer affiliation) are summarized for the exploration of association rules and to calculate the support, confidence and importance of each rule. In terms of the importance of the association rule, if the value is greater than 0, it means that this rule is important. Therefore, it is argued that the significant rule patterns should not only satisfy the minimum support and confidence levels, but should also satisfy the condition of importance. Through the observation of changes in the association rule, the most suitable threshold value is found, from which potential valuable rule information for customer churn can also be discovered.

The established rules are then verified in the next stage and the support, confidence and importance of each rule is calculated in both the experimental and verification stages. Only rules found to satisfy support, confidence and importance levels in both the experimental and verification stages, have significance.

Table 5. Screening Conditions of Association Rules

Category code	Customer category	Number of transactions	Proportion of total	Condition of support	Condition of confidence		Condition of importance
	A	B	C	D>(C/30)	E	Remarks	F>0%
1	Surviving customers	95,323	84.82%	>2.83%	>92.41%	Proportion of surviving customers + (proportion of potential churn customers + proportion of volunteer churn customers)/2	>0%
2	Potential churn customers	15,179	13.51%	>0.45%	>27.02%	E = C * 2	>0%
3	Volunteer churn customers	1,875	1.67%	>0.06%	>3.34%	E = C * 2	>0%

4.2. Experimental Results and Discussion

The association rules are used to categorize customer behavior patterns into 3 categories: surviving customers, potential churn customers and volunteer churn customers. Given the unbalanced distribution in the quantity of various types of customers, different values are set for support, confidence and importance, as shown in Table 5, to help screen for useful rules. The customers' behavior patterns are described below.

4.2.1. Surviving Customers

Among the surviving customers, significance is reached only when the levels of support, confidence and importance, determined in both the experimental and verification stages, all surpass the threshold. The detection index conforms to the rule pattern where support is greater than 2.83%, confidence is greater than 92.41% and importance is greater than 0, as shown in Table 6. The rules are described below.

4.2.2. Potential Churn Customers

Rules for potential churn customers are screened for support greater than 0.45%, with a confidence level greater than 60% and importance greater than 0% both in the experimental and verification stages. The important rule patterns are shown in Table 7, and the rules are described below.

4.2.3. Volunteer Churn Customers

Among volunteer churn customers, the support for the rule is greater than 0.6%, confidence is greater than 60% and importance is greater than 0%, both in the experimental and verification stages. The pattern is shown in Table 8 and the rules are described below.

Table 6. Association Rules for Surviving Customers

Rule No.	Rule pattern	Training period			Test period		
		Support	Confidence	Importance	Support	Confidence	Importance
1	Trend of balance of installment = I, trend of cycle interest = S, complex later payment = L>L	3.1%	98.4%	1.2	3.4%	96.5%	1.2
2	Complex billing amount = N/H>H, trend of billing amount = I, complex later payment = L>L	4.0%	97.7%	1.2	3.9%	95.4%	1.2
3	Complex billing amount = H>N/H, trend of billing amount = D, complex later payment = L>L	4.0%	97.0%	1.2	4.0%	94.3%	1.2
4	Complex billing amount = H>N/H, trend of billing amount = D, complex outgoing calls for care (marketing) = L>L	3.7%	96.9%	1.12	3.7%	94.4%	1.2
5	trend of billing amount = I, age category = 4, complex outgoing calls for care (marketing) = L>L	4.3%	93.1%	1.12	4.8%	86.8%	1.1

Rule 1: Those whose credit card installment payments have an upward trend and who have no later bill payments will likely become surviving customers. To maintain customer relationships the bank provides 3-stage and 6-stage installment marketing plans with no service fees charged for a long time. Indications show that this works and these customers are willing to continue using this bank's credit card.

Rules 2-4: Those whose billing amount is higher or higher than normal easily become surviving customers. They are loyal customers and bring a lot of service fee revenue to the bank related to credit card payments. Banks should provide better service to increase customer loyalty, promote customer finances and increase their earnings.

Rule 5: The card use habits of those whose billing amount shows an upward trend and who are more than 40 years old are not be affected by outgoing calls for care. Customers in this age group are important, as they have the ability to consume and to invest in financial commodities.

4.3. Managerial Implications

The proposed model can be used as an early warning tool for managers to improve marketing strategies

Table 7. Association Rules for Potential Churn Customers

Rule No.	Rule pattern	Training period			Test period		
		Support	Confidence	Importance	Support	Confidence	Importance
1	Complex outgoing calls for care (marketing) = L>N, complex billing amount = L>L, customer affiliation = 3 (general customer)	1.0%	52.9%	0.62	1.3%	59.1%	0.73
2	Complex billing amount = N/L>L, trend of billing amount = D, complex cycle credit balance = L>L	2.6%	60.0%	0.7	2.4%	56.5%	0.683
3	Complex billing amount = N>L, trend of billing amount = D, complex cycle credit balance = L>L	1.4%	66.3%	0.78	1.3%	60.9%	0.743
4	Complex billing amount = L>N/L, Complex outgoing calls for care (marketing) = L>L, complex balance of installment= L>L	1.3%	70.8%	0.838	2.0%	68.6%	0.84
5	Complex billing amount = L>N/L, Complex balance of installment = L>L, complex cycle credit balance = L>L	2.4%	71.2%	0.838	2.1%	66.9%	0.82

Rule 1: For general customers, if marketing calls made by the bank for over half a year cannot encourage them to pay by credit card in a later period, they become potential churn customers. Banks need to have a deep understanding of the requirements of potential churn customers and offer promotional activities in a timely manner; otherwise, they may become volunteer churn customers.

Rules 2-5: If the customer's billing amount changes from normal or lower than normal consumption to lower than normal or no consumption, it means that the bank has lost or is losing that customer. Such customers have less loyalty to the bank. Banks should plan exclusive activities for reestablishment of faltering customer relationships.

Table 8. Association Rule of Volunteer Churn Customers

Rule No.	Rule pattern	Training period			Test period		
		Support	Confidence	Importance	Support	Confidence	importance
1	Trend of cycle credit balance = D, complex billing amount = L>L, complex balance of installment = L>L	0.68%	66.1%	0.78	0.56%	67.3%	0.83
2	Complex frequency of incoming calls to customer service center = L>N, complex billing amount = L>L, complex balance of installment = L>L	0.54%	62.6%	0.77	0.40%	60.8%	0.75
3	Complex outgoing calls for care (marketing) = N>L, complex billing amount = L>L, customer affiliation = 3 (general customer)	0.86%	51.5%	0.60	0.47%	45.0%	0.55
4	Trend of cycle interest = D, place of residence = 02, complex outgoing calls for care (marketing) = L>L	1.6%	86.0%	1.0	1.3%	83.4%	1.0
5	Trend of cycle credit balance = D, customer affiliation = 3 (general customer), complex balance of installment = L>L	2.0%	85.6%	1.01	1.5%	83.1%	1.0

Rules 1, 4, 5: Those whose cyclical credit balance or cyclical interest shows a downward trend with no more consumption are very like to become volunteer churn customers.

Rule 2: Customers with no further consumption who do not pay credit card installment payments may call the customer service center to cease use of the credit card.

Rule 3: Customers living in the greater Taipei area whose cyclical interest shows a downward trend. If there are no timely outgoing calls for care, such customers are likely to become volunteer churn customers.

to retain customers. These managers should be interested in recognizing the characteristics of about-to-be-churn customers. Our findings allow them to address the factors leading to churn in addition to targeting customers before they decide to leave.

Most surviving customers regularly use credit cards to make purchases and monthly billing amounts are high. Management should provide value added services to increase customer loyalty and to stimulate consumption. Banks could offer different marketing campaigns aimed at different types of customers according to the length of time since they have used the credit card.

More importantly, the study provides managers with a guide to help select the appropriate method to identify "Potential Churn Customers". There are usually reasons such customers seldom use their credit card. The call center might call them to inform them of some new service or information. Managers should design activities to encourage reuse if the credit card. Providing special offers could reduce the probability of customers cutting out their cards and reduce the rate of churn.

5. CONCLUSION AND FUTURE STUDIES

Given today's tough business environment, as well as resource and budget limitations, it is crucial for banks to analyze consumer behavior in order to efficiently allocate resources to achieve the optimal outcome. The most important issue for management is to provide strategies to prevent customer churn. The process of customer churn always leaves a trail of evidence and significant changes in the transaction volume and behavior of high profile customers do not occur overnight. Marketing managers hope to establish relationships with customers through improving credit card commodities and nurturing the opportunities to make legitimate contact with customers. Ideally they can provide financial services that match what the customer wants and need.

This study complies a customer behavior dataset including three types of data: the customers' credit card billing data for a six month period, the customers' demographic characteristics and customer relationship data. The method of temporal abstraction is used to understand the process of change in customer behavior over time and association rule mining is applied to mine for potential rules. Finally, the rules established through consultation with domain experts are used to explain potential management implication, to provide a reference for senior management in future decision making.

Credit card customer churn has become an extremely important issue affecting the growth of banking operations. This study has discovered that credit card customer churn follows certain rules. Customers do not go from being loyal customers to ex-customers in one day. The time factor has to be added to the detection of trends in customer behavior. In the past, banks have analyzed customer behavior from only one perspective. In this study, customer behavior is analyzed in combination with demographic characteristics and bank/customer relationships as well as consideration of temporal trends. This allows banks to obtain more complete reference information which can be used to plan relevant and realistic strategies, actively care for customers and reestablish faltering customer relationships.

Some limitations remain. It is common for banks to adopt marketing strategies such as cross selling and customer loyalty programs to increase customer value and customer engagement. However, in this study, this information is not collected, and the effect of these activities is not considered. Social media, such as Facebook and Twitter, have become important platforms for customer management, and factors related to the usage of social media can be included in future work. Finally, in the future we should incorporate different classification models to predict churn customers, and deal with the problem of imbalanced data.

ACKNOWLEDGMENT

We wish to thank the anonymous reviewers for their valuable suggestions and careful reading of our manuscript. The authors would like to express our gratitude to the reviewers for their suggestions which have led to a substantial improvement in our paper.This study was supported in part by the Ministry of Science and Technology of Taiwan under grant number:NSC 102-2410-H-031 -058 -MY3, MOST 105-2410-H-031 -035 -MY3 and MOST 106-3114-E-007-007

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