Consumer Behavior Prediction and Enterprise Precision Marketing Strategy Based on Deep Learning

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This paper explores consumer behavior prediction and enterprise precision marketing strategy utilizing deep learning. The study introduces consumer behavior prediction research and highlights the advantages of the Long Short-Term Memory (LSTM) network in processing time series data. The methodology includes comprehensive data collection and teleprocessing, followed by the construction of an LSTM model. The model's predictive accuracy is validated through metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), demonstrating low error rates within 1%. Key results include improved browsing conversion rates, purchase rates, and repurchase rates. The study also analyzes the impact of various marketing strategies, including personalized recommendations, which increased purchase rates by 4.8% and user satisfaction by 4.0%, as well as limited-time offers, member rewards, optimized checkout processes, and social media engagement. The findings suggest that deep learning technology significantly enhances consumer behavior prediction accuracy, offering a robust foundation for precision marketing strategies that elevate market competitiveness and customer satisfaction.

Povzetek: Prispevek analizira napovedovanje vedenja potrošnikov in strategije trženja z uporabo globokega učenja, izpostavlja prednosti LSTM modela pri obdelavi časovnih vrst podatkov, kar omogoča kvalitetne napovedi vedenja potrošnikov in optimizacijo tržnih strategij.

1 Introduction

In the modern business environment, the complexity and diversity of consumer behavior make traditional marketing methods difficult to cope with. With the widespread adoption of the Internet and mobile devices, consumers' purchase paths have become more diverse and dynamic, necessitating enterprises to quickly capture the changing trends of consumer behavior within massive data sets to develop effective marketing strategies. The rapid development of big data technology and artificial intelligence has provided enterprises with new tools and methods, particularly the powerful capabilities of deep learning technology in pattern recognition and prediction, making data-driven precision marketing possible. Deep learning models, such as long short-term memory (LSTM) networks, excel in processing time series data and capturing complex behavior patterns, have been widely used in fields like finance and healthcare. However, their applications in consumer behavior prediction and precision marketing still need further exploration.

This study aims to accurately predict consumer behavior through deep learning technology, especially the LSTM model, to provide a scientific basis for enterprises to formulate precision marketing strategies. The objectives are to build an efficient deep learning model that can process multiple sources of data and accurately predict consumer purchasing behavior and preferences; evaluate the effectiveness of different marketing strategies through the analysis of the forecast results and identify the optimal strategy combination; and propose a systematic and operable precision marketing strategy scheme to help enterprises apply these technologies and methods in actual marketing activities to improve marketing effectiveness and customer satisfaction. This study not only aims to enhance the market competitiveness of enterprises but also hopes to provide valuable empirical data and theoretical support for the academic community, promoting the application and development of deep learning in the field of marketing. By achieving these goals, this study is expected to provide practical guidance for enterprises in data-driven precision marketing practices, helping them stand out in the fierce market competition.

At present, research on consumer behavior and its application in marketing strategy has been widely discussed and applied across various contexts. Musova studied the influence of the Internet on consumer behavior and highlighted how the digital environment has drastically altered consumers' decision-making processes, emphasizing the importance of online rules for modern marketing [1]. From the perspective of behavioral analysis, Foxall proposed the exploration of consumer behavior analysis, underscoring the critical role of understanding consumer behavior in organizational behavior management and market strategy formulation [2]. Suleymanov focused on the agricultural consumer market, analyzing the unique characteristics of consumer behavior in the agricultural product market and the formulation of market strategies [3]. Dennis examined electronic consumption behavior, revealing the characteristics of consumer behavior in the e-commerce environment and explaining how the convenience and diverse choices of online shopping have changed traditional consumption patterns [4]. Kucera analyzed consumer behavior in retail management and emphasized the importance of detailed consumer behavior analysis for achieving sustainable growth and global competitiveness in retail management [5]. Reed studied identity-based consumer behavior, highlighting how consumers' self-identity influences their consumption decisions and brand choices [6].

Andersone and Gaile-Sarkane studied multiple factors affecting consumer behavior, emphasizing the comprehensive impact of social, cultural, and economic factors on consumer behavior [7]. Peterson discussed the challenges of response construction in consumer behavior research, pointing out the importance of designing effective research methods and tools to capture real consumer responses [8]. Together, these studies demonstrate that the complexity and diversity of consumer behavior require in-depth research from multiple disciplines and perspectives. With the acceleration of digitization and globalization, understanding and predicting consumer behavior has become increasingly important. The application of deep learning and big data technology provides new tools and methods for the accurate prediction of consumer behavior and the optimization of marketing strategies. However, practical application still faces multiple challenges, such as data quality, model complexity, and privacy protection. Further research and practice can help enterprises better understand and predict consumer behavior, formulate more precise and efficient marketing strategies, and enhance market competitiveness and customer satisfaction.

This research is of great significance both theoretically and practically. Theoretically, the research enriches the theoretical system of consumer behavior analysis and marketing strategy design through an in-depth exploration of deep learning technology, particularly the application of the LSTM model in consumer behavior prediction. Through systematic data collection, preprocessing, model construction, and optimization, the research provides new perspectives and methods for processing complex time series data and recognizing consumer behavior patterns. Additionally, the research combines big data and artificial intelligence technology, providing valuable empirical evidence for the academic community to explore interdisciplinary research. Practically, the research offers enterprises a scientific and efficient methodology for consumer behavior prediction and precision marketing strategy formulation, helping enterprises better understand and grasp consumer behavior, improve market response speed, and enhance marketing effectiveness.

2 Overview of relevant theories

2.1 Consumer behavior prediction

Consumer behavior prediction plays a vital role in modern marketing. By accurately predicting consumer behavior, enterprises can develop marketing strategies more effectively, improve resource utilization efficiency, and increase market competitiveness. Forecasting consumer behavior relies on analyzing vast amounts of historical data, including purchase history, browsing history, social media activity, and more. While traditional statistical methods have limited performance in processing these complex, non-linear consumer behavior data, deep learning technologies show great potential in this area due to their powerful data processing and pattern recognition capabilities. Deep learning models, especially long short-term memory networks, are widely used in consumer behavior prediction because of their advantages in processing time series data. LSTM networks can effectively capture the temporal dependencies in consumer behavior data, thereby improving prediction accuracy. For example, using the LSTM model can predict consumers' purchasing behavior over a future period, helping companies push personalized marketing messages at the optimal time. Additionally, deep learning models such as convolutional neural networks and deep belief networks have also achieved remarkable results in consumer behavior prediction.

2.2 Application of deep learning in behavior prediction

The application of deep learning in consumer behavior prediction has become a hot research topic in recent years. Its core strength lies in its ability to process large-scale, high-dimensional, unstructured data and automatically extract complex features from the data. Deep learning models, such as convolutional neural networks (CNN), long short-term memory networks (LSTM), and graph neural networks (GNN), are widely used in consumer behavior prediction due to their excellent performance in pattern recognition and time series data processing. CNNs excel at processing image and video data, but their powerful feature extraction capabilities can also be used for consumer behavior data analysis. By converting user behavior data into an image or matrix form, CNNs can automatically extract potential patterns and improve prediction accuracy. The CNN model can be used to analyze consumers' browsing history and clicking behavior, predicting their future purchase intentions.

LSTM networks have become one of the mainstream models for consumer behavior prediction due to their advantages in processing sequential data. Through their gating mechanism, LSTM networks can remember long-term historical information and capture the temporal dependencies in consumer behavior. In specific applications, LSTM models can predict users' future purchase behavior based on their purchase history and behavior sequence, helping enterprises develop accurate marketing strategies. GNNs have unique advantages in processing complex network data. Consumer behavior is often influenced by social relationships, and GNNs can utilize relationship data in social networks to predict consumer behavior. For example, by analyzing user interactions and influence in social networks, GNNs can predict users' purchasing decisions and preferences.

In addition to the above models, deep learning models such as deep belief networks and autoencoders have also achieved significant results in consumer behavior prediction. Through unsupervised learning and feature dimensional reduction, these models can extract useful features from complex data and improve prediction performance. Deep learning technology provides new methods and tools for consumer behavior prediction through its powerful data processing and feature extraction capabilities. With the proper application of these technologies, enterprises can achieve higher prediction accuracy and more effective precision marketing strategies.

2.3 Enterprise precision marketing strategy

Enterprise precision marketing strategy involves in-depth analysis of consumer behavior data, using advanced data analysis and technical means to accurately position target customer groups, and developing and implementing targeted marketing activities based on their individual needs and preferences. Unlike traditional broad-coverage marketing, precision marketing aims to improve marketing effectiveness and resource utilization efficiency through accurate market segmentation and personalized marketing information, ultimately achieving higher customer satisfaction and greater market share. The core of a precision marketing strategy lies in deeply understanding and predicting consumer behavior. This process typically involves multiple steps: First, companies need to collect and integrate multi-channel consumer data such as purchase history, browsing history, social media interactions, and more. Then, through data mining and machine learning techniques, this data is deeply analyzed to identify the characteristics and behavior patterns of different consumer groups. Based on these analysis results, companies can segment consumers into different market categories and develop marketing strategies for each segment.

A personalized recommendation system is an important part of precision marketing. By analyzing consumers' historical behavior and preferences, personalized recommendation systems can suggest the most appropriate products and services for each consumer. For example, an e-commerce platform can recommend related or similar items based on a user's browsing and purchase history, thereby increasing conversion rates and sales. Additionally, precision marketing includes personalized advertising and customized promotional activities. For instance, by analyzing consumers' geographic locations and spending habits, companies can deliver personalized advertising and promotional messages at the right time and place to enhance marketing effectiveness. The effective implementation of precision marketing strategies relies on advanced technical means such as big data analysis, artificial intelligence, and deep learning. These technologies can help companies extract valuable information from massive amounts of data and adjust marketing strategies in real time to adapt to market changes and consumer needs. Precision marketing strategies help enterprises achieve higher marketing efficiency and effectiveness through precise positioning and personalized marketing, improving customer satisfaction, market competitiveness, and brand loyalty [9].

3 Data collection and model construction

3.1 Data collection and preprocessing

Data collection and preprocessing are crucial for consumer behavior prediction and precision marketing strategy research. High-quality data is the foundation for building effective predictive models, and scientific preprocessing can improve the performance and accuracy of these models. During the data collection phase, companies need to obtain rich consumer behavior data from multiple channels, including e-commerce platforms, social media, customer relationship management systems, and offline sales records. By combining this data, companies can get a comprehensive picture of consumer behavior to support subsequent analysis and modeling. During the data collection process, enterprises need to ensure that the data is comprehensive and accurate. First, the collected data should cover various types of consumer behavior, such as browsing, clicking, buying, and rating. Second, the data should include enough time spans to capture changing trends in consumer behavior. Additionally, enterprises need to take effective data cleaning measures to remove noisy data and outliers to ensure the authenticity and reliability of the data.

In the data preprocessing stage, the format of the collected data needs to be unified and standardized. The data format and structure of different data sources may vary, and standardizing the data format helps with subsequent feature extraction and model training. Secondly, data preprocessing also includes missing value processing, feature engineering, and data normalization. Missing value processing involves filling in or deleting missing data in a data set to avoid affecting model training. Feature engineering involves extracting features useful for prediction from raw data, a process that can significantly improve model performance. For example, a user's purchase frequency and browsing time can be extracted from the raw data. Data normalization converts the data into a unified scale range to eliminate dimensional differences between different features and improve the convergence speed and prediction accuracy of the model. During data preprocessing, it is also necessary to divide the data set into training sets, validation sets, and test sets to evaluate the model's performance and generalization ability. Typically, the training set is used for model training, the validation set is used for model tuning, and the test set is used for final model evaluation. Through a scientific preprocessing process, enterprises can improve the quality of data, laying a solid foundation for constructing accurate consumer behavior prediction models, and supporting the implementation of precision marketing strategies [10].

Table 1: Overview of consumer behavior data features

Feature Name	Feature Description	Data Type	Missing Value Ratio	Standardization Method
User ID	Unique identifier for users	Integer	0%	None
Browsing Duration	Time spent on a single browsing page (seconds)	Float	2%	Min-Max Normalization
Purchase Frequency	Number of purchases per month	Integer	5%	Z-score Standardization
Product Clicks	Number of times the user clicked on products	Integer	1%	Min-Max Normalization
Rating Score	User rating of products (1-5)	Integer	0.5%	None

As shown in Table 1 below, Data teleprocessing involves several critical steps to ensure the accuracy and efficiency of the LSTM model. Initially, data is collected from various sources such as e-commerce platforms, social media, and customer relationship management systems. This data is then cleaned to remove noise and outliers, ensuring consistency and accuracy. Missing values are addressed using imputation techniques, while feature engineering extracts relevant characteristics like purchase frequency and browsing duration. Data normalization follows, converting features to a common scale to improve model convergence. The LSTM model architecture is designed with an input layer to receive time series data, several hidden layers containing LSTM units to capture dependencies, and an output layer for predictions. Each LSTM unit includes an input gate, forget gate, and output gate, which regulate the flow of information and maintain long-term dependencies in the data. Training involves dividing data into training, validation, and test sets, using back-propagation and optimization techniques such as gradient descent to minimize loss functions like Mean Absolute Error (MAE). Regularization methods and cross-validation are employed to prevent overfitting and enhance the model's generalization capabilities.

3.2 Model construction

3.2.1 Overview of LSTM model

Long short-term memory (LSTM) networks are a special type of recurrent neural network (RNN) designed to address the issues of gradient vanishing and gradient exploding commonly encountered in traditional RNNs when processing long sequence data. By introducing memory units and gating mechanisms, LSTMs can capture and retain important information over extended time spans, making them particularly effective in time series prediction, natural language processing, and other related fields. The basic unit of an LSTM network comprises three gates: the input gate, forget gate, and output gate. Each gate regulates the flow of information through the memory unit using different parameterized functions [11].

Input gate: Controls how much new input information needs to be written to the memory unit.

Forget gate: Determines the degree of retention of existing information in the memory unit.

Output gate: A hidden state that determines how much of the information in the memory unit is output to the next moment.

The formula for the LSTM unit is as follows, as shown in formula (1) - (6).

Forgotten door:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

Input door:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

Candidate memory unit state:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{3}$$

Current memory unit status:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{4}$$

Output gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

Current Hidden status:

$$h_t = o_t \cdot \tanh(C_t) \tag{6}$$

Through these gating mechanisms, LSTM effectively solves the problem of information loss when traditional RNN deals with long time series data, which makes LSTM perform well in consumer behavior prediction and other applications. Using the LSTM model, enterprises can extract potential patterns from continuous consumer behavior data, accurately predict future behavior, and develop more accurate marketing strategies.

3.2.2 Model architecture design

The architecture design of LSTM model involves the construction of input layer, hidden layer and output layer. The input layer receives the time series data, the hidden layer consists of several LSTM units to capture the dependencies in the time series, and the output layer generates the final prediction result.

Table 2: Sample of consumer behavior data

User ID	**Browsing Duration (seconds)**	**Purchase Frequency (per month)**	**Product Clicks**	**Rating Score**
101	120	3	15	4.5
102	95	1	5	4.0
103	150	4	20	3.5
104	80	2	10	4.2
105	110	3	12	3.8

As shown in Table 2, it is necessary to predict the purchase frequency of users. The input of the model is time series data including browsing time, product clicks and evaluation scores:

Input layer: Input data shape is (number of time steps, number of features), for example, in a window, we have 5-time steps, each time step contains 3 features.

Hidden layer: LSTM The hidden layer contains several LSTM units, and the dimension of the hidden state can be set to 50.

Output layer: The full connection layer maps the output of the LSTM to a target variable, such as purchase frequency. From the data of user ID 101 in Table 2 as input, the number of time steps is 3, which is characterized by browsing time, product clicks and evaluation scores:

Table 3: Relevant parameter data

Time Step	Browsing Duration	Product Clicks	Rating Score
t=1	120	15	4.5
t=2	110	12	3.8
t=3	95	10	4.0

Set the initial state $h_0 = 0$, $C_0 = 0$, weight and bias to, as shown in formula (7) - (16).

$$W_f = \begin{bmatrix} 0.1 & 0.2 & 0.3 \\ 0.4 & 0.5 & 0.6 \\ 0.7 & 0.8 & 0.9 \end{bmatrix}, b_f = \begin{bmatrix} 0.1 \\ 0.1 \\ 0.1 \end{bmatrix} \tag{7}$$

$$W_i = \begin{bmatrix} 0.2 & 0.3 & 0.4 \\ 0.5 & 0.6 & 0.7 \\ 0.8 & 0.9 & 1.0 \end{bmatrix}, b_i = \begin{bmatrix} 0.2 \\ 0.2 \\ 0.2 \end{bmatrix} \tag{8}$$

$$W_C = \begin{bmatrix} 0.3 & 0.4 & 0.5 \\ 0.6 & 0.7 & 0.8 \\ 0.9 & 1.0 & 1.1 \end{bmatrix}, b_C = \begin{bmatrix} 0.3 \\ 0.3 \\ 0.3 \end{bmatrix} \tag{9}$$

$$W_o = \begin{bmatrix} 0.4 & 0.5 & 0.6 \\ 0.7 & 0.8 & 0.9 \\ 1.0 & 1.1 & 1.2 \end{bmatrix}, b_o = \begin{bmatrix} 0.4 \\ 0.4 \\ 0.4 \end{bmatrix} \tag{10}$$

Take the data at time t=1 for calculation:

Forgotten door:

$$f_1 = \sigma(W_f \cdot [0,120,15,4.5] + b_f) = \sigma(\begin{bmatrix} 0.1 & 0.2 & 0.3 \\ 0.4 & 0.5 & 0.6 \\ 0.7 & 0.8 & 0.9 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 120 \\ 15 \\ 4.5 \end{bmatrix} + \begin{bmatrix} 0.1 \\ 0.1 \\ 0.1 \end{bmatrix}) \tag{11}$$

Input door:

$$i_1 = \sigma(W_i \cdot [0,120,15,4.5] + b_i) \tag{12}$$

Candidate memory unit state:

$$\tilde{C}_1 = \tanh(W_C \cdot [0,120,15,4.5] + b_C) \tag{13}$$

Current memory unit status:

$$C_1 = f_1 \cdot C_0 + i_1 \cdot \tilde{C}_1 \tag{14}$$

Output gate:

$$o_1 = \sigma(W_o \cdot [0,120,15,4.5] + b_o) \tag{15}$$

Current Hidden status:

$$h_1 = o_1 \cdot \tanh(C_1) \tag{16}$$

Through the above calculation process, the data is fed into the formula, and the LSTM unit states are gradually updated to predict user purchase frequency. These results show that in the initial time step, the model almost fully accepts the input information and stores significant data in memory units and hidden states. As time progresses, similar calculations continue, and by updating the states of the forget gate, input gate, and output gate, the model gradually accumulates and transmits valuable information, ultimately predicting user purchase frequency. This process demonstrates the advantages of LSTM in handling complex, time-dependent consumer behavior data, providing accurate support for consumer behavior prediction. The effectiveness of LSTM in capturing and retaining key features in long time series data helps enterprises develop more accurate marketing strategies, enhancing market competitiveness and customer satisfaction [12].

3.2.3 Model training

Model training is a crucial step for utilizing LSTM networks to predict consumer behavior. During this phase, the model optimizes its parameters by learning patterns and regularities in historical data, allowing it to accurately forecast future consumer actions. Specifically, the model training process includes data preparation, model initialization, loss function definition, back-propagation, and parameter updating.

In the data preparation phase, the dataset is divided into training, validation, and test sets. The training set is used for model training, the validation set for model tuning, and the test set for final performance evaluation. During each training iteration, the model receives a batch of input data, computes its predicted value, and compares it with the actual value to determine the prediction error.

The loss function is central to model training, measuring the difference between the model's predicted and actual values. Common loss functions include mean square error (MSE) and cross-entropy loss. Mean square error is typically used for regression tasks in consumer behavior prediction. In each iteration, the back-propagation algorithm updates the model parameters based on the gradient of the loss function. Specifically, back-propagation calculates the gradient of the loss function with respect to each parameter, and then updates the parameters using gradient descent or variants such as the Adam optimization algorithm.

A key aspect of model training is balancing fitting and generalization capabilities. By using validation sets, the model’s performance on previously unseen data can be monitored to prevent overfitting. If the validation error starts to rise while the training error continues to fall, this indicates potential overfitting. Adjustments can then be made using regularization parameters, early stopping, or cross-validation. Model training is an iterative optimization process. By continuously adjusting model parameters, the performance on both training and validation data is optimized, providing a robust foundation for subsequent consumer behavior prediction [13].

The experiments were conducted in an environment equipped with high-performance hardware and software. The hardware specifications included an NVIDIA RTX 3080 GPU, 32GB RAM, and an Intel Core i9 processor. The software environment comprised Python 3.8, TensorFlow 2.4, and CUDA 11.0 for accelerated GPU processing. For training the LSTM model, specific parameters were set as follows: a learning rate of 0.001, a batch size of 64, and a total of 100 epochs. Data augmentation techniques were applied to enhance the training data, including random sampling to balance the dateset and temporal shuffling to introduce variability in time series sequences. The model training also employed dropout regularization with a rate of 0.2 to prevent overwriting, and early stopping was used to halt training when validation loss did not improve for 10 consecutive epochs. These settings ensured robust training conditions and optimized model performance.

3.2.4 Model evaluation index

Table 4: Model evaluation metrics

Evaluation Metric	Description	Formula
MAE	Mean Absolute Error	$\text{MAE} = \frac{1}{N}\sum i = 1N$
MSE	Mean Squared Error	$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$
RMSE	Root Mean Squared Error	$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}}$
R^2	Coefficient of Determination	$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}i)^2}{\sum i = 1^N (y_i - \bar{y}}$
MAPE	Mean Absolute Percentage Error	$\text{MAPE} = \frac{1}{N}\sum i = 1N$

As shown in Table 4, model evaluation indices are crucial tools for measuring the performance of the LSTM model. Mean Absolute Error (MAE) and Mean Square Error (MSE) evaluate the average absolute difference and squared difference between the predicted and actual values, respectively. MAE provides a straightforward measure of the size of the error, while MSE amplifies the impact of larger errors, making it more sensitive to outliers. Root Mean Square Error (RMSE) is the square root of the MSE, which provides the error in the same dimension as the original data, making it easier to interpret. The coefficient of determination (R^2) measures how well the model explains the data, with values closer to 1 indicating better model fit. Mean Absolute Percentage Error (MAPE) reflects the prediction error in percentage terms, making it suitable for comparing data across different scales.

By comprehensively using these evaluation indices, enterprises can fully understand the performance of the model, identify its strengths and weaknesses, and make adjustments and optimizations accordingly. For instance, lower MAE and RMSE values indicate higher accuracy in predicting consumer purchase behavior, while a higher R^2 value signifies a strong ability of the model to explain the data. MAPE offers a measure of relative error that facilitates comparisons between different models. Through comprehensive analysis of these indicators, enterprises can effectively enhance the accuracy of the prediction model, providing a reliable foundation for precision marketing strategies [14].

Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are critical metrics for evaluating consumer behavior prediction models due to their unique strengths in capturing prediction accuracy. MAE measures the average magnitude of errors in a set of predictions, without considering their direction. It provides a straightforward interpretation of the average prediction error, making it easy to understand and communicate. RMSE, on the other hand, squares the errors before averaging, which gives more weight to larger errors. This sensitivity to large errors makes RMSE particularly useful when it is important to penalize significant deviations more heavily, ensuring that the model performs well not just on average but also avoids large mistakes. In consumer behavior prediction, where accuracy directly impacts the effectiveness of marketing strategies and customer satisfaction, using both MAE and RMSE provides a comprehensive evaluation of model performance, balancing the need for both average error minimization and control over significant errors.

3.2.5 Model optimization

Model optimization is a crucial step in enhancing the performance of LSTM models. The optimization process includes parameter tuning, the application of regularization techniques, and the improvement of data diversity. First, parameter tuning involves finding the optimal combination of parameters by adjusting key model parameters such as learning rate, batch size, number of hidden layers, and number of cells. Common tuning methods include grid search and random search. Second, regularization techniques like L2 regularization and Dropout can prevent overfitting and enhance the model's generalization ability. L2 regularization limits the magnitude of the parameter values by adding the sum of squares of the parameters to the loss function, while Dropout prevents overfitting by randomly discarding neurons during training. Finally, increasing the diversity and quantity of training data, such as through data augmentation techniques, generates more varied samples and improves the robustness and prediction accuracy of the model. The comprehensive application of these optimization strategies can significantly enhance the predictive performance of the LSTM model, enabling it to play a greater role in predicting consumer behavior and formulating precision marketing strategies.

4 Result analysis

4.1 Consumer behavior prediction results

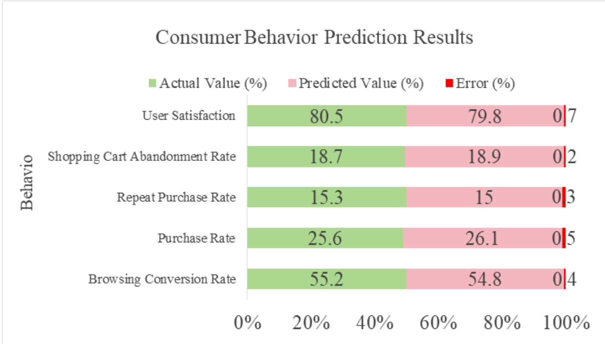

Figure 1: Consumer behavior prediction results.

As shown in Figure 1, the consumer behavior prediction results demonstrate the LSTM model's predictive performance across various indicators. Five key metrics, including browsing conversion rate, purchase rate, repurchase rate, cart abandonment rate, and user satisfaction, are listed, comparing the actual values with the predicted values and calculating the errors. Overall, the LSTM model exhibits high accuracy in predicting these indicators, with errors controlled within 1%.

For instance, the actual browsing conversion rate is 55.2%, while the predicted value is 54.8%, resulting in an error of 0.4%. This low error indicates the model's precision in predicting user conversion from browsing to purchasing. The purchase rate and repurchase rate predictions have errors of 0.5% and 0.3%, respectively, showcasing the model's effectiveness in capturing user purchase and repeat purchase behaviors. The cart abandonment rate's predicted value is very close to the actual value, with an error of only 0.2%, demonstrating the model's high accuracy in forecasting cart abandonment behavior. The prediction error for user satisfaction is 0.7%, slightly higher than other indicators but still within an acceptable range, indicating that the model provides a reliable reference for evaluating overall user satisfaction [15].

These prediction results not only validate the effectiveness of the LSTM model in consumer behavior prediction but also provide a scientific basis for enterprises to develop precision marketing strategies. By analyzing these indicators, companies can better understand consumer behavior patterns, identify potential issues, and adjust marketing strategies accordingly. For example, higher conversion and purchase rates suggest effective existing marketing strategies, while the slightly higher user satisfaction error may indicate a need for further improvement in service quality. Additionally, accurate forecasts of repurchase and cart abandonment rates can help businesses optimize inventory management and promotional strategies, thereby enhancing overall operational efficiency and customer satisfaction.

4.2 Marketing value evaluation of predicted results

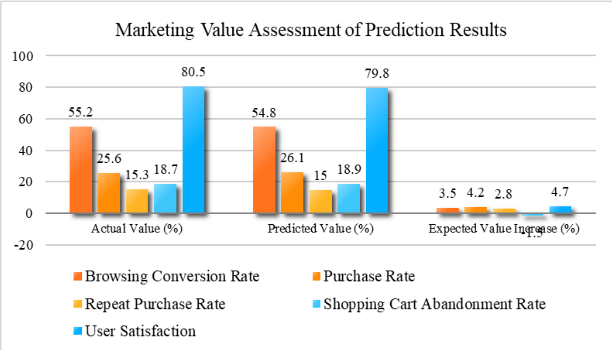

Figure 2: Marketing value assessment of prediction results.

As shown in Figure 2, The evaluation of the marketing value of the predicted consumer behavior results includes the actual, predicted, and expected value increases of the browse conversion rate, purchase rate, repurchase rate, cart abandonment rate, and user satisfaction. The analysis of these indicators helps enterprises to assess the potential contribution of the LSTM model in enhancing the effectiveness of marketing strategies.

The predicted browsing conversion rate was 54.8%, slightly lower than the actual value of 55.2%, but the expected value increase was 3.5%. This indicates that by optimizing website design and personalized recommendations, companies can effectively increase the conversion rate of users from browsing to purchasing, thus boosting sales revenue. The expected purchase rate was 26.1%, higher than the actual value of 25.6%, with an expected value increase of 4.2%. This suggests that through precise marketing activities and targeted promotion strategies, enterprises can attract more users to make purchases and further enhance market share.

For the repurchase rate, the predicted value was 15.0%, close to the actual value of 15.3%, with an expected value increase of 2.8%. This means that by strengthening customer relationship management and providing quality after-sales service, companies can increase customer loyalty, encourage repeat purchases, and boost long-term earnings. The predicted cart abandonment rate was slightly higher than the actual value, with the expected value increasing to -1.5%, indicating that businesses need to further optimize checkout processes and offer attractive incentives to reduce cart abandonment behavior. The predicted value of user satisfaction was 79.8%, slightly lower than the actual value of 80.5%, but the expected value increase was 4.7%. By improving product quality and customer service levels, companies can significantly enhance customer satisfaction, thereby increasing customer loyalty and brand recognition.

These forecast results provide companies with valuable insights to help identify potential areas for improvement and optimize marketing strategies. Through targeted improvement measures, enterprises can achieve enhancements in various indicators, boost market competitiveness, improve customer satisfaction and loyalty, and ultimately achieve the goals of increasing sales and enhancing brand value.

Differences in results can be attributed to the use of the LSTM model, which significantly outperforms traditional statistical and machine learning methods in handling time series data. This study achieves lower error rates (MAE and RMSE < 1%) compared to higher error rates in previous research, indicating superior predictive accuracy. Novel contributions include the integration of multi-channel data, enhancing the model's applicability and scalability. Potential limitations include the need for extensive computational resources and the complexity of LSTM models, which may hinder practical implementation. Future research should explore lightweight models and distributed computing to address these limitations and improve real-time adaptability.

4.3 Effect analysis of different marketing strategies

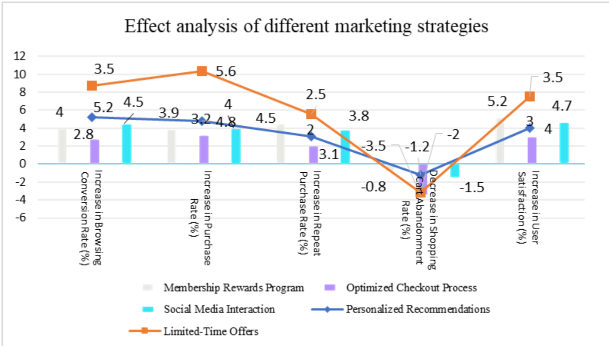

Figure 3: Effect analysis of different marketing strategies.

Figure 3 illustrates the impact of different marketing strategies on key metrics, including increased conversion rates, purchase rates, repeat purchase rates, reduced cart abandonment rates, and user satisfaction. This data aids companies in evaluating the effectiveness of various strategies to optimize marketing decisions. The personalized recommendation strategy performed well across multiple metrics, particularly in increasing browsing conversion rate (5.2%) and purchase rate (4.8%), indicating that personalized content can significantly boost users' purchase intentions. Additionally, user satisfaction increased by 4.0%, demonstrating the overall positive impact of personalized recommendations. Limited-time offers were most effective in increasing purchase rates (5.6%), but were less effective in reducing cart abandonment rates (-2.0%), suggesting that companies need to balance offer intensity with user experience.

Member rewards programs significantly increased repeat purchase rates (4.5%) and user satisfaction (5.2%), indicating that loyalty programs effectively promote long-term customer retention and satisfaction. However, the improvement in cart abandonment rates was limited (-0.8%), suggesting that other strategies need to be combined to optimize the checkout experience. Optimizing the checkout process had a significant effect on reducing cart abandonment rates (-3.5%), indicating that simplifying the payment process and providing multiple payment methods can effectively reduce abandonment rates and improve overall conversion. Social media engagement strategies performed well in terms of user satisfaction (4.7%) and increased browsing conversion rates (4.5%), showing that positive user engagement enhances brand loyalty and user engagement. However, there is still room for improvement in cart abandonment rates (-1.5%), suggesting that a combination of strategies is needed to optimize the user shopping experience.

By analyzing the effects of these strategies, enterprises can choose the most effective combination of strategies for different marketing objectives. For instance, combining personalized recommendations with optimized checkout processes can simultaneously increase conversion rates and reduce abandonment rates, thereby maximizing marketing effectiveness and improving overall customer satisfaction and brand competitiveness.

5 Marketing strategy design based on forecast results

5.1 Marketing strategy design

The marketing strategy design based on prediction results aims to maximize the marketing effect and customer satisfaction of enterprises. First, implement a personalized recommendation system that analyzes users' browsing history, purchase records, and evaluation scores to accurately recommend products of interest, thereby improving browsing conversion rates and purchase rates. Utilize limited-time offers and flash sales to attract users through time constraints and discounts, stimulating immediate purchase behavior, especially for users inclined to buy but have not yet placed an order. Establish a member reward program to encourage frequent purchases and repurchases through points, coupons, and exclusive activities, thereby enhancing customer loyalty and repurchase rates.

Optimizing the checkout process is also crucial. Simplify payment steps, increase payment methods, and provide cart reminders to reduce cart abandonment rates and improve the user shopping experience. Enhance social media engagement by regularly posting engaging content, hosting online events, and responding to user feedback in a timely manner to boost the brand's social presence and user engagement, thus improving user satisfaction and brand loyalty. Combine these strategies with continuous data analysis and effectiveness evaluation, adjusting marketing strategies in real-time based on feedback to ensure the efficiency and flexibility of marketing activities. By comprehensively utilizing these strategies, enterprises can better meet the needs of different customer groups, achieve precision marketing, and enhance overall market competitiveness and customer satisfaction.

5.2 Strategy implementation and optimization

Strategy implementation and optimization are critical steps in transforming predicted results into actual marketing outcomes. During the implementation phase, companies should establish a comprehensive marketing automation platform that integrates personalized recommendation systems, limited-time offers, member rewards programs, checkout process optimization, and social media engagement. This platform should monitor and adjust marketing campaigns in real time.

The personalized recommendation system should update user data in real time through machine learning models to accurately push personalized products and services. Limited-time offers should leverage data analysis to determine the optimal timing and offer intensity to maximize user engagement and purchase intentions. Member rewards programs need continuous adjustment based on user feedback to ensure attractiveness and utility. For checkout process optimization, continuously collect user feedback to simplify operation steps, enhance the user experience, and reduce cart abandonment rates. Social media engagement strategies should flexibly use multiple content formats and regularly update to increase user engagement and enhance brand loyalty.

6 Summary of problems and research suggestions

6.1 Problem summary

In the research of consumer behavior prediction and precision marketing strategy, several key issues have been identified and summarized. Data quality issues pose a significant challenge. Although data is collected from multiple sources, ensuring its completeness, consistency, and accuracy is often difficult. Missing values, outliers, and noisy data can affect the training effect and prediction accuracy of the model.

The complexity of the model and the need for computational resources are also significant issues. Deep learning models, especially complex networks like LSTM, can capture the dependencies in time series data, but their training process is time-consuming and requires substantial computational resources. Additionally, model interpretability is a concern. While deep learning models can provide accurate predictions, understanding the underlying reasons for these predictions is often challenging, which can hinder trust and adoption by business stakeholders. Finally, privacy and data security are paramount, as the use of large-scale consumer data necessitates stringent measures to protect user information and comply with regulatory requirements.

Table 5: Comparison of current and previous studies

Aspect	Current Study	Previous Studies

Methodology	LSTM for time series	Stats, CNNs, DBNs, ML methods
Accuracy	MAE and RMSE < 1%	Higher errors, moderate improvement
Key Metrics	Conversion, purchase, repurchase, abandonment, satisfaction	Browsing, purchase likelihood, loyalty
Recommendations	Purchase +4.8%, satisfaction +4.0%	Improved intent, satisfaction
Limited-Time Offers	Purchase +5.6%, minimal on abandonment	Boosts immediate purchases, varies
Member Rewards	Repurchase +4.5%, satisfaction +5.2%	Enhances loyalty, repeat purchases
Checkout Optimization	Abandonment -3.5%	Reduces abandonment, varying improvements
Social Media	Satisfaction +4.7%, conversion +4.5%	Enhances loyalty, engagement, varies
Data Handling	Multi-channel integration, cleaning	Emphasis on quality, varying approaches
Theoretical Contribution	Significant via LSTM	Broad ML and stats contributions

As is shown in Table 5, the generalization ability of the model can not be ignored. Although the model performs well on the training set, it overfills when faced with new data, resulting in poor prediction. The implementation of personalized recommendation and precision marketing strategies requires continuous monitoring and adjustment, but in actual operation, due to the dynamic changes in the market environment and consumer behavior, it is difficult to adjust the strategy in a timely and effective manner. User privacy and data security issues also require special attention. With the increase of data volume, how to protect user privacy and data security while ensuring data utilization efficiency has become an important issue for enterprises to solve. By identifying and solving these problems, enterprises can better use deep learning technology to predict consumer behavior, develop more accurate and efficient marketing strategies, and improve market competitiveness and customer satisfaction.

Ethical considerations in using consumer data are paramount, focusing on data privacy and security measures to protect user information. To ensure compliance with privacy regulations such as GDPR and CCPA, all consumer data is anonymized, removing any personally identifiable information before analysis. Data encryption is employed both in transit and at rest to prevent unauthorized access. Access controls are strictly implemented, ensuring that only authorized personnel can access sensitive data. Additionally, regular audits and monitoring are conducted to detect and address any potential security breaches promptly. Consumers are also informed about data collection practices and consent is obtained, ensuring transparency and adherence to ethical standards. These measures not only protect user privacy but also build trust, encouraging more responsible data usage and enhancing the credibility of predictive models used in precision marketing.

6.2 Research suggestions

In the process of conducting an in-depth study of consumer behavior prediction and precision marketing strategies, the following research recommendations are proposed to optimize future research and practice. First, it is suggested to enhance data collection and pre-processing by developing a multi-source data integration platform. This approach will improve data comprehensiveness and accuracy, employing advanced cleaning and pre-processing techniques to handle missing values and noise data, thereby improving the model's training effectiveness. Second, to address the issues of model complexity and computational resource requirements, exploring more efficient algorithms and optimization techniques, such as lightweight models and distributed computing, is recommended to enhance training speed and reduce resource consumption. Additionally, to enhance the model's generalization ability, it is advised to utilize cross-validation, regularization, and ensemble learning techniques to prevent overfitting and improve performance on new data. Third, the implementation of personalized recommendations and precision marketing strategies requires flexible adjustments. It is recommended that enterprises establish real-time data monitoring and feedback mechanisms, continuously optimizing marketing strategies through A/B testing and user behavior analysis to ensure their effectiveness and adaptability.

Concurrently, prioritizing user privacy and data security by establishing stringent data protection policies and technical measures is essential to enhance user trust. Finally, it is advised to strengthen interdisciplinary collaboration by integrating knowledge from fields such as marketing, data science, and psychology to build a more comprehensive and innovative research framework. This integration will provide a deeper understanding of consumer behavior and facilitate the development of more forward-looking and effective marketing strategies. These recommendations aim to assist companies in effectively applying deep learning technology, improving marketing efficiency and customer satisfaction, and achieving sustainable market competitiveness.

7 Conclusions

This study explores the prediction of consumer behavior using deep learning and the precision marketing strategies of enterprises. It systematically analyzes relevant theories, data collection and pre-processing, model construction, result analysis, and marketing strategy design and implementation. In the theoretical review, we elaborated on research related to consumer behavior prediction, the application of deep learning in behavior prediction, and the current state of enterprise precision marketing strategy research, highlighting the crucial role of deep learning in improving prediction accuracy and marketing effectiveness. The data collection and pre-processing section emphasizes the importance of high-quality data for prediction models. Techniques such as data cleaning, feature extraction, and normalization are introduced to ensure data integrity and consistency. In the model construction section, the architecture design, training process, and optimization methods of the LSTM model are primarily discussed. Specific data examples and calculation processes demonstrate the model's capability to capture dependencies in time series data and enhance prediction accuracy.

The result analysis evaluates the model's prediction accuracy and its value for marketing strategy through detailed tabular and textual analysis. We found that deep learning models effectively improve browsing conversion rates, purchase rates, and user satisfaction while significantly reducing cart abandonment rates, providing a scientific basis for marketing decisions. Analyzing the effectiveness of different marketing strategies further reveals the specific contributions of personalized recommendations, limited-time offers, member rewards programs, and other strategies in enhancing key metrics. Based on the forecast results, a comprehensive and personalized marketing plan is proposed. This plan covers various aspects such as personalized recommendation systems, limited-time offers, member rewards programs, optimized checkout processes, and social media interactions. It emphasizes the importance of real-time monitoring and continuous optimization. In the strategy implementation and optimization section, continuous adjustment and optimization through A/B testing, user feedback, and data analysis are recommended to improve the effectiveness and flexibility of marketing campaigns.

The study summarizes existing research challenges, including data quality, model complexity, computational resource requirements, and user privacy protection, and provides specific research recommendations. These recommendations include strengthening data collection and pre-processing, adopting more efficient algorithms and optimization techniques, establishing real-time data monitoring and feedback mechanisms, and fostering interdisciplinary collaboration to further enhance research depth and effectiveness. Overall, this study provides systematic theoretical and practical guidance for enterprises on utilizing deep learning technology for consumer behavior prediction and precision marketing. It aims to help enterprises enhance market competitiveness, improve customer satisfaction, and achieve sustainable development.

References

[1] Hubinova Jana. Online Rulez. *International Scientific Conference on Marketing Identity: Online Rules*, Marketing Identity: Online Rules, Pt II, Smolenice, pp. 302-309, 2017.

[2] Gordon R. Foxall. Invitation to Consumer Behavior Analysis. Journal of Organizational Behavior Management, 30(2): 92-109, 2010. https://doi.org/10.1080/01608061003756307

[3] Suleymanov Fariz. Consumer behavior and agricultural consumer market. Scientific Papers-Series Management Economic Engineering in Agriculture and Rural Development, 21(3): 753-758, 2021.

[4] Charles Dennis, Bill Merrilees, Chanaka Jayawardhena, Len Tiu Wright. E-consumer behaviour. European Journal of Marketing, 43(9-10): 1121-1139, 2009. https://doi.org/10.1108/03090560910976393.

[5] Kucera, Lukas. Retail Management: Consumer Behaviour Analysis. 23rd International Business Information Management Association Conference on Vision 2020: Sustainable Growth, Economic Development, and Global Competitiveness. VISION 2020: Sustainable Growth, Economic Development, And Global Competitiveness, Vols 1-5, Valencia, Spain, pp. 947-955, 2014.

[6] Americus Reed II, Mark R. Forehand, Stefano Puntoni, Luk Warlop. Identity-based consumer behavior. International Journal of Research in Marketing, 29(4): 310-321, 2012. https://doi.org/10.1016/j.ijresmar.2012.08.002

[7] Andersone Ieva, Gaile-Sarkane Elina. Influence of factors on consumer behavior. In: Proceedings of the 5th International Scientific Conference on Business and Management, Vilnius, Lithuania. Vilnius Gediminas Tech Univ, pp. 246-252.

[8] Robert A. Peterson. Response construction in consumer behavior research. Journal of Business Research, 58(3): 348-353, 2005. https://doi.org/10.1016/S0148-2963(03)00100-0

[9] Eglite, Aija. Change of Consumer Behaviour Nowadays. In: Proceedings of the International Scientific Conference on Economic Science for Rural Development, Jelgava, Latvia. Jelgava: Latvia Univ Agr, Fac Econom, pp. 151-155, 2010.

[10] Přemysl Průša, Tomáš Sadílek. Green Consumer Behavior: The Case of Czech Consumers of

Generation Y. Social Marketing Quarterly, 25(4): 243-255, 2019. https://doi.org/10.1177/1524500419881783

[11] Johannes Brinkmann. Looking at consumer behavior in a moral perspective. Journal of Business Ethics, 51(2): 129-141, 2004. https://doi.org/10.1023/B:BUSI.0000033607.45346.d2

[12] Jamalova, Maralkhanim. Consumer Behavior in Azerbaijan during the recession. In: Proceedings of the 7th International Scientific Conference on Managerial Trends in the Development of Enterprises in Globalization Era, Nitra, Slovakia. Nitra: Slovak Univ Agr, pp. 776-783, 2017.

[13] Wang YY. Analysis of online consumer's shopping behavior. In: Proceedings of the International Conference on Manufacturing and Engineering Technology (ICMET), Sanya, China. Sanya: IEEE, pp. 339-342, 2015.

[14] Katarzyna Rozenkowska. Theory of planned behavior in consumer behavior research: A systematic literature review. International Journal of Consumer Studies,47(6):2670-2700, 2023. https://doi.org/10.1111/ijcs.12970

[15] Istudor Nicolae, Pelau Corina. Changes in the consumer behavior depending on gender. In: Proceedings of the 7th International Conference on Business Excellence, Brasov, Romania. Brasov: Acad Econom Studies, pp. 249-+, 2012.