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# *Big Data - Driven Financial Customer Relationship Management Outsourcing Ecosystem Construction and XGBoost Competitiveness Enhancement Model*

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***Keywords:*** Financial Customer Relationship Management; Information Technology Outsourcing; Big Data; XGBoost; Machine Learning; Precision Marketing

***Abstract:*** With the acceleration of digital transformation in the financial industry and the widespread adoption of information technology outsourcing (ITO), financial institutions' demand for more refined and intelligent customer relationship management (CRM) is increasing. Traditional CRM models face significant bottlenecks in data processing, customer identification, and precision marketing, making them inadequate in handling the challenges of massive, high-dimensional, and unstructured financial data. Against this background, this paper proposes a "Big Data - Driven Financial CRM Outsourcing Ecosystem Construction and XGBoost Competitiveness Enhancement Model," aiming to integrate big data technologies, machine learning algorithms, and outsourcing service ecosystems to achieve intelligent customer relationship management and systematic improvements in marketing effectiveness. This study first constructs a multi-level financial CRM outsourcing ecosystem covering the entire process of data collection, cleaning, modeling, application, and feedback, with an emphasis on data security, compliance, and cross-institutional collaboration mechanisms. On this basis, the XGBoost machine learning model is introduced to perform high-precision prediction and classification on financial customer behavioral data, providing intelligent support for key aspects such as potential customer identification, customer value segmentation, and churn warning. Compared with traditional algorithms such as K-Means, decision trees, and random forests, XGBoost demonstrates superior performance on key metrics such as AUC and F1 scores, showing stronger predictive capability and business adaptability. This paper further applies the SHAP interpretability framework to visualize and analyze the XGBoost model, clarifying the influence mechanisms of various feature variables on prediction results, thereby enhancing the model's transparency and credibility in business scenarios. From the dimensions of organizational structure, technical support, talent development, and institutional evaluation, the paper proposes an implementation guarantee system to ensure the feasibility and effectiveness of the model in real financial ITO environments. This study not only provides financial institutions with a systematic solution for optimizing CRM under the ITO context but also offers theoretical support and practical pathways for the deep integration of big data and machine learning in financial marketing.

## 1. Introduction

With the rapid development of financial technology and the deepening of digital transformation, financial institutions' demand for more refined and intelligent customer relationship management (CRM) has become increasingly urgent. Traditional CRM models show clear limitations when dealing with massive, multi-source, and high-dimensional financial data, particularly in key areas such as customer identification, value segmentation, churn prediction, and precision marketing, where efficient decision-making is difficult to achieve. At the same time, information technology outsourcing (ITO) has become an important way for financial institutions to reduce operating costs and improve technical capabilities, but many challenges remain in terms of customer data integration, model construction, and business collaboration.

Against this background, the integration of big data and machine learning technologies offers new possibilities for upgrading financial CRM. Based on a systematic analysis of existing literature and industry practices, this paper proposes the construction of a "Big Data‑Driven Financial CRM Outsourcing Ecosystem" and introduces the XGBoost algorithm to build a customer behavior prediction and competitiveness enhancement model. The model aims to achieve efficient management of the entire customer lifecycle through data-driven intelligent methods, thereby enhancing financial institutions' core capabilities in customer acquisition, retention, and cross-selling.

This study not only expands the theoretical boundary of CRM applications in financial ITO contexts but also provides practical technical solutions and implementation pathways for enterprises. It has significant theoretical value and practical significance for promoting the intelligent transformation of customer management in the financial industry.

## 2. Related Research

Against the backdrop of rapid developments in big data technologies and the deep integration of machine learning methods, financial CRM is undergoing systemic transformation. Roh Y [1] pointed out that the integration of machine learning and data management is driving data collection technologies toward greater efficiency and intelligence, laying the foundation for large-scale customer behavior analysis. Wang J [2] further elaborated on big data service architectures and technical processing frameworks, providing systematic support for the collection, storage, and intelligent analysis of massive datasets. Balios D[3] emphasized that big data and analytics not only significantly improve external audit efficiency but also drive the adaptability of regulatory and talent systems. Aryal A[4], from the perspective of disruptive technological evolution, examined the practices and managerial challenges of IoT and big data analytics in supply chains and related fields.

In the area of customer relationship management, Moser M A[5] highlighted the crucial role of scientific CRM system design in knowledge management and sales growth, proposing design standards that serve as an important reference for subsequent system development. With the acceleration of digitalization, Nuseir M[6], through empirical studies, confirmed that digital marketing capabilities significantly enhance firm performance, a finding particularly prominent in industries such as insurance. Other scholars have contributed from different perspectives: Hassine M B[7] confirmed the significant positive impact of managers' technological perceptions and IT capabilities on the application of customer data analytics; Wiid J A[8] pointed out that SMEs especially rely on strong customer relationships to improve survival and sales capacity, underscoring the foundational role of CRM.

In specific financial customer management contexts, Vijai C[9] analyzed the structural development of fintech and its challenges to traditional finance, revealing the profound impact of technological change on industry structures. Manoharan G[10] focused on the specific applications of artificial intelligence in financial CRM, including personalized services, risk management, and compliance challenges, and emphasized AI’s potential to enhance customer loyalty and business success.

Technology-driven customer management models continue to emerge and evolve. Dewnarain S[11], based on social CRM theory, found that SCRM promotes service innovation and customer interaction in the hotel industry, though its direct effect on word-of-mouth communication was not supported. In precision marketing, Qianyi Z U[12] demonstrated that precision marketing in O2O models significantly enhances customer loyalty, while switching costs have no significant impact, necessitating targeted strategies and multi-channel outreach to strengthen customer stickiness. To further improve data-driven marketing effectiveness, Li X[13] combined the artificial bee colony algorithm with K-means to achieve fine-grained clustering and precision marketing in telecommunications; Kong C[14] introduced homomorphic encryption to build secure digital precision marketing schemes, providing innovative solutions to data-sharing security issues.

As the requirements for data processing and predictive capabilities increase, ensemble learning and advanced algorithms have been widely applied and continuously improved. Shilong Z[15] systematically compared XGBoost and random forests, evaluating their performance in terms of time complexity, accuracy, and reliability, providing a theoretical basis for algorithm selection. Fatima S[16] applied ensemble learning methods to improve student performance prediction models, significantly enhancing prediction accuracy and demonstrating the advantages of ensemble learning in complex prediction tasks. Asselman A[17] developed an XGBoost-based sales forecasting model, verifying its efficiency and low resource consumption on public datasets, providing a practical tool for sales forecasting.

As enterprises outsource more information system functions, the construction of CRM outsourcing ecosystems has become an important research direction. Erixon C[18] proposed analyzing outsourcing management challenges using the “business relationship triad” framework, offering a theoretical basis for outsourcing decisions. Chibo W K[19] studied the effects of different forms of IT outsourcing on business performance, revealing the importance of outsourcing model choices. De Carvalho V D H[20] explored how to maintain strong relationships in outsourcing partnerships from a relational perspective, providing practical guidance for managing outsourcing cooperation.

These studies [21] provide comprehensive support from three dimensions: theoretical foundation, technical approach, and management practice when building a big data-driven financial CRM outsourcing ecosystem. They also reveal an important direction: when machine learning is integrated with data management technologies, especially with advanced algorithms such as XGBoost, it can significantly improve the accuracy of customer prediction and enhance the competitiveness of enterprises. This finding also provides a valuable reference for the financial industry to promote customer relationship management innovation in the digital era.

## 3. Construction of a Big Data－Driven Financial CRM Outsourcing Ecosystem and Technical Support

### 3.1 System Design of the Financial CRM Outsourcing Ecosystem

Now that digital transformation is deepening, the financial industry is experiencing a growing demand for information technology outsourcing (ITO) models. Against this backdrop, the benefits of building an adaptable and intelligent financial customer relationship management (CRM) outsourcing ecosystem are clear: not only can it help financial institutions improve the efficiency of their customer management, but it also allows companies to hold on to their advantage in a competitive marketplace. In fact, a well-designed financial CRM outsourcing ecosystem means more than that - it is an important way to improve customer satisfaction and enhance customer loyalty, as well as the key to ensuring the success of CRM outsourcing.

In order for the business processes of the financial CRM outsourcing ecosystem to run smoothly, the system must be designed with a multi-layered architecture to ensure that each layer can efficiently complete its own tasks, but also work closely with other layers. The core logic of this system is to continuously improve the intelligence of customer relationship management through reasonable architectural design and technology integration. This can help financial institutions in the complex market environment, to make accurate business decisions. The system architecture should be designed with both stability and flexibility, and it is recommended to build it in a modular way. Each module should have independent functions, and at the same time be able to make flexible adjustments in future technology updates and business expansion. For example, customer data management, customer behaviour analysis, marketing automation, risk assessment of these modules, they should be able to work independently, but also with each other. In this way, in addition to meeting current business needs, when financial institutions have business changes and technological developments in the future, the entire system can also be adjusted and expanded to better suit new needs.

In the financial CRM outsourcing ecosystem, big data, machine learning algorithms, cloud computing, data security and other advanced technologies are widely used. First look at big data technology, which can help financial institutions to efficiently deal with the massive amount of customer data from various channels, and with these processed data, subsequent analysis of customer behaviour and precision marketing will have support. Machine learning algorithms are even more critical, such as XGBoost, a highly efficient model that can make predictions based on past customer behaviour - for example, determining whether a customer will be lost, whether there is a potential need to buy, and with these predictions, the financial institution will be able to develop a personalised marketing strategy and a more accurate customer management programme. There is also the cloud computing platform, which can provide powerful storage and computing power to the system. Even in cross-institution and cross-platform scenarios, financial institutions can efficiently process data, promote business and make the system run more efficiently. In addition, the needs of the financial industry and technology are always changing, so the CRM outsourcing ecosystem must have good scalability and compatibility. The system architecture should be able to flexibly adapt to the business needs of different financial institutions, and also be able to quickly respond to changes and optimise the management process by adding new modules or adjusting the functionality of existing modules when the variety of financial products and customer management needs increase in the future. This flexibility and scalability can not only cope with the current market changes, but also provide strong support for future technology upgrades and business development.

In the financial industry, data security and compliance is a major event that can never be sloppy, so the financial CRM outsourcing ecosystem must do things in accordance with the Data Security Act, GDPR and other relevant regulations. For example, customer data must be encrypted, and who has access to the data and where the data can be used must be strictly controlled, and restrictions cannot be relaxed. Especially when different organisations work together, the system has to consider the issue of data sharing and privacy protection. All organisations involved in the co-operation should share data within the scope of compliance, and there should be no information leakage or indiscriminate use of information. Only when these security measures are implemented can the financial CRM outsourcing ecosystem function properly in the long run.

To ensure the effective implementation of the system design of financial CRM outsourcing ecosystem, it is necessary to support the corresponding organisational structure. Based on the concepts of platformisation and agility, this paper has designed the following organisational structure, which aims to clarify the roles of each functional department in the ecosystem and the collaboration mechanism. From the point of view of the system design itself, it not only needs to meet the requirements of functional comprehensiveness and technological advancement, but also needs to take into account the flexibility and scalability of the system. Only in this way can the system maintain efficient operation in the dynamically changing market environment and deliver market competitiveness for financial institutions.

### 3.2 Data Governance and Technology Platform Development

In the financial CRM outsourcing ecosystem, data governance and technology platform construction are the most basic support to make the whole system run smoothly. Now that we have entered the era of big data, financial institutions will have a large number of various types of customer data in their hands. Whether or not these data can be managed and used well is directly related to whether or not the efficiency of customer relationship management can be improved, which is also the key to improving management effectiveness. Therefore, the construction of data governance system and technology platform, not only to meet the needs of one side, not only to establish an efficient integration of data, standardise the governance of data mechanisms, but also to have a strong big data processing capabilities, while building a good system that can support the application of machine learning.

First of all, the core of the data layer construction is to build a perfect multi-source data integration and governance mechanism. When financial institutions carry out CRM outsourcing, they will come into contact with a variety of data sources, such as customer transaction data, social media data, market dynamics data, and data obtained from third parties. However, these data often have a lot of problems, such as inconsistent format, good and bad quality, so the key to the data governance mechanism is to ensure that the quality of the data is up to standard and the content is consistent through data cleansing, removing duplicate data, and unifying data standards. In addition, in order to make the data work better, financial institutions have to effectively integrate data from different sources, break the ‘information silo’ situation, and build a unified data platform. This platform must have the ability to process data efficiently, quickly integrate data from different systems and channels, and provide accurate and reliable basic data support for subsequent data analysis and prediction of customer behaviour.

Then look at the construction of the technical layer, which needs to be based on the big data platform and machine learning support system. The big data platform is the core technology pillar of the financial CRM outsourcing ecosystem, providing efficient data storage, management, calculation and analysis functions. With the help of cloud computing technology, financial institutions can flexibly expand the storage and computing capacity of the platform, even in the face of massive data processing needs, to ensure that the system always maintains efficient and stable operation. The machine learning support system is the key to improving the intelligence of financial CRM. With the integration of efficient machine learning algorithms such as XGBoost, the system is able to mine potential patterns from customer behavioural data to achieve accurate customer prediction, churn risk assessment and other tasks. With the continuous optimisation of machine learning models, financial institutions can also adjust their marketing strategies based on real-time data, making customer management more accurate and personalised, and ultimately building a differentiated competitive advantage.

In the final analysis, to build a big data-driven financial CRM outsourcing ecosystem, data governance and technology platform construction is the foundation that cannot be bypassed. Specifically to do two aspects of work, the establishment of multi-source data integration and governance mechanisms to control the quality and consistency of the data; build a powerful big data platform and machine learning support system, so that accurate analysis and prediction of customer behaviour, for financial institutions to make decisions to provide a basis. This system not only makes customer management more efficient, but also helps financial institutions to maintain an advantage in the fierce market competition. Looking at the actual application results, the CRM outsourcing ecosystem built on the data governance and technology platform mentioned earlier has been positively evaluated by customers. As shown in Figure 1, customers recognise the key technical indicators of ‘data security’, ‘system stability’ and ‘data integration capability’, and the average scores of each are not low, which directly indicates that the previous platform construction work has been effective. This shows that the previous platform construction work is effective. These scores can also provide valuable reference for the platform's subsequent continuous optimisation.

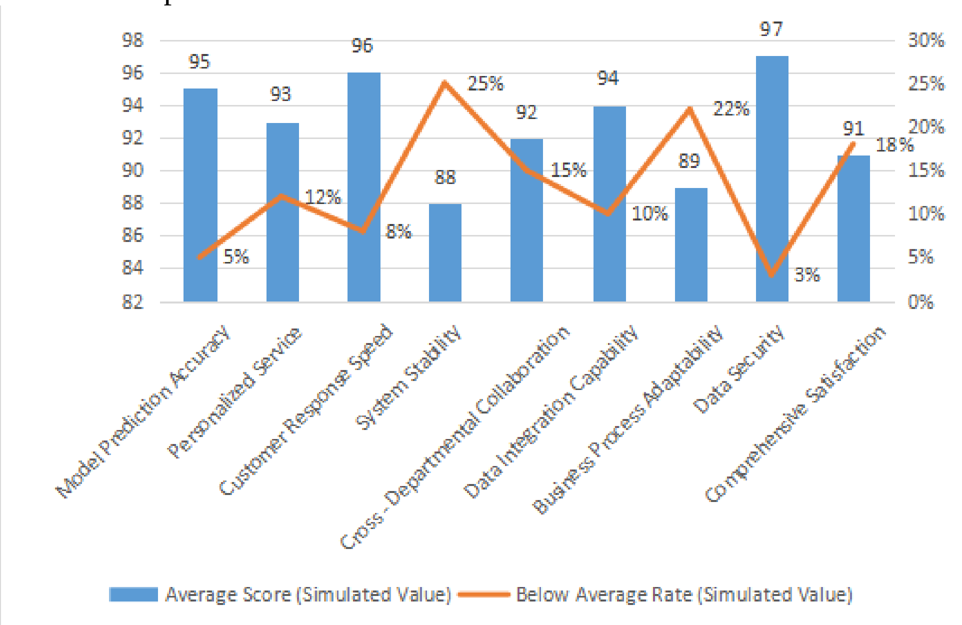


*Figure 1:Average Score and Below Average Rate of CRM Outsourcing Ecosystem Indicator Satisfaction*

## 4. XGBoost Model Construction, Validation, and Business Applications

### 4.1 Construction and Optimization of the XGBoost Model

In the financial customer relationship management supported by big data, XGBoost model has become one of the core tools for analysing customer behaviours and making relevant predictions due to its efficient computational power and excellent prediction performance. In this paper, we will talk about how to build and optimise XGBoost model, especially its specific applications in feature engineering, variable selection, model training and hyper-parameter optimisation. To build an XGBoost model, the first step is to do a good job of data feature engineering and variable selection. In the financial field, the data related to customer behaviour often has many dimensions and complex internal relationships, so it is very critical to design a good feature engineering step. xGBoost model has an ‘objective function’, which can combine the model's prediction error and regularization term, so as to optimize the model, as shown in formula 1：

$$m_{\{f_t\}} L \sum_{i=1}^{n} l\,(y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega\,(f_t), \Omega(f) = \gamma T + \frac{\lambda}{2} \sum_{j=1}^{T} w_j^2 \qquad \text{formula 1}$$

where $\hat{y}_i = \sum_{t=1}^{T} f_t\,(x_i)$ denotes the predicted value of the model. To measure prediction accuracy, XGBoost adopts a commonly used binary classification loss function, as shown in formula 2:

$$l(y, \hat{y}) = -[y \log \sigma() + (1 - y) \log(1 - \sigma())], \sigma(z) = \frac{1}{1+e^{-z}} \qquad \text{formula 2}$$

Moving on to feature engineering, we filter out the features that are most helpful for the two tasks of ‘Predicting whether a customer will churn or not’ and ‘Identifying potential customer buying behaviour’. Common features include basic customer information (e.g. age, gender, income), historical transaction records, social behaviour data, etc. From these features, we select the ones that have a greater impact on the model's predictions using techniques such as correlation analysis, information gain, and recursive feature elimination (RFE). At the same time, ‘constructing features’ is also a key step, which is often done by combining the original features, transforming the format, or generating new features through aggregation. For example, the average purchase frequency and cumulative total consumption of customers are features that can more clearly reflect the behavioural patterns of customers.

Once the feature engineering is completed, the model training phase is completed, and the XGBoost model adopts the Gradient Boosting Tree (GBT) algorithm framework to achieve the prediction task through the collaborative combination of multiple decision trees. The core logic is that each newly generated decision tree takes the prediction residuals (i.e., the deviation of the prediction result from the actual result) of the previous decision trees as the learning target, and continuously optimises the prediction accuracy of the overall model by gradually correcting the errors.XGBoost has several inbuilt advantages, such as support for handling missing values, efficient incremental training, automatic feature selection, etc., which together guarantee the model can still perform well under large-scale dataset scenarios. large-scale dataset scenarios, these features work together to ensure that the model still maintains efficient and stable operation performance.

In the training process, the optimisation of hyper-parameters is the key to improve the model performance, and the hyper-parameters of XGBoost include the number of trees, the learning rate, the maximum depth, the minimum number of sample splits, etc. These hyper-parameters have a significant impact on the model performance. In order to find the combination of hyperparameters with optimal effect, methods such as grid search, random search or Bayesian optimisation are usually used. By reasonably adjusting these hyperparameters, not only can the model effectively avoid overfitting problems, but also can improve the model's ability to adapt to new data and prediction accuracy. Take the learning rate as an example, it is used to control the magnitude of each step of the update: too large a learning rate will easily lead to the model converging to the local optimum, triggering overfitting; too small a learning rate will prolong the model training cycle and reduce the convergence efficiency. The above hyper-parameter optimisation process ensures that the model achieves the desired performance on both the training and validation sets.

The optimised XGBoost model can help financial institutions to do a good job of predicting customer churn and stratifying customer value, as well as providing support for precision marketing strategies. With the results from the model, organisations can identify those customers who are at high risk of churn, and can also anticipate what potential customers might want, so they can take targeted measures to make customers happier, more loyal and more competitive in the marketplace. In addition, the model is very interpretable and makes the decision-making process more transparent. Decision makers know exactly what factors are influencing customer behaviour, so that the decisions made are more scientific and credible.

### 4.2 Model Interpretability and Business Implementation

Machine learning technology [22] is increasingly widely used in the financial industry, and improving model interpretability, especially clarifying the basis of judgement of XGBoost and other 'black box' models, has gradually become a key research topic in financial customer relationship management. From the perspective of enhancing decision transparency and strengthening customer trust, SHAP (Shapley Additive Explanations) value for interpretability analysis enables financial institutions to clarify the influence of each feature on the model prediction results, and lays a reliable theoretical and practical foundation for the construction of precision marketing and churn early warning mechanism.

SHAP [23] values are an explanation method based on game theory. By quantifying the influence of each feature on model outputs, SHAP reveals the importance of features across different customer groups. Within the XGBoost model, SHAP values not only help us grasp the overall decision logic of the model but also allow us to drill down to the individual sample level, analyzing how specific features affect customer behavior predictions. As shown in Figure 2, the SHAP framework demonstrates the impact of different feature values on the model's outputs, enabling a clearer understanding of which features play a critical role in predicting customer behavior.

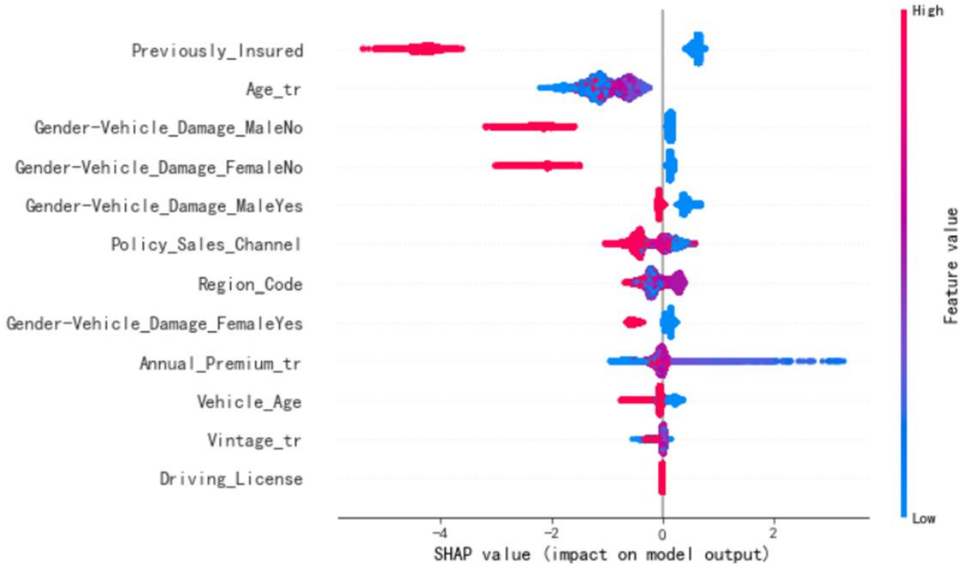


*Figure 2:Feature Impact Analysis of SHAP Values on Customer Behavior Prediction*

To quantitatively describe the impact of each feature on the prediction results, we employed the Shapley value method based on game theory. The calculation of Shapley values involves evaluating all possible combinations of feature subsets to measure the contribution of a specific feature to the final prediction. As shown in formula 3, this formula illustrates how to compute the contribution of a given feature to the overall prediction, thereby helping us understand its importance in customer behavior forecasting. By using this method, financial institutions can identify which features significantly influence predictions of behaviors such as customer churn and potential purchases.

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|F|!}{|S|!(|F|-|S|-1)!} \left(f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)\right) \quad \text{formula 3}$$

Characteristic importance analysis with the help of SHAP provides a theoretical basis for financial institutions to do precision marketing. By analysing the characteristics of customers in depth, institutions can develop more tailored marketing strategies based on their actual needs. For example, if it is found that certain customers have a higher risk of churning due to specific behaviours or their own attributes, it can recommend products to them or provide customised offers to precisely reach these customers, thereby increasing their loyalty and satisfaction. At the same time, through interpretable analysis of key features such as customer age and past behaviours, institutions can also accurately match and push the right financial products to different customer groups, so as to achieve the best marketing results.

The design of the churn early warning mechanism also needs to rely on the ‘interpretability’ of the model. With the XGBoost model's accurate prediction of customer churn, financial institutions can identify high-risk customers who are likely to ‘leave’ in advance, and then take corresponding retention or service measures. For example, through SHAP analysis, the model may pinpoint ‘older customers’ as the main reason for churn. The financial institution can then address this characteristic and proactively push appropriate products or customised service solutions to such customers, reducing churn and enabling them to bring more value to the institution during the cooperation cycle. The churn early warning mechanism can also be combined with other circumstances, such as the frequency of interaction between the customer and the organisation and the customer's rating of the service, etc., to assess the customer's situation from multiple perspectives, making the early warning mechanism both comprehensive and efficient.

In the financial ITO scenario, the interpretability of the XGBoost model not only helps to enhance the transparency of customer relationship management, but also effectively supports business decision-making and optimisation. Through the visual display of SHAP values, financial institutions are able to clearly see the impact of each feature and then adjust their strategies according to actual business needs. This enables organisations to have a more scientific and controllable basis for decision-making in complex market environments, and also promotes the accurate pushing of financial products to target customers, making marketing more effective.

To sum up, combining SHAP's interpretable analysis with XGBoost model not only enables financial institutions to manage customer relationships more accurately, but also provides practical solutions for business implementation. Specifically, by analysing which customer characteristics are more important, formulating precise marketing strategies, and building a churn alert mechanism, financial institutions can better understand customer needs, optimise the customer experience, and reduce customer churn.

## 5. Conclusion and Outlook

This research used big data technology and the XGBoost algorithm to make a ‘Customer Relationship Management (CRM) Outsourcing System’ for the financial industry, the core of which is to enable financial institutions to manage their customers more efficiently and respond to the market faster. We started by doing systematic processing of the data - such as refining key features, filtering useful variables, and also optimising the core parameters of the model. After these steps, the XGBoost model performed exceptionally well at two things: predicting which customers are likely to churn, and identifying potential new customers. It outperformed traditional machine learning algorithms. This study effectively improves the decision transparency of the XGBoost model by conducting interpretable analyses in conjunction with SHAP values. This process helps financial institutions to clearly identify the key features that influence customer behaviour, providing theoretical support for precision marketing and personalised services. In addition, by applying the constructed churn early warning mechanism with the XGBoost model, financial institutions can target high-risk churn customers in advance and formulate interventions that match their needs. The result is both a reduction in churn and an increase in long-term customer loyalty.

This study has achieved some results, but it still has some shortcomings. First, the dataset used primarily covers a subset of customers within the financial sector; future work could expand the dataset scope to test the model's applicability across other industries and diverse customer groups. Second, optimization of the XGBoost model requires significant computational resources; future research could explore more efficient models to improve computational efficiency in practical applications. Additionally, although SHAP values enhance interpretability, how to translate these explanations into concrete business decisions remains a topic for further investigation.

Looking ahead, with continuous advancements in artificial intelligence, big data, and cloud computing, financial CRM outsourcing ecosystems will become increasingly intelligent and automated, capable of responding to market demands in real time. Future studies could incorporate deep learning and reinforcement learning techniques to further improve prediction accuracy and timeliness, as well as integrate multi-source data and cross-industry applications to drive more precise customer behavior forecasting and marketing strategy implementation. Moreover, financial institutions can leverage increasingly sophisticated technology platforms to develop more personalized and differentiated CRM solutions, thereby strengthening market competitiveness and customer loyalty.

In conclusion, this study not only provides financial institutions with an effective solution for optimizing CRM in an ITO environment but also offers a practical pathway for the deeper integration of big data and machine learning in financial marketing. With the ongoing evolution and application of technology, future financial CRM outsourcing ecosystems will bring smarter, more precise customer management models to the financial industry, driving continuous innovation and development.

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