

Retraction

Retracted: A Prediction Model of Customer Churn considering Customer Value: An Empirical Research of Telecom Industry in China

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] M. Zhao, Q. Zeng, M. Chang, Q. Tong, and J. Su, "A Prediction Model of Customer Churn considering Customer Value: An Empirical Research of Telecom Industry in China," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 7160527, 12 pages, 2021.

Research Article

A Prediction Model of Customer Churn considering Customer Value: An Empirical Research of Telecom Industry in China

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Customer churn will cause the value flowing from customers to enterprises to decrease. If customer churn continues to occur, the enterprise will gradually lose its competitive advantage. When the growth of new customers cannot meet the needs of enterprise development, the enterprise will fall into a survival dilemma. Focusing on the customer churn prediction model, this paper takes the telecom industry in China as the research object, establishes a customer churn prediction model by using a logistic regression algorithm based on the big data of high-value customer operation in the telecom industry, effectively identifies the potential churned customers, and then puts forward targeted win-back strategies according to the empirical research results. This paper analyzes the trends and causes of customer churn through data mining algorithms and gives the answers to such questions as how the customer churn occurs, the influencing factors of customer churn, and how enterprises win back churned customers. The results of this paper can better serve the practice of customer relationship management in the telecom industry and provide a reference for the telecom industry to identify high-risk churned customers in advance, enhance customer loyalty and viscosity, maintain “high-value” customers, and continue to provide customers with “value” and reduce the cost of maintaining customers.

1. Introduction

Loyal customers play an important role in improving business performance and can promote the core competitiveness of enterprises [1, 2]. Loyal customers can help enterprises reduce the cost of publicity and negotiation and attract more new customers with herd mentality, thus reducing customer development costs and increasing the opportunities and time for enterprises to obtain basic profits. They can increase the opportunity and time for enterprises to obtain basic profits and help enterprises obtain premium income, consolidate market position, reduce market risks, and increase entry barriers for other enterprises. Many enterprises focus on how to obtain new customers, ignoring

how to keep existing customers and tap more consumption potential from them. Reichheld et al. found that the longer the business relationship between an enterprise and its customers lasts, the more profits the enterprise will make from its existing customers. For every 5% increase in customer retention rate, the net present value of customers in the business environment will increase by 25% to 95% [3]. Jones and Sasser's [4] research shows that when the customer churn rate of an enterprise decreases by 5%, the average profit rate of the enterprise will increase by 25%–85%. Therefore, the practical significance of customer churn prediction is that it will bring economic benefits to enterprises. Firstly, compared with new customers, the retention rate of loyal customers is higher, and the probability of

competitive marketing activities is lower, and because the enterprise knows the preferences of the existing customers, the cost of providing services is lower. Secondly, churned customers may bring other customers in the social network to competitors, while loyal customers will attract more new customers. Thirdly, customer churn will lead to missed opportunities of cross-selling and up-selling, resulting in a decline in profits. For enterprises, predicting customer churn behavior, analyzing the root causes of customer churn, finding the links that need to be improved in the process of operation and management, winning back churned customers, and establishing a stronger customer relationship have become the strategic focus.

Jain et al. [5] state that the market in telecom is fiercely competitive. Companies have to determine the customer churn by analyzing their behavior and try to put effort into retaining the customers. Zhao et al. [6] state that customer churn management is the need for the survival and development of the telecom industry. Alboukaey et al. [7] believe that customer churn is one of the most challenging problems which affects revenue and customer base in mobile telecom operators. For the telecom industry in the era of big data, the growth bonus gradually disappears, the transformation continues to deepen, and the pressure from investment and construction costs for future is huge. How to operate the customer resources that have entered the era of stock management and realize the double growth of revenue and profit is a very important issue for telecom operators. The telecom industry is facing a new competitive situation of merging and bundling to expand user scale, low price to seize traffic share, and innovative channels to achieve differential competition. The competition for customers is becoming increasingly fiercer, the market saturation is getting higher and higher, and the homogenization competition of products and services is intensifying. Market development and customer needs force operators to launch more attractive personalized products, but this still cannot alleviate the severe situation of high churn rate. In the face of the new competition pattern, the competition among enterprises has gradually shifted from taking products as the core to taking customers as the core, and the core competitiveness of the industry has turned to the direction of maintaining the scale effect of users. While competing for customers, the enterprises are facing the churn of existing customers. Reducing customer churn has become the focus of telecom operators.

The main problem to be solved in this paper is to realize the prediction of high-value customer churn based on the existing research and combined with the customer attribute characteristics of the telecom industry. According to the analysis of big data in the telecom industry and historical information estimation of customers, combined with logistic regression algorithm, this paper realizes the customer churn prediction based on the telecom industry. By analyzing the characteristics of customer churn behavior in the telecom industry, it digs out the potential churned customers in customer library and helps enterprises take targeted win-back measures according to the characteristics of the potential churned customers.

The following content of this article is arranged as follows. Section 2 is the literature review, which puts forward the key points and innovations of this study on the basis of summarizing the existing research. Section 3 brings forward five research hypotheses to be tested in this paper. Section 4 is the introduction of data sources and the explanation of variables. In Section 5, the business data of high-value customers in a certain area of the telecom industry are used to build a churn prediction model to predict the churned customers and evaluate the prediction model. Section 6 is the conclusion and prospect.

2. Literature Review

Customer churn refers to the phenomenon that customers no longer buy products or services of enterprises for various reasons [8, 9]. With regard to the problem of customer churn in the telecom industry, scholars mainly carry out relevant research in the aspects of churn reasons, win-back strategies, and building models.

Research on churn reasons and win-back strategies: according to Kim and Kwon's [10] research, the network scale has an important relationship with the churn of Korean telecom customers. Lee et al. [11] investigated the influence of customer satisfaction and switching cost on customer churn of French mobile communications and believed that when the customer satisfaction remained unchanged, the higher the switching cost is, the less likely it is to churn. Madden et al. [12] found that the main factors affecting customer churn include monthly ISP consumption and household income. Amin et al. [13] analyzed the reasons for customer churn from the perspectives of enterprises, competitors, and customers and put forward the win-back strategies. Han et al. [14] discussed the relationship between consumer sentiment, switching barriers, customer satisfaction, and customer retention and believed that customer satisfaction was positively correlated with customer retention. After analyzing the reasons for customer churn, Oghojafor et al. [15] put forward strategies for reducing churn rate. Stauss and Friege [16] believed that effective customer win-back should trace the reason for customer churn. Tokman et al. [17] held that the reason for customer churn is an important variable to judge whether customers can be won back, which can provide a judgment basis for the selection of a win-back strategy.

Research on churn algorithm and model: the existing research mainly focuses on regression, neural network, decision tree, and other algorithms. Neslin et al. [18] predicted customer churn with decision tree and artificial neural network algorithm. Sato et al. [19] compared the effects of principal component analysis and decision tree algorithm on customer churn prediction and the laws. Bi et al. [20] proposed a new clustering algorithm called Semantic Driven Subtractive Clustering Method to predict the customer churn. Feng and Cai [21] used a decision tree algorithm to analyze the behavior characteristics of churned customers in the telecom industry. Zhou et al. [22] compared the prediction results of decision tree and neural network algorithm. Adwan et al. [23] used the MLP

algorithm to predict customer churn. Vafeiadis et al. [24] evaluated the applicability of the data mining algorithm to customer churn prediction by comparing decision tree, SVM, logistic regression, Naive Bayes, and other algorithms.

A comprehensive analysis of the existing studies shows that, in academic circles, customer churn research is an important issue in customer relationship management, while in management practice, customer churn will bring huge losses to the profits and future development of enterprises [25]. The research on winning back churned customers has gradually become the focus and key of customer relationship management [26]. But in the era of big data, there are few researches on customer churn in the telecom industry, and customer churn management has not been realized really yet. In addition, previous studies did not carry out customer screening and seldom focused on high-value customers whose consumption amount reached a certain level. On the other hand, the choice of factors affecting the churn was relatively scattered. On the basis of previous studies, this paper puts forward theoretical hypotheses from five dimensions: price, product, customer, business, and service, fully considering the customer value, as well as the change of consumers' dependence from voice services to data networks. This paper selects the top 20% of high-value customers that can bring profit to the company's high-value customers' business data as the analysis object, conducts churn prediction by logistic regression to explore the factors affecting customer churn, and puts forward targeted win-back measures.

3. Research Hypotheses

The reasons for customer churn may be different: price factor, personal factor, service factor, product factor, market factor, marketing strategy, and competitors' market intervention; all of them may lead to customer churn. Finding the reason(s) of customer churn is the key to recover the churned customers and reduce the customer churn rate. According to the summary of the main influencing variables of customer churn in recent years, it is found that scholars' research on influencing factors of customer churn in the telecom industry mainly focuses on three aspects: first, consumption-related variables, such as call duration [27] and consumption amount [27, 28], followed by customer statistical variables [29–31], including identity information and age [32, 33], customer income [33, 34], and customer satisfaction [35, 36], and finally enterprise-related variables, such as enterprise channel operation ability [37] and purchase of related products [38].

Telecom operators have shifted from a “price model” to a “value model,” from a “network capability service provider” to a “business capability service provider,” and from traffic operations to nontraffic business operations. Competition among operators develops to the advanced stage, from price wars to business bundling, process optimization, and customer relationship management as well as competition upgrades in the value chain. Based on the existing research, customer relationship management theory, and customer value, this paper puts forward the following research

hypotheses from five dimensions: price factor, product factor, customer factor, business factor, and service factor.

3.1. Price Factor. Under the condition that the factors such as product quality and service are homogenized, customers tend to buy products or services with lower prices. From the perspective of customers, enterprises should provide products or services that meet or even exceed customer expectations, so as to make customers get delivered value and improve customer satisfaction. Customers may be willing to buy products and services continuously because of corporate behavior and trust and rely on the delivered value of the enterprise emotionally. For price-sensitive customers, price promotion is an effective win-back strategy [17, 26]. The reason for the repeated purchase of products or services is that the prices offered by enterprises meet their expectations, and the price is the key determinant of their repeated purchase behavior. From the perspective of enterprises, enterprises should establish and maintain a long customer life cycle through delivered value, so as to maximize the profits brought by customers.

In the past decade, the penetration rate of communication users has been close to 100%. On the one hand, there are a large number of low-end users, who just regard communication as a rigid demand in daily life and are extremely sensitive to price; on the other hand, the network coverage difference of operators is getting smaller and smaller, and the homogenization of services is serious. For users, the price of products will, to a large extent, affect their consumption behavior.

Hypothesis 1. Price can significantly affect customers' willingness negatively, and the increase of monthly consumption will increase the customer churn rate.

3.2. Product Factor. The reason for customer churn caused by product factor is that there are defects in product design or the real needs of customers and the market are not fully considered when designing products, which has an inhibitory effect on customer consumption. Life cycle value theory holds that the future profit potential of each customer is not equal. Generally speaking, the closer the time between customers to purchase products, the higher the purchase frequency, the greater the monetary value they pay, the more likely they are interested in subsequent transactions, and the less likely they are to churn [39]. These customers are more likely to introduce more other customers to help enterprises gain more market share and profits. Enterprises will take the groups with higher product dependence and higher life cycle value as their marketing priority customers and put in more resources. However, the previous consumption experience and behavior of the churned customers determine whether they are willing to return to the previous service providers.

Hypothesis 2. Previous consumption has a positive impact on customers' repeated purchase behavior. For customers with behavioral stickiness, the more they depend on the products, the lower the churn rate.

3.3. Customer Factor. Verhoef [29] and Reinartz and Kumar [30] believed that user characteristics are also the main factors affecting customer churn, and Reinartz and Kumar [30] found that user statistics, such as consumption level and personal income, can affect the churn rate. User characteristics reflect the customer value, which can be used as a key indicator to evaluate customer contribution. In order to better identify customers, customers are subdivided into valuable customers, midvalue customers, low-value customers, no-value customers, and below-zero customers. Gerpott et al. [40] found that high-income customers tend to sign service contracts and have an obvious preference for the bundled sales of convergence business and services. The signing of service contracts can not only reduce the customer churn rate but also significantly promote the win-back of churned customers. Sohn and Lee [41] held that customers with higher spending power and better income are less likely to churn. Customer value is closely related to customer loyalty and it is directly proportional to market share. Companies with high customer value usually have lower operating costs. The higher the customer value, the higher the loyalty, the better the customer stability, and the less likely the customers are to churn. In addition, with the increase of customer income level, the win-back performance will be improved accordingly [17, 26].

Hypothesis 3. The statistical variable of customers will have an impact on customer loyalty. The higher the customer value, the lower the churn rate.

3.4. Business Factor. Convergence business is a common means of retaining customers, and the synergy of product mix can be used to create more value for customers. Customers hope that they could purchase all required products and services from the same service provider. Enterprise can save costs for promotion and marketing. Bundling can realize a reduction in expenditure and psychological costs, and convergence business is also a key business type which has been assessed by telecom operators in recent years; the convergence of the SIM card with family broadband, television, terminal privileges, and other businesses cannot only enable users to enjoy more additional services but also increase the user churn cost and threshold. Reinartz and Kumar [30] insisted that a short-term service contract could improve the customer retention rate. Gerpott et al. [40] stated that the service contract reduces the customer churn rate and also has an obvious impact on the winning back of the lost customers. Wangenheim et al. [42] showed that the diversification of service contracts is an effective means of meeting customer demands. Kim and Yoon [43] stated that a service contract can improve the two-way communication between an enterprise and its customers, so that the enterprise cannot only accurately understand its customer demands but also raise the customer engagement, feel the corporate culture and services, and lower the customer churn rate.

Hypothesis 4. Convergence business has an adverse impact on customer churn and the churn rate of customers signing the bundling contract is reduced.

3.5. Service Factor. Zeithaml et al. [36] believed that the perception of service quality is also one of the main factors influencing customer churn. According to the theory of customer relationship management, the higher the customer satisfaction is, the more difficult the customer churn is [42]. Customer relationship management can maintain a better relationship between an enterprise and its customers, promote this relationship, and reduce the customer churn rate. For enterprises, service is their core product. If there is a gap between the service quality perceived by customers and the expected service quality, customers will feel disappointed at enterprises, and some customers will express their dissatisfaction with enterprises through complaints. The customer churn is typically caused by a failure of products and services provided by an enterprise to meet their expectations or their dissatisfaction with the use of products or services, other than a reduction in their demands. The rivals may spare no effort to attract customers with better services. Therefore, if an enterprise desires to increase customer loyalty, it shall improve customer satisfaction and be dedicated to creating more value for its customers.

Hypothesis 5. Relationship investment can significantly increase customer confidence, and there is a negative correlation between customer satisfaction and customer churn; i.e., the lower the customer satisfaction is, the higher the customer churn rate is.

4. Data and Variables

Before customer churn, to accurately identify the cause of churn is the key to winning customers back and terminating this factor to result in customer churn again. The customer churn prediction can realize the connection between an enterprise and its customers. According to the prediction results, an enterprise can win back and retain those customers that might be lost for a win-win situation; i.e., customer demands can be met and customers can be provided with higher-quality services, and meanwhile, the recognition and reputation of the enterprise can be improved. The research by Bhattacharya, an American scholar, shows that the cost for an enterprise to attract one new customer is 5-6 times higher than that to retain an old customer [44]. Customer churn is an important content of customer relationship management; it is the core objective for customer relationship management to prevent customers from flowing to its rivals and provide the enterprise with sustainable profit. The best time to win customers back is before the termination of the commercial relationship between an enterprise and its customers. If an enterprise knows that customer churn is to occur as early as possible and take measures actively and timely to retain customers, the possibility of customer churn will be lowered. In this part, the cause of customer churn of the telecom industry is analyzed and logistic regression is used to predict the trend in customer churn, with the aim of providing the theoretical reference based on which the telecom industry can respond to the customer churn phenomenon, develop the win-back strategy, maintain the share of users, and strengthen the competitiveness of an enterprise.

4.1. Data Sources. When making decisions about customers and dealing with customer churn, customer value is an important criterion that needs to be considered. Customers are the assets of an enterprise and high-value customers are the golden assets of an enterprise. The number of high-value customers is limited for each enterprise, and given that not all of the churned customers are worthy to be won back, an enterprise should selectively input its resources in those high-value target customers that can bring profit to it. Based on the relevant statistics, only 20% of customers will bring profits to an enterprise, 30% will realize basic balance, and the remaining 50% will bring negative profits [45]. This paper takes the 20% of high-value customers who can bring profits to the enterprise as the research object. According to the big data analysis of the telecom industry in a province, the average monthly consumption of all customers is taken as the base, the data of the first 20% of customers are extracted to determine these customers as the key customer group to be maintained throughout the province, and in these 20% of customers, the minimum average monthly consumption (RMB 60) is the judgment criterion. Consequently, this paper takes the operating data of the high-value customers with the average monthly consumption of higher than RMB 60 as the analysis objects, and the data used in the prediction model are from the historical data of the telecom industry in a province in the recent period. The telecom operators selected in this paper are the leading operators in the telecommunications industry in the province. The personal business market share exceeds 60%, and the new share exceeds 50%. The home broadband business market share exceeds 50%, and the new share exceeds 60%. Its development trend is more representative. Generally speaking, the billing period of the communications industry is measured in month. For a huge quantity of data, in order to achieve a better prediction effect, the sample data are selected randomly. The data of high-value customers with the average monthly consumption of over RMB 60 for three consecutive months were randomly sampled in the middle of 2020, and finally, 11,255 samples were taken. The binary variable, Y , is used to indicate whether there is customer churn or not: if customer churn occurs, it will be denoted by $Y=1$; if no customer churn occurs, it will be denoted by $Y=0$.

4.2. Description of Variables. If the product price is higher than the previous purchase price paid by customers, the customer churn might be caused by a “rise in price” and if the product price is higher than the expected price by customers through the perception or the reference price offered by a competitive enterprise, customers might change an enterprise due to this “high price.” The customer consumption of the current month selected in this paper, i.e., monthly amount consumed by customers, is the first technical indicator, representing the price factor.

In the 4G and 5G eras, users’ dependency on the communication network has changed; i.e., users rely on the data network traffic, other than relying on the simple voice call, SMS, and MMS business carried on the 2G network.

From the perspective of user’s usage scenario, most of the businesses relating to the consumption of communications are dependent on the traffic, so that a variety of APPs can operate normally, and according to the users’ assessment, the network quality of communication operators has been changed from voice quality to Internet quality. The dependency on the data network reflects the strength of communication of customers, i.e., the more the network business a customer has, the higher the cost for the customer to change the number and the more difficult the customer churn. From the perspective of the communication operator’s revenue structure, the overall revenue proportion of the voice business has been reduced to 10%, while the traffic revenue proportion is being increased. The traffic of the current month selected in this paper, i.e., monthly traffic consumed by customers, is the second technical indicator, representing the product factor.

From the perspective of communication operators, the users having higher package value tend to recognize the services provided by them, and these users can enjoy more additional services and spend more money. However, once users plan to leave the network, they tend to reduce their consumption and transfer to another operator until they are completely not dependent on the current SIM card according to the analysis of user behaviors. The current package value of customers selected in this paper, i.e., the amount of package corresponding to the user’s mobile phone number, is the third technical indicator, representing the customer value.

A service contract can improve the two-way communication between an enterprise and its customers, so that the enterprise cannot only accurately understand its customer demands but also raise customer engagement, feel the corporate culture and services, and lower the customer churn rate [46]. Convergence business can assist customers in raising the number of connections established in the network, and the conversion cost for leaving the network is also increased accordingly. As a result, the higher the network connectivity is, the more difficult the customer churn is. In this paper, to sign a contract for broadband business or not is the fourth technical indicator, representing the convergence business.

If the customer’s demand cannot be understood or met, it will be very difficult to establish a long-term relationship of cooperation between an enterprise and customers, so an enterprise shall configure resources base on the customers’ requirements to ensure customer satisfaction and customer loyalty. In this paper, to make a complaint or not is the fifth technical indicator, representing customer satisfaction.

The specific meanings of these five technical indicators are shown in Table 1.

4.3. Correlation among Variables. To further understand the correlation between variables, the variables listed in Table 1 are utilized to conduct the thermodynamic chart analysis as shown in Figure 1, and the degree of correlation between variables can be judged according to the magnitude of correlation coefficients corresponding to the colors of

TABLE 1: Variable interpretation.

Variable symbol	Variable title	Variable definition
Y	Churned user (loss)	It refers to the churn of users observed every month. 1 = user churn; 0 = user retention
X ₁	Average revenue per user (ARPU)	It refers to a measure of the revenue generated by one user per month
X ₂	Discharge of usage (DOU)	It refers to the data consumed by one user per month
X ₃	Current package value (pack-type)	It refers to the package amount corresponding to a customer's mobile phone number
X ₄	Convergence business (contract)	Decide whether to sign a contract for broadband services: 1 = yes; 0 = no
X ₅	Complaint	A customer decides whether to make a complaint: 1 = yes; 0 = no

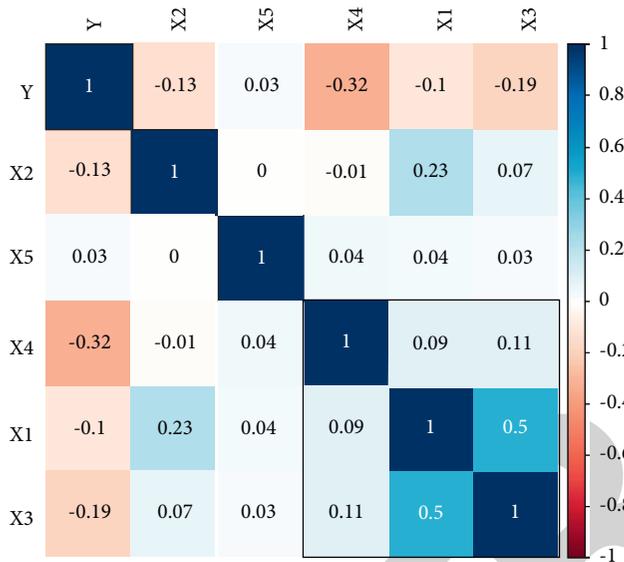


FIGURE 1: Correlation coefficients.

different blocks in the correlation coefficient diagram. It should be noted that the correlation coefficient can only measure the linear correlation between variables; that is to say, the higher the correlation coefficient is, the higher the linear correlation between variables is. If the coefficient of correlation between two variables is small, it only shows that the linear correlation between these variables is weak. However, it does not mean that there are no other correlations, e.g., curve linear relationship.

In the diagram of correlation coefficients, the right graduation shows the degree of difference among colors corresponding to different correlation coefficients. It can be seen from the diagram that the correlation between the current package value and the ARPU is 0.5 which is higher than that of any other variable, each coefficient of correlation between other variables is less than 0.5, and the negative correlation coefficient is equal to or more than -0.32 ; i.e., multicollinearity is not obvious. In its essence, customer churn is a binary classification problem. The logistic regression model is a powerful method of multiclass classification. It cannot only provide the probability of explicit classification except for classification label information but also analyze the predicted values of all type data, e.g., continuous variable, discrete variable, and dummy variable,

while no restriction hypothesis is required for normal distribution or homoscedasticity matrix of predictor variables and there is no need to consider the failure of a prior probability. Compared with the discriminant analysis, this model is less influenced when the normality of the predictive factor cannot be hypothesized. Furthermore, with the very strong robustness to low-level noise in data, the logistic regression model will not be particularly influenced by slight multicollinearity. Therefore, these five variables can be used to build a prediction model based on the logistic regression algorithm.

5. The Customer Churn Prediction Model

The traditional customer churn prediction is based on the experience of enterprise managers, which is actually simple inductive reasoning, so managers can conduct the churn prediction for the existing customers according to the characteristics of churned customers. However, the experience might be unreliable; especially in case of a complicated problem, no good guidance can be given by just experience, while the resources of an enterprise are limited, so resources shall be first invested in winning back those customers with a high possibility of churn. The traditional prediction method cannot well predict which customers are most likely to churn or which customers are less likely to churn. As a result, if an enterprise desires to realize the scientific prediction for customer churn, it shall adopt mathematical tools and use “machines” to identify the relationship between technical indicators and customer churn and judge whether customers are churned and also provide the probability of customer churn. The logistic regression algorithm produces a better prediction effect, based on which the level of importance of customer churn factors can be seen. In this part, the logistic regression model is used to predict the trend in customer churn, assist enterprises in finding out the early warning signals of customer churn, and determine the tendency of customer churn.

The aim of modeling is to focus on the prediction problems, so independent variables are taken from the data of the current period (i.e., current month) and dependent variables from the data of the lag period (i.e., next month), and such logistic regression is required to be repeated three times; that is, the independent variables of the current month are used to predict the dependent variables of the next month. First of all, the R software is used for data

neutralization, so that regression coefficients are comparable to some extent, and then the data of each month are randomly divided into training set and testing set.

The logistic regression model is built according to 5 technical indicators:

$$P(Y_{t+1} = 1) = \frac{\exp(\beta^0 + \beta^1 X_{t1} + \beta^2 X_{t2} + \beta^3 X_{t3} + \beta^4 X_{t4} + \beta^5 X_{t5})}{1 + \exp(\beta^0 + \beta^1 X_{t1} + \beta^2 X_{t2} + \beta^3 X_{t3} + \beta^4 X_{t4} + \beta^5 X_{t5})},$$

$$P(Y_{t+1} = 0) = \frac{1}{1 + \exp(\beta^0 + \beta^1 X_{t1} + \beta^2 X_{t2} + \beta^3 X_{t3} + \beta^4 X_{t4} + \beta^5 X_{t5})}.$$
(1)

The predictor variables, i.e., X_1 , X_2 , X_3 , X_4 , and X_5 , separately denote the following technical indicators: ARPU, DOU, current package value, convergence business, and complaint. The parameter estimates and relevant statistics of the model in three months can be separately obtained.

Based on the aforesaid analysis results, the logistic regression model of predicted customer churn in three months can be separately obtained:

(1) Month one

$$\hat{P}(Y_{t+1} = 1) = \frac{\exp(0.8978 + 3.662X_{t1} - 3.1082X_{t2} - 13.617X_{t3} - 2.8788X_{t4} + 2.734X_{t5})}{1 + \exp(0.8978 + 3.662X_{t1} - 3.1082X_{t2} - 13.617X_{t3} - 2.8788X_{t4} + 2.734X_{t5})},$$

$$\hat{P}(Y_{t+1} = 0) = \frac{1}{1 + \exp(0.8978 + 3.662X_{t1} - 3.1082X_{t2} - 13.617X_{t3} - 2.8788X_{t4} + 2.734X_{t5})}.$$
(2)

(2) Month two

$$\hat{P}(Y_{t+1} = 1) = \frac{\exp(0.1044 + 4.0571X_{t1} - 1.811X_{t2} - 12.289X_{t3} - 1.1949X_{t4} + 1.9744X_{t5})}{1 + \exp(0.1044 + 4.0571X_{t1} - 1.811X_{t2} - 12.289X_{t3} - 1.1949X_{t4} + 1.9744X_{t5})},$$

$$\hat{P}(Y_{t+1} = 0) = \frac{1}{1 + \exp(0.1044 + 4.0571X_{t1} - 1.811X_{t2} - 12.289X_{t3} - 1.1949X_{t4} + 1.9744X_{t5})}.$$
(3)

(3) Month three

$$\hat{P}(Y_{t+1} = 1) = \frac{\exp(1.056 + 16.697X_{t1} - 7.1294X_{t2} - 18.9864X_{t3} - 1.5714X_{t4} + 2.234X_{t5})}{1 + \exp(1.056 + 16.697X_{t1} - 7.1294X_{t2} - 18.9864X_{t3} - 1.5714X_{t4} + 2.234X_{t5})},$$

$$\hat{P}(Y_{t+1} = 0) = \frac{1}{1 + \exp(1.056 + 16.697X_{t1} - 7.1294X_{t2} - 18.9864X_{t3} - 1.5714X_{t4} + 2.234X_{t5})}.$$
(4)

It can be seen from Table 2 that these five variables pass the test of significance at different levels of significance. In logistic regression, the response variable is the log odds of $Y = 1$. By taking Model (2) as an example, if X_1 is increased

by 1 unit, the logarithm of the odds (LOD) score will be increased by 0.8978 unit; i.e., a positive correlation exists between ARPU and customer churn, so similarly, a positive correlation exists between X_5 and customer churn and a

TABLE 2: Parameter estimates and relevant statistics of the logistic regression model.

	Estimate	Std. error	z value	Pr (> z)	Signif. codes
Month one					
β_0	0.8978	0.1552	5.783	7.33E-09	***
β_1	3.662	0.8292	4.416	1.00E-05	***
β_2	-3.1082	1.1399	-2.727	0.00639	**
β_3	-13.617	1.1765	-11.574	<2e-16	***
β_4	-2.8788	0.1826	-15.767	<2e-16	***
β_5	2.734	0.9403	2.907	0.00364	**
Month two					
β_0	0.1044	0.1666	0.627	5.31E-01	.
β_1	4.0571	0.9981	4.065	4.81E-05	***
β_2	-1.811	0.876	-2.067	3.87E-02	*
β_3	-12.289	0.9594	-12.809	<2e-16	***
β_4	-1.1949	0.2138	-5.588	2.30E-08	***
β_5	1.9744	1.1587	1.704	8.84E-02	.
Month three					
β_0	1.056	0.2019	5.23	1.69E-07	***
β_1	16.697	4.3928	3.801	1.44E-04	***
β_2	-7.1294	1.487	-4.795	1.63E-06	***
β_3	-18.9864	1.0119	-18.763	<2e-16	***
β_4	-1.5714	0.2313	-6.794	1.09E-11	***
β_5	2.234	1.0505	2.127	3.35E-02	*

Signif. codes: 0 “***,” 0.001 “**,” 0.01 “*,” and 0.05 “.”.

negative correlation exists between X_2 , X_3 , and X_4 and customer churn, provided that other variables remain unchanged. The above-mentioned five hypotheses are proven.

Next, a table of confusion (also called a confusion matrix) of binary classification (observation and prediction) is used to describe the results of classification in detail, as shown in Table 3.

Total precision (TP) is the total sample proportion correctly predicted:

$$TP = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$\begin{aligned} \text{Sensitivity} &= \frac{\text{quantity of samples that are correctly predicted as churn}}{\text{quantity of churned samples observed}} = \frac{TP}{TP + FN}, \\ \text{Specificity} &= \frac{\text{quantity of samples that are correctly predicted not to be churned}}{\text{quantity of unchurned samples observed}} = \frac{TN}{TN + FP}. \end{aligned} \tag{6}$$

The area under the ROC curve (AUC) represents the probability of correct ranking of two different types of measurements. The corresponding functions in PROC of R package are used to draw the ROC curve and get the relevant statistics in this paper.

The data obtained in three months are separately used to calculate the total precision, sensitivity, and specificity and

TP is the simplest indicator used for estimation prediction, but it cannot reflect the losses corresponding to different errors in practice, so the ROC curve is used to evaluate the precision of churn. Different thresholds are set to calculate sensitivity and specificity. The threshold has a great influence on the prediction effect of the model. The threshold of the logistic regression can be selected between 0 and 1 according to the data sample situation. The R software will give an optimal threshold during the calculation process to obtain the optimal prediction effect. And, the corresponding confusion matrix can be obtained by the following equations:

draw the ROC curve for the evaluation of prediction precision, as shown in Figures 2–4.

We utilize the ROC curve analysis method to evaluate the prediction effects of Models (2)–(4). The optimal thresholds corresponding to three months are separately selected, i.e., 0.138, 0.119, and 0.293, to calculate the predicted class, and then the predicted class obtained from the

TABLE 3: Confusion matrix for the evaluation of binary classification.

	Actual class 1 (observation retention: $Y_t = 0$)	Actual class 2 (observation retention: $Y_t = 1$)
Predicted class 1 (prediction retention: $\hat{Y}_t = 0$)	TN	FN
Predicted class 2 (predicted churn: $\hat{Y}_t = 1$)	FP	TP

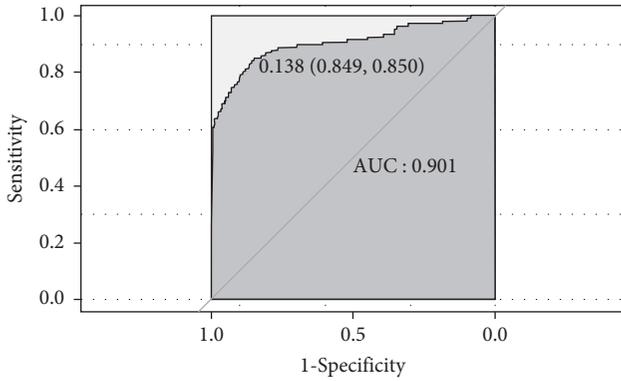


FIGURE 2: ROC curve for month one.

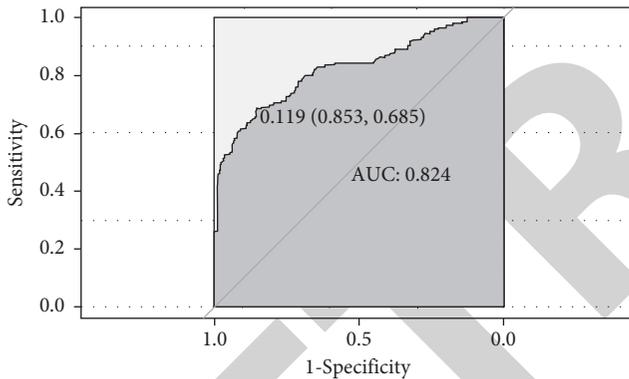


FIGURE 3: ROC curve for month two.

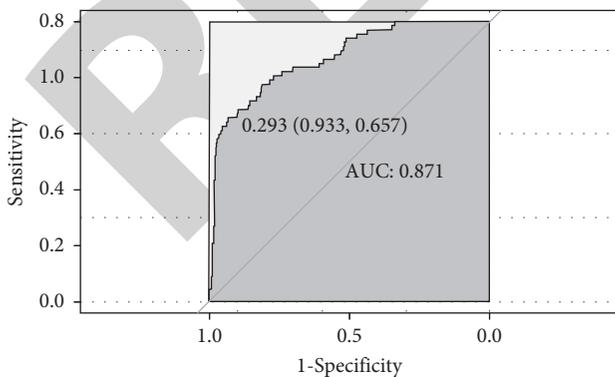


FIGURE 4: ROC curve for month three.

training set and the actual class from the testing set are used to establish the confusion matrix of binary classification, as shown in Table 4. Next, the total precision, sensitivity, and

specificity of the actual confusion matrix of three months are separately calculated.

- (1) Month one: according to the actual confusion matrix, calculate the total precision = $(91 + 676/91 + 676 + 120 + 16) \approx 0.849$, sensitivity = $(91/91 + 16) \approx 0.850$, and specificity = $(676/676 + 120) \approx 0.849$
- (2) Month two: according to the actual confusion matrix, calculate the total precision = $(100 + 1070/100 + 1070 + 185 + 46) \approx 0.835$, sensitivity = $(100/100 + 46) \approx 0.685$, and specificity = $(1070/1070 + 185) \approx 0.853$
- (3) Month three: according to the actual confusion matrix, calculate the total precision = $(44 + 1014/44 + 1014 + 73 + 23) \approx 0.917$, sensitivity = $(44/44 + 23) \approx 0.657$, and specificity = $(1014/1014 + 73) \approx 0.933$

The area under the ROC curve (AUC) can be used to judge the classification effect of a classifier (prediction model), and generally speaking, the larger the AUC is, the better the classification effect is. Where the AUC is equal to 1 ($AUC = 1$), it is an excellent classifier, and in this case, the predicted class can be precisely obtained, regardless of how the threshold is set; where the AUC lies between 0.5 and 1 ($0.5 < AUC < 1$), the classification effect is better than the random guess; where the AUC is equal to 0.5 ($AUC = 0.5$), the classification effect is the same as the random guess; where the AUC is less than 0.5 ($AUC < 0.5$), the classification effect is worse than the random guess. It can be seen from Figures 2–4 that the sensitivity is 0.850, the specificity is 0.849, the AUC is 0.901, and the classification effect is excellent in month one when the threshold is 0.138; the sensitivity is 0.685, the specificity is 0.853, the AUC is 0.824, and the classification effect is excellent in month two when the threshold is 0.119; the sensitivity is 0.657, the specificity is 0.933, the AUC is 0.871, and the classification effect is excellent in month three when the threshold is 0.293. It is measured in month, and the analysis of data obtained in three months proves that the performance of prediction of the logistic regression model based on the five factors (i.e., ARPU, DOU, current package value, current package value, and complaint) is excellent.

In this paper, the customer consumption data of the telecom industry are utilized to research the problem of customer churn. The research results show that a rise in monthly consumption will result in an increase in customer churn rate; the higher the dependency of customers on products is, the more difficult the customer churn is; the higher the package value customers have, the lower the probability of customer churn; i.e., customer value is directly proportional to customer loyalty; the churn rate of

TABLE 4: True confusion matrix for the evaluation of customer churn performance.

Month one	0 (prediction retention)	0 (observation retention)	1 (observation churn)
	1 (prediction churn)	676	16
Month two	0 (prediction retention)	1070	46
	1 (prediction churn)	120	91
Month three	0 (prediction retention)	185	100
	1 (prediction churn)	1014	23
		73	44

customers signing a bundling contract will be reduced; the lower the customer satisfaction is, the higher the probability of customer churn is.

Consequently, price is still a key factor of customer churn on the premise of the same quality of products; corporate brand building is still important, which shall be centered on customer demands, and different special products shall be launched for varied market segments to improve the dependency of customers on products; customer value is an evaluation index of customer contribution, and enterprises shall better identify customers and put more resources into high-value customers to improve the satisfaction of high-value customers; convergence business is an effective means of increasing the dependency of customers on products and the transfer cost for leaving the network; the customer's complaints shall be handled on the basis that "the customer is always right" and the efficiency of complain handling increased, playing a role in winning back customers.

6. Conclusions

The phenomenon of customer churn in the telecommunications industry is inevitable due to several reasons. The most confusing thing about customer churn is that it is difficult to control. The reasons for customer churn are complex, some are obvious, and some are not obvious. However, operators in the telecommunications industry should be aware that customer loss will happen sooner or later, and they must take precautions and respond in advance. For telecom operators, solving the problem of customer churn has become the key to their survival.

All industries face the problem of customer churn, but customer churn in different industries differs according to industry characteristics. Although the problem of customer churn in the telecommunications industry is not unique and the experience and lessons of customer management can be learned from other industries, the telecommunication industry has its own distinctive features compared to the retail and financial industries. The telecommunications industry is a product of technology. Due to changes in technology, the high-tech telecommunications industry will face the persistent problem of customer loss for a long time. Therefore, the telecommunications industry is actually an industry based on customer churn. It can be considered that customer churn is the blood that maintains the vitality of this industry

and is also the key to the sustainable and healthy development of the industry.

6.1. Management Implications. The loss of customers in the telecommunications industry is always happening. The research in this paper is of reference significance to the following aspects: how to predict customer churn by enterprises, alleviate the risks of customer churn, win churned customers back, and ensure that customers can continuously bring benefits to enterprises.

Firstly, customer churn is inevitable, but customer churn is not all negative. Customer churn is inevitable, but customer churn is not entirely only negative. Customer churn is actually a period of opportunity for enterprises. For most telecom operators, customer churn leads to a decline in revenue and an increase in marketing expenses. However, when customer churn appears in the market, competitors cannot avoid it either. For enterprises, dealing with customer churn is the golden time to completely change their market position. On the one hand, customer churn can reflect the problems in the business operation, help companies understand their business better, and take targeted measures to prevent customer churn and also improve their operation and management. On the other hand, enterprises can have a more precise understanding of the products and services required by customers and carry out reform according to customer churn, which will completely change the profitability and market position of enterprise.

Secondly, through the prediction of churn customers, analyze the personalized reasons for the churn of customers. Enterprises shall take an increase in revenue as the core, meet customer demands, stabilize the scale of customers, realize that customer satisfaction takes a leading position in the same industry, analyze the actual demands of potential churned customers according to different causes of customer churn, and take customized measures to maintain the customer relationship and further to retain customers. For example, an adjustment to marketing strategies, guidance of public opinion, policy responses, inputs in costs, and other measures are taken to maintain customer relationship properly, and the portability costs of customers are increased to effectively decrease the customer churn rate.

Thirdly, the cause of customer churn is accurately identified, which is a key to the formulation of win-back strategies. For enterprises, it is not the ultimate goal to find out the reasons and influencing factors of customer churn.

Enterprises need to implement customized win-back strategies according to the specific needs of customers. Enterprises shall closely associate win-back strategies with the causes of customer churn and take targeted measures. For example, for the customers considering emotional needs as the most important demands, the relationship investment shall be used as the first win-back strategy, and for the customers whose demands are driven by economic benefits, price shall be used as the main means of economic stimulus. In addition, research shows that win-back strategies should not be taken immediately when customers are hurt emotionally, because customers will be very dissatisfied and then gradually restored to reason, and if measures are taken forthwith, customer dissatisfaction might be increased, instead of winning back customers. Therefore, enterprises shall carry out win-back strategies all in good time.

Fourthly, predictive response judgment based on customer value is the best way to manage customer churn. There are many reasons for customer churn, and the decision of customer churn is the result of the continuous combination of complex spirit and emotion. Not all customers have the same value. Treating all customers equally is not the best choice for customer management. The scientific approach is to allow high-value customers to get more attention, reduce the input for low-value customers, and maintain different “values” for customers with different values.

6.2. Limitations and Future Research. The operating data from only one telecom operator are taken into account in the research; that is to say, the selection of data is limited to some extent, so the future research may consider cross-platform data to improve the comprehensiveness and externality of research. In addition, for telecom enterprises, customer churn is a long-term behavior, but the research is measured in month for customer churn prediction, and the continuity of data selection is not sufficient, so the time interval of subsequent research can be extended.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this study.

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