

Research on the Optimization of Artificial Intelligence-Driven Customer Relationship Management Systems

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Abstract

This study focuses on the optimization of Artificial Intelligence-driven Customer Relationship Management (AI-CRM) systems, taking domestic fast-moving consumer goods (FMCG) retail enterprise A as the research object. By integrating transactional, behavioral, and textual data, an AI-CRM system covering precise customer segmentation, consumption demand prediction, and intelligent customer service optimization is constructed. The research adopts K-Means clustering, the LSTM neural network, and the BERT model to realize customer stratification, demand prediction, and sentiment analysis, respectively. After the system went online, the monthly average sales growth reached 340%, the marketing conversion rate increased to 23%, the customer churn rate dropped to 16%, and the customer service response time was shortened to 8 seconds. A control group experiment verified that AI technology directly contributed approximately 75% to sales growth, proving the significant effect of the AI-CRM system in improving enterprise operational efficiency and customer loyalty.

Keywords

Artificial Intelligence, Customer Relationship Management, Fast-Moving Consumer Goods Retail, Precision Marketing

1. Introduction

As a core link connecting production and consumption, the retail industry is facing three major challenges: difficulty in understanding customer needs, inaccuracy in marketing resource allocation, and difficulty in ensuring consistent experiences. Data from iResearch in 2023 shows that the conversion rate of precision

marketing for domestic retail enterprises is only 8% - 12%, while a survey by Bain & Company indicates that the churn rate of high-value customers has reached 25% - 30%. Traditional CRM systems rely on manual entry and simple data statistics, with three core flaws: first, data silos across multiple channels make it impossible to form a unified view of data from online e-commerce platforms, offline stores, and social media; second, customer segmentation relies on traditional models such as RFM, without integrating multi-dimensional features like behavioral preferences; third, lack of predictive capabilities makes it difficult to proactively respond to customer needs and churn risks [1]. Breakthroughs in artificial intelligence (AI) technology have provided a new path for CRM system upgrades. Technologies such as computer vision (CV), natural language processing (NLP), and machine learning (ML) can realize in-depth data mining and intelligent decision-making, addressing the bottlenecks of traditional systems. Against this backdrop, researching the optimization path of AI-driven CRM systems holds significant practical significance for retail enterprises to enhance customer lifetime value (CLV) [2].

The core research questions of this paper include: How can an AI-CRM technical framework adapted to retail scenarios be constructed? What is the adaptability of algorithms such as K-Means, LSTM, and BERT in various CRM modules? What are the improvement effects and attribution mechanisms of AI-CRM systems on the operational indicators of retail enterprises? The theoretical significance lies in supplementing the insufficient details on the application of AI-CRM technologies in existing research and clarifying the selection logic and verification criteria of different algorithms. The practical significance lies in taking Enterprise A as an empirical case to provide a complete solution, including data processing, model construction, and scenario implementation, thereby providing a reference transformation template for similar enterprises.

This paper adopts the research path of “theoretical combining - scheme design - empirical verification - discussion and summary.” Firstly, it sorts out the research status of Customer Relationship Management (CRM) and Artificial Intelligence (AI) technology; secondly, it designs an AI-CRM system optimization scheme based on the needs of Enterprise A; then, it verifies the optimization effect through empirical data and completes the attribution analysis; finally, it summarizes the research conclusions and future prospects.

2. Related Theories and Literature Review

2.1. Research Status of Customer Relationship Management (CRM) Systems

CRM theory originated from the “customer-centric” concept in the 1990s, with the core of maximizing customer value through data integration. Early research focused on the design of CRM system functional modules, such as Salesforce’s customer information management platform; recent research has shifted to multi-channel data integration. Cui Can and Hu Mengzhi [2] (2025) proposed a CRM

data integration framework based on CDP to achieve unified identification of online and offline data, but did not involve the in-depth application of AI technology. Most CRM research in the retail industry revolves around customer stratification. Traditional methods rely on the RFM model (Recency-Frequency-Monetary), but this model only covers the value dimension and ignores behavioral and preference characteristics. Research by Ma Chao [3] (2020) shows that a multi-dimensional stratification model incorporating product preferences and channel preferences can increase the marketing conversion rate by more than 50%, but the model construction still relies on manual feature engineering, which is inefficient.

2.2. Research Progress of Artificial Intelligence Technology in CRM

The application of machine learning in customer segmentation has been initially verified. Wu Jinfeng [4] (2024) used the K-Means algorithm to stratify retail customers, and the clustering effect was better than that of the traditional RFM model, but did not explain the algorithm parameter settings and verification methods. In the field of demand prediction, LSTM neural networks have gradually replaced traditional models such as ARIMA due to their ability to capture temporal dependencies. Research by Du Jingyi [5] (2024) shows that the prediction error of LSTM for consumption demand is 32% lower than that of regression models, but it does not combine the feature engineering details of specific retail scenarios.

The application of natural language processing technology in customer service focuses on sentiment analysis. The BERT model improves the accuracy of semantic understanding by virtue of its bidirectional encoding advantage. Li Lingyu and Jia Junshuai [6] (2024) applied BERT to customer service dialogue analysis, with an emotion recognition accuracy of 92%, but did not form a link with the customer portrait module of the CRM system.

2.3. Deficiencies of Existing Research

Comprehensive analysis of existing research reveals three major gaps: first, fragmented technical applications, lacking an AI-CRM framework covering the entire process of “segmentation-prediction-service”; second, an unclear basis for algorithm selection, failing to explain adaptability combined with retail data characteristics; third, empirical research lacking academic verification details, with the absence of key information such as data indicators and model parameters, making it difficult to reproduce the results. This paper conducts research to address the above deficiencies.

3. Research Design and Methods

3.1. Research Object and Data Sources

The research object is domestic FMCG retail enterprise A, which has 120 offline stores and an online APP, mainly engaged in beauty, clothing, and other categories. The total number of members reached 1.2 million in 2023, facing problems

such as waste of marketing resources and lagging identification of high-value customers. The data sources include three categories: first, transactional data (2022-2023), including consumption amount, frequency, category, and other information; second, behavioral data, including APP browsing, store stay, social sharing, and other records; third, textual data, including 200,000 customer service dialogues and 50,000 product reviews. The data has been de-identified to comply with privacy protection requirements.

3.2. Data Preprocessing and Feature Engineering

3.2.1 Data Preprocessing Steps

1) Missing value handling: Median filling is used for numerical data, such as consumption amount, and mode filling is used for categorical data, such as payment methods.

2) Outlier elimination: Abnormal orders with a single consumption exceeding 5000 yuan (accounting for 0.3%) are eliminated through the 3σ criterion.

3) Standardization: All feature variables are subjected to Z-Score standardization to eliminate dimensional differences.

3.2.2. Indicator and Feature System

Customer segmentation adopts 12 quantitative indicators, covering three dimensions: basic attributes (age group, region, membership level), behavioral attributes (consumption frequency, repurchase interval, promotion sensitivity), and value attributes (average customer price, number of category purchases, number of after-sales consultations); demand prediction constructs 18 feature variables, including 365-day historical daily consumption data (amount, frequency), seasonal index, promotion intensity, competitor price index, and other temporal and static features [7].

3.2.3. Feature Selection Method

The Pearson correlation coefficient is used to eliminate redundant features, removing variables with a correlation coefficient with consumption amount lower than 0.1 (such as the number of delivery address changes); 7-day sliding window features are constructed for time series data to capture short-term consumption trends and improve prediction accuracy.

3.3. Model Selection and Parameter Settings

Table 1. Core model parameters and verification description of the AI-CRM system.

Model	Hyperparameter Settings	Training Scheme	Verification Strategy and Evaluation Indicators
K-Means Clustering (Customer Segmentation)	Number of clusters $K = 4$ (determined by the elbow method), number of iterations = 100, distance metric = Euclidean distance	Full dataset of 1.2 million members, unsupervised training	Silhouette coefficient (0.72), clustering purity

Continued

LSTM Neural Network (Demand Prediction)	2 hidden layers, 64 hidden units, learning rate = 0.001, dropout rate = 0.2, number of iterations = 50	Data split: 7:1.5:1.5 (training: validation: testing), Adam optimizer	5-fold cross-validation, mean absolute error (MAE)
BERT Model (Sentiment Analysis)	Pre-trained model = bert-base-chinese, learning rate = 0.0001, batch size = 32	250,000 annotated texts (manually labeled emotion polarity), cross-entropy loss function	Accuracy (94%), F1-score (0.92)

Three types of algorithms are selected according to the needs of retail scenarios, and parameters are determined through grid search and cross-validation. The specific settings are shown in **Table 1**.

4. Research Results and Analysis

4.1. AI-CRM System Optimization Scheme

4.1.1. Precise Customer Segmentation Module

Based on K-Means clustering, customers are divided into four categories, and differentiated strategies are formulated in combination with feature labels:

- 1) High-value loyal customers (accounting for 12%): $R \geq 7$ days, $F \geq 12$ times/year, providing personal shopping guides and priority purchase rights;
- 2) High-value potential customers (18%): $R \leq 14$ days, $F \geq 6$ times/year, promoting new product trials and exclusive discounts;
- 3) Active regular customers (45%): $R \leq 30$ days, $F \geq 3$ times/year, sending personalized full-reduction coupons;
- 4) At-risk churn customers (25%): $R \geq 90$ days, triggering recall text messages and first-order return discounts.

Reasons for selecting K-Means: Customer segmentation in retail requires unsupervised mining of potential groups. This algorithm has high efficiency in processing 12 multi-dimensional indicators. The elbow method can objectively determine the number of clusters, avoiding manual subjective biases. A silhouette coefficient of 0.72 indicates a good clustering effect.

4.1.2. Consumption Demand Prediction Module

The LSTM model is used to predict customers' consumption demand in the next 30 days, including purchase probability, category preferences, and consumption amount. The system pre-allocates inventory according to the prediction results and triggers precision marketing: for example, if a customer is predicted to purchase infant milk powder, the inventory information of surrounding stores and full-reduction coupons are pushed in advance [8].

Explanation of LSTM adaptability: Customer consumption has seasonal (such as 618 promotion) and periodic (repurchase interval) characteristics. LSTM can capture the long-term dependencies of time series data, and the fitting degree of non-linear consumption data is improved by 40% compared with traditional regression models.

4.1.3. Intelligent Customer Service Optimization Module

The BERT model is embedded into the customer service system to analyze the emotional polarity and core needs of customer consultations in real-time. For consultations with implied dissatisfaction (such as “Why can’t this coupon be used”), they are automatically escalated to manual agents and the customer portrait is synchronized; for routine questions (such as logistics inquiries), intelligent robots respond immediately to improve response efficiency.

Reasons for selecting BERT: Its bidirectional encoder structure can deeply understand contextual semantics, solving ambiguous expressions that are difficult to handle with traditional text classification. The emotion recognition accuracy reaches 94%, which is 18% higher than the TF-IDF + SVM model.

4.1.4. Potential Application of Computer Vision Technology

To enhance the coherence of the technical system, the implementation path of computer vision is planned: collect customer behavioral data (shelf stay time, product pick-up frequency) through in-store cameras, and integrate it with online data to optimize portraits. For example, identify customers who frequently view beauty products offline but do not purchase, and synchronize to the CRM system to push online exclusive discounts, realizing omni-channel collaboration. This direction is included in the subsequent optimization plan of enterprise A [9].

4.2. Optimization Effect Data

The AI-CRM system was launched in July 2023. Comparing the data of 6 months before and after the launch, the core operational indicators have been significantly improved: 1) Sales volume: monthly average growth of 340%, from 12 million yuan to 52.8 million yuan; 2) Marketing conversion rate: increased from 9% to 23%; 3) Customer churn rate: decreased from 28% to 16%; 4) Customer service response time: shortened from 45 seconds to 8 seconds.

4.3. Effect Attribution Analysis

To exclude the interference of other factors, a control group experiment is designed: 10 stores not connected to the AI system are selected as the control group, and only regular operations are carried out during the same period. The results show that the sales growth of the control group is 85%, which is much lower than the 340% of the experimental group. After calculation, the direct contribution of the AI-CRM system to sales growth accounts for approximately 75%, and the remaining 25% comes from regular operational optimizations (such as employee training).

Explanation of attribution logic: The growth of the experimental group mainly comes from three aspects—precision marketing reduces customer acquisition costs (saving 32% of marketing expenses), demand prediction improves inventory turnover (inventory turnover days reduced from 45 to 28 days), and intelligent customer service improves customer experience (satisfaction score increased from 72 to 91), verifying the core driving role of AI technology.

5. Discussion

This paper constructs a “data-model-scenario” trinity AI-CRM framework, compensating for the fragmented defects of existing research; clarifies the selection basis and verification standards of K-Means, LSTM, and BERT in retail CRM, providing a reference for algorithm adaptability research; and improves the evaluation system of AI technology application effects through control group experiments and quantitative attribution.

Transformation suggestions for retail enterprises: 1) Data level: Prioritize integrating omni-channel data and building a three-dimensional label system of “basic-behavior-value”; 2) Technology level: Select algorithms according to scenario needs, such as K-Means for unsupervised scenarios and LSTM for time series scenarios; 3) Implementation level: Adopt the strategy of “launch core modules first, iterate potential technologies later” to reduce transformation risks.

This paper has two limitations: first, the research object only covers FMCG retail, and the applicability of the conclusions in segmented fields such as fresh food and luxury goods needs further verification; second, the model effect does not consider the impact of extreme events (such as epidemics and large-scale promotions), and future research can add robustness analysis of abnormal scenarios.

6. Conclusions

AI technology can effectively solve the core pain points of traditional CRM: K-Means clustering enables precise customer stratification, LSTM improves demand prediction accuracy, and BERT optimizes the customer service experience; the AI-CRM system can significantly improve the sales volume and customer loyalty of retail enterprises, with a direct contribution of 75% to sales growth; the standardized process of “data preprocessing-feature engineering-model verification” can ensure the reliability and reproducibility of research results.

Future research can be carried out in three aspects: first, expand research scenarios and apply the AI-CRM framework to other retail segmented fields; second, integrate more technologies, such as introducing reinforcement learning to realize dynamic optimization of marketing strategies; third, deepen attribution analysis and combine causal inference models to more accurately quantify the contribution of AI technology. Enterprise A will prioritize the implementation of the integrated application of computer vision and CRM to build an omnichannel customer service closed loop.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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