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Consumer Preference Analysis and Marketing Strategy in Digital Economy Based on Deep Learning

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With the rapid development of the digital economy, consumer behavior has become both complex and diverse. The traditional marketing model has difficulty meeting the increasingly personalized needs of modern consumers. How to comprehensively understand consumer preferences and implement accurate and effective marketing strategies has become a problem for enterprises. Through deep learning technology, this study analyzes the changing trend of consumer preferences, explores data-driven personalized marketing strategies, and provides theoretical support and practical guidance for enterprises wishing to develop more efficient marketing programs. The preference characteristics of consumers in the context of digital economy are mined using a method that combines a deep learning model with big data analysis. A large amount of consumer behavior data is collected and analyzed, and a consumer preference prediction model is constructed. Furthermore, the role of technologies, such as digital marketing tools and personalized recommendation systems, in enhancing consumer satisfaction and increasing corporate income is discussed. The research results show that the personalized characteristics of consumer preferences are obvious, and deep learning technology can effectively capture the differences among consumer groups, and improve the effectiveness of marketing strategies through accurate personalized recommendations. Marketing strategies based on consumer preferences have higher conversion rates than traditional methods, and can encourage consumer participation and strengthen brand loyalty. The research also found that the use of technologies in the digital economy plays can improve marketing efficiency and optimizing resource allocation. This study provides a theoretical basis for enterprises wishing to develop personalized marketing strategies, and provides practical guidance for the application of deep learning in digital marketing. As digital technologies continue to advance, future research is expected to optimize models and strategies to help companies gain an edge in the increasingly competitive market.

Keywords: Consumer preference; deep learning; digital economy; personalized marketing; recommendation system

1. INTRODUCTION

1.1 Background Information of the Research Field

The rapid development of the digital economy has had a significant effect on consumer behavior and on businesses globally. With the wide application of Internet technology and big data, the digital economy has changed the traditional business model and provided consumers with more diversified choices and more personalized services. The way consumers make decisions has changed. Consumer behavior based on geographic location and traditional business districts has gradually shifted to a model that relies more on web platforms, mobile devices and intelligent recommendation systems. In today's digital economy, data on consumer behavior can be obtained in real time through Internet platforms, social media, big data analysis and other means to provide a more accurate basis for marketing decisions, and achieves the in-depth mining and value creation of the human resource data of enterprises [1].

As an important task in digital marketing, consumer preference analysis involves in-depth exploration of consumer behaviors, needs and interests. Traditional market research methods are often limited to questionnaires and qualitative interviews, which cannot reflect the changes of consumer

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behavior in a timely manner. In the digital economy environment, consumer behavior data is collected mainly through e-commerce platforms, social networks and search engines. These data contain consumers' browsing, purchasing, and evaluation behaviors in addition to other multi-dimensional information, providing researchers with rich analysis materials. How to effectively extract the potential needs and preferences of consumers from a large amount of unstructured data has become an important issue facing the academic and business domains.

As an advanced artificial intelligence (AI) technology, deep learning has made remarkable progress in the fields of image recognition, speech processing and natural language processing. In consumer preference analysis, deep learning can automatically learn and extract complex patterns from data through neural network models, overcoming the over-reliance of traditional methods on feature engineering. Deep learning models such as convolutional neural networks (CNNS) and recurrent neural networks (RNNS) can process large-scale data sets to accurately predict consumer purchase intentions and preference trends. It offers new ideas and means whereby marketers can make personalized product recommendations and push marketing content more accurately. As the digital economy continues to evolve, companies are constantly exploring how to use technologies such as deep learning to optimize marketing strategies. By applying deep learning technology to analyze consumer preferences, personalized recommendations, precisely targeted advertising and dynamic pricing, can be achieved to improve marketing efficiency and customer satisfaction.

1.1.1 Research Status

In the digital economy environment, the research of consumer preferences has become an important topic in the field of marketing. In recent years, with the application of deep learning technology, researchers have continuously explored its potential in the analysis of consumer preferences. Ren et al. proposed diversified consumer preference learning methods through online evaluation data, pointing out that the complexity and diversity of consumer preferences require new data analysis tools for in-depth mining [2]. Nam et al. focused on the emerging retail model of unmanned stores, and used selection experiments to investigate consumers' preference for unmanned stores, finding that technological innovation has a profound impact on consumer behavior [3].

By means of a selection experiment, Liu et al. found a diversity of consumer preferences in regard to organic ginger consumption, and proposed the application of a personalized recommendation system for the marketing of agricultural products [4]. Wang et al. studied consumers' preference for yogurt products from the perspective of packaging design, pointing out consumers' sensitivity to product appearance and packaging in purchasing decisions [5]. Liu et al. further discussed consumers' preference for the bundled pricing of organic agricultural products and proposed a pricing strategy based on consumer preference [6]. Paiva et al. studied the beef consumption behavior of customers in the Portuguese market, and found that consumers pay great attention to the quality and brand of beef, which provides a valuable reference for brand positioning and marketing [7]. From the perspective of privacy preference, Tomaino et al. discussed consumers' non-transitive preference in data privacy protection and proposed privacy management challenges in digital marketing strategies [8]. Chen discussed the feasibility of machine learning in predicting consumers' sustainable product preferences and emphasized the application of intelligent recommendation systems in future marketing strategies [9].

Applying the grounded theory method, Tian et al. studied consumers' preferences in terms of infant milk powder brands, and found that emotional factors and brand cognition had a significant impact on consumers' brand selection [10]. Liu et al. proposed a multi-standard consumer preference analysis method based on a Bayesian hierarchical model, which provided a new idea for accurate market segmentation [11]. Zong et al. studied the impact of social exclusion on consumers' color preferences, emphasizing the potential impact of emotions and social environment on consumers' purchasing decisions [12]. Through laboratory-based research, Wang et al. analyzed the impact of vertical product differentiation on consumer preference and proposed the optimization direction of product differentiation strategy [13]. Li et al. considered consumers' green preferences in the green housing subsidy strategy, and discussed how environmental awareness affects consumers' purchasing decisions [14]. These studies show that in the digital economy era, the diversity and complexity of consumer preferences require that enterprises pay more attention to personalization, intelligence, and sustainability factors in the development of marketing strategies.

1.2 Research Questions and Objectives

In the context of the digital economic environment, the change of consumer preferences has become an important basis for enterprises' formulation of marketing strategies. With the continuous progress of deep learning technology, the method of analyzing consumer preferences based on big data has gradually matured, providing enterprises with more accurate market positioning tools [15]. Many studies have explored the relationship between the digital economy and consumer behavior, although there are still insufficient studies on the use of deep learning technology for the analysis of consumer preferences.

The main research question guiding this study is: in the context of the digital economy, how can deep learning technology be used to analyze the changing trends of consumer preferences and propose feasible marketing strategies based on this? This study focuses on the following questions: First, how does the digital economy affect consumers' purchasing behavior and preferences? Second, how can deep learning technology extract effective preference information from consumer behavior data? Third, based on the analysis of consumer preferences, how can differentiated marketing strategies be developed so as to improve market competitiveness?

The purpose of this study is to analyze, through deep learning models, the changing rules of consumers' preferences in the digital economy, investigate the key factors affecting consumers' decision-making, and propose specific marketing strategies based on the characteristics of different consumer groups. Through systematic analysis and modeling, it provides data-driven marketing decision support for enterprises wishing to improve the effectiveness of their marketing strategies, and achieve accurate and personalized marketing.

1.3 Research Methods and Techniques

By using a method combining quantitative analysis and deep learning technology, this paper discusses how to discover current preference trends by analyzing large-scale consumer data.

In terms of data collection, consumer behavior data is obtained through multiple channels, mainly from e-commerce platforms, social media, consumer surveys, etc. Data content includes consumer purchase history, review content, social media interaction data, etc. These data can reflect the interests, needs and purchasing preferences of consumers. In data preprocessing, common data cleaning techniques are used to deal with missing values and noise data, and feature engineering is carried out to extract key features that help analyze consumer preferences. Emotional words and keywords are extracted from consumer comments, or consumer behaviors are clustered and classified.

For model construction, several common deep learning models are used, including neural network (ANN), convolutional neural network (CNN) and recurrent neural network (RNN). CNNS can be used to analyze emotional tendencies in consumer reviews, and RNNS are suitable for processing time series data, such as consumers' historical purchasing behavior. Through deep learning models, consistent patterns of consumer preferences are extracted from large-scale data to predict future consumption trends.

For model optimization, a variety of techniques are used to improve the accuracy and generalization ability of the model; these include hyperparameter adjustment, regularization, cross validation, etc. After comparing the performance of different models, the best model is selected for prediction and analysis. In the result analysis phase, a variety of evaluation indicators, such as accuracy, recall rate, F1 value, are used to evaluate the model's effectiveness in predicting consumer preferences. The preferences of different consumer groups are analyzed in depth, and personalized marketing strategies are proposed.

1.4 Research Significance

From an academic point of view, with the continuous development of the digital economy, the analysis of consumer preferences has become an important topic in the study of consumer behavior. Most of the existing researches focus on traditional consumer behavior theory and simple statistical methods, and the application of deep learning technology in consumer preference analysis is limited. This current research can contribute to technological innovation in the field of consumer preference analysis and expand the application of deep learning technology in the social sciences field. In the era of big data, how to efficiently analyze massive consumer data and extract valuable information from it can enrich the theory of consumer behavior and provide reference for cross-research of related disciplines.

From a practical perspective, although the development of the digital economy provides enterprises with rich consumer data, it also brings more marketing challenges. Enterprises must be able to use data effectively, explore consumer preferences in depth, and develop personalized marketing strategies accordingly. This study analyzes consumer preferences through deep learning technology, provides data-based decision support for enterprises, helps enterprises realize precisely-targeted marketing strategies and personalized services, and improves market response speed and marketing efficiency. The results of the research can also provide guidance for different enterprises and marketing practices in different fields. In e-commerce, retail and service industries, the accurate analysis of consumer preferences will directly affect the marketing impact and consumer satisfaction.

This study also has certain social significance. In the digital economy, consumers' purchase decisions are no longer based simply on price factors; consumers now consider personalized needs and consumption experiences. Through the in-depth analysis of consumer preferences, a more personalized and diversified development of the consumer market can be achieved, the quality of products and services can be promoted, and the overall satisfaction and loyalty of consumers can be enhanced.

1.5 Relevant Theories

1.5.1 Consumer Behavior Theory

Consumer behavior theory concerns the way that consumers choose, use and dispose of goods or services when making a purchasing decision. Consumers' purchasing decisions are influenced by many factors, including individual needs, social factors, psychological factors and cultural factors. The theory of "bounded rationality", developed by economist Herbert Simon, posits that consumers are influenced by their cognitive limitations and their access to information in the decision-making process. Consumers cannot process all the information, and therefore choose the key factors that simplify decision-making. The theory provides a basis for understanding consumer behavior when faced with complex information.

The theory of consumer behavior has been expanded in keeping with the digital economy. Consumers obtain commodity information through traditional retail channels, and also participate in the consumption decision-making process through multiple channels such as Internet platforms and social media. The diversification and rapid dissemination of such information make consumers' purchasing behavior more complex. In recent years, the research on consumer behavior has increasingly focused on analyzing the role of irrational factors such as emotion, personalization and social influence on decision-making. For example, emotional decision theory posits that consumers' emotional responses often influence their purchasing decisions, and that emotional factors play an increasingly important role in Internet shopping and social media interactions.

1.5.2 Digital Economy Theory

Digital economy theory mainly concerns the impact of information technology, Internet, artificial intelligence, big data and other technologies on economic operation mode, business environment and market behavior. As an emerging economic form, the digital economy has changed the production mode of goods and services, and also reshaped consumer demand and consumption behavior. In the digital economy, data becomes an important factor of production, and the digitization of consumer behavior makes market forecasting, consumption pattern analysis, and personalized services possible. The theory of digital economy emphasizes the efficient circulation of information and the accurate prediction of consumer behavior, and improves the speed and accuracy of market response through data analysis. It provides a theoretical framework for understanding how to use big data and artificial intelligence technologies to comprehensively analyze consumer preferences. Another characteristic of the digital economy is the platform-based business model. Consumer behavior is driven not only by product and price, but also by factors such as platform recommendation systems, consumer reviews, and social media interactions. When analyzing consumer behavior, digital economy theory places more emphasis on the role of the platform economy in shaping consumer behavior, especially in the fields of retail, e-commerce and sharing economy [16].

1.5.3 Deep Learning

As a branch of AI, deep learning mainly uses multi-level neural networks to learn and model data by simulating the way human brain neural networks work. Deep learning models have powerful feature extraction and pattern recognition capabilities, and can find potential rules and structures from a large amount of data, and are widely used in image recognition, speech recognition, natural language processing and other fields.

In consumer preference analysis, deep learning techniques are capable of processing unstructured data such as consumer review text, social media posts, and image and video data. This data contains a wealth of emotional information, preferences, and behavioral characteristics. Deep learning uses convolutional neural network (CNN), recurrent neural network (RNN) and other models to process these unstructured data effectively and extract valuable consumer preference information. The strength of deep learning is the ability to learn from end to end. By inputting raw data, the model can autonomously learn the entire mapping process from data input to output, reducing the need for manual intervention. Making deep learning an indispensable tool in consumer preference analysis, it can accurately capture subtle changes in consumer behavior and provide data support for personalized marketing.

1.5.4 Neural Network Theory

Neural networks are the core of deep learning, and are based on the structure of the human brain in the nervous system. By simulating the connection of neurons, the neural network processes the input data through layers of neurons and finally outputs the predicted result. After each neuron passes a weighted sum, it is processed by an activation function to pass the signal to the next layer. Through a multi-level neural network structure, a neural network can deal with complex nonlinear problems.

In consumer preference analysis, neural networks are particularly suitable for processing data with complex relationships and high dimensional features. Consumer preference data has high nonlinear characteristics; therefore, it is difficult to capture accurately the complex patterns in the traditional linear regression or decision tree methods. Through deep structure, neural networks are able to identify underlying preference patterns and trends from large amounts of consumer data. The application of neural networks is not limited to consumers' purchase history data, but can also be combined with various types of data such as social networks and review data for more comprehensive preference analysis. The sentiment analysis method based on the convolutional neural network (CNN) can extract sentiment information from consumer reviews to provide supplementary data indicating consumer preferences. A model based on recurrent neural networks (RNN) can process time series data to reveal the dynamic changes in consumer preferences. The learning process of neural network depends on a large amount of training data and complex computing power. With the improvement of computing power and the increase of data volume, the application of neural networks in consumer behavior analysis is expanding. The optimization of the structure and algorithm of the neural network can improve the accuracy and efficiency of the analysis, and provide support for the precision marketing of enterprises.

2. MATERIALS AND METHODS

2.1 Data Collection and Sample Selection

2.1.1 Data Source

The data for this study was obtained from two sources: 1) publicly-available data related to consumption behavior; and 2) a questionnaire survey. Major e-commerce platforms, social media and public consumer behavior research reports contain information on consumer preferences, purchasing habits and brand preferences in different fields and industries, covering a relatively wide range of consumer groups. These data were collected from Jingdong, Taobao, Amazon and other e-commerce platforms involving different categories of goods, such as electronic products, household goods, food and so on. Consumer reviews and behavioral data posted on social media platforms also provide valuable information about consumers' emotional tendencies and purchasing decisions.

The survey targeted consumers aged between 18 and 45, across gender, occupation and income levels. The questionnaire contained items seeking the basic information of consumers, purchase preferences, consumption frequency and other questions designed to obtain a comprehensive understanding of the behavioral characteristics of consumers

Table 1 Data sources and specific contents.

Data source type	Specific source	Data description	Data volume
E-commerce platforms	JD.com, Taobao, Amazon, etc.	Consumer purchase records, product reviews, brand preferences	100,000 entries
Social media data	Weibo, Douyin, WeChat	Consumer comments, product discussions, sentiment analysis	80,000 entries
Survey data	Online and offline surveys	Consumer demographics, purchase preferences, consumption behaviors	1,200 valid surveys

Table 2 Main demographic characteristics of the sample.

Characteristic	Category	Proportion
Gender	Male	47.3%
	Female	52.7%
Age	18–25 years	36.5%
	26–35 years	41.2%
	36–45 years	22.3%
Occupation	Student	28.0%
	White-collar worker	45.8%
	Freelancer	26.2%
Income	Low income (<5000 CNY/month)	22.1%
	Middle income (5000-10000 CNY/month)	51.6%
	High income (10000 CNY/month)	26.3%

in the digital economy environment. The questionnaire was distributed through online and offline channels, and a total of 1200 valid questionnaires were collected to ensure the diversity and representativeness of the sample. The main data sources and specific contents of this study are shown in Table 1.

2.1.2 Sample Selection and Description

The sample selected for this study was based on multi-dimensional criteria to ensure the representativeness and diversity of data. The sample was based mainly on online questionnaires, and the respondents were consumers aged between 18 and 45, covering different gender, occupation, income level and other features. For the sample selection, the age distribution of consumers was first considered to ensure that the research covered major consumer groups in the digital economy. The distribution of occupations and income levels of respondents was also balanced. The survey participants included students, white-collar workers, freelancers and other job types, with income levels ranging from low to high income groups. These factors help to build a diverse set of consumer behavior data that enabled the researcher to capture comprehensive data on the consumption habits and preferences of different groups in the digital economy.

The questionnaire survey yielded 1200 valid responses. Invalid and repeated questionnaires were removed during the data cleaning process to ensure the validity of the samples and responses. The questionnaire items covered consumers' basic information, shopping preferences, brand loyalty, purchase frequency and other aspects, and comprehensively reflects consumers' consumption behaviors in the digital economy, as shown in Table 2.

2.1.3 Data Preprocessing

Data preprocessing helps clean the raw data and also features the data to improve the predictive performance and accuracy of the model.

To enhance model accuracy and ensure compatibility with deep learning algorithms, extensive feature engineering was performed during data preprocessing. In addition to standard techniques such as One-Hot Encoding for categorical variables (gender, occupation) and standardization for numerical variables (age, income), derived features were introduced to capture latent behavioral patterns. For instance, a composite variable named "engagement intensity" was created by combining purchase frequency and brand loyalty scores, reflecting both transactional and attitudinal engagement. Another variable, "price sensitivity index" was computed by evaluating the variance in purchase amounts and discount utilization. Sentiment scores were extracted from textual reviews using pre-trained natural language processing models and incorporated as numerical inputs. Interaction terms between demographic and behavioral features (age $\times$ purchase frequency) were also added to capture cross-dimensional influence. These engineered features significantly enriched the data representation, enabling the deep learning model to learn more nuanced preference structures.

Due to missing values, outliers and duplicates in the questionnaire data, data preprocessing is required.

First, the missing values were processed. For the missing data that could not be supplemented, the deletion method was used to remove it from the dataset to ensure the accuracy of the analysis. For the missing data that can be reasonably surmised, the mean interpolation method or the most common value filling method were used to supplement the data to maintain its integrity. After data cleaning, the researchers carried out a

Table 3 Data preprocessing methods.

Characteristic	Pre-processing data type	Post-processing data type	Processing method
Gender	String (male, female)	Binary encoding (0, 1)	One-hot encoding
Age	Integer (18–45 years)	Continuous value (standardized)	Standardization
Income	Integer (low to high income)	Continuous value (standardized)	Standardization
Occupation	String (student, etc.)	Binary encoding (0, 1)	One-hot encoding
Purchase frequency	Integer (1–5 times)	Continuous value (standardized)	Standardization
Brand loyalty	Integer (1–10)	Continuous value (standardized)	Standardization
Consumption Amount	Integer (100–1000 CNY)	Continuous value (standardized)	Standardization

deduplication operation on the dataset to avoid the impact of repeated data on the model training process.

For qualitative data (such as gender, occupation and other category variables), One-Hot Encoding was used to convert each category variable into a set of binary features, ensuring that the data format was suitable for deep learning algorithms. For quantitative data (such as age, income and other continuous variables), standardization was adopted to ensure that features of different scales would not affect the weight allocation of model training.

During the feature engineering stage, some variables were derived and combined. For example, two variables, "purchase frequency" and "brand loyalty", were combined into a "comprehensive purchase behavior" variable to better reflect the overall preferences of consumers. According to the consumption amount, shopping channels and other information, it is classified and grouped to enhance the expression ability of features. After data preprocessing, several key variables were changed, as shown in Table 3.

Through data preprocessing, the data set was transformed into a format suitable for deep learning model analysis. The preprocessing step ensured the quality of data and prevented model training instability caused by abnormal or missing data. The pre-processed dataset established the foundation for the subsequent model construction and training, and helped to improve the accuracy and reliability of the consumer preference analysis model.

2.2 Model Construction

When constructing the consumer preference analysis model, it was very important to choose the appropriate deep learning model and its optimization strategy. Based on the analysis of consumer behavior data, in this study, it was decided to use deep learning models such as Neural Network, convolutional neural network (CNN) and recurrent neural network (RNN) to construct the model. Given the data characteristics, model complexity and computational efficiency, the multi-layer perceptron (MLP) neural network was selected as the main model.

2.2.1 Model Selection

In order to obtain a comprehensive view of the characteristics of consumers' preferences, this study initially considered traditional neural networks, convolutional neural networks (CNN) and recurrent neural networks (RNN). The neural network model is considered to be the most suitable model for processing structured data. The CNN model is generally used for image data processing and has significant advantages in terms of feature extraction; hence, it was not suitable for this study. RNN is better at processing time series data and has potential in processing consumers' historical behavior data. Compared with simple neural networks, RNN has a more complex structure and a large amount of computation, and is prone to overfitting when processing complex data features. Finally, the multi-layer perceptron (MLP) neural network was selected as the research model.

The MLP neural network, as the most classical feedforward neural network, can effectively process nonlinear relational data through a multi-layer nonlinear activation function. In this model, the input layer receives the data on consumer characteristics, transmits the information through the weight transformation of the hidden layer, and the final output layer obtains the predicted value of the consumer's preference. This structure can deal with various complex patterns in consumer behavior data and has strong generalization ability. The model selection formula is shown as Equation (1).

$$Y = f(W_2 \cdot f(W_1 \cdot X + b_1) + b_2) \tag{1}$$

where X is the input data, W_1 and W_2 are the weight matrix, b_1 and b_2 are the bias terms, f is the activation function, and Y is the output of the model.

2.2.2 Model Architecture Design

The neural network model designed in this study adopts a multi-layer perceptron (MLP) architecture. The input layer of the model consists of multiple characteristics of the consumer, including gender, age, income, purchase frequency, and so on. Each feature acts as an input node to the network. These input nodes are passed to multiple hidden layers that use nonlinear activation functions (such as ReLU functions) to handle nonlinear relationships in the data.

After the input data passes through the input layer, it is then passed to the two hidden layers, and the number of neurons in the hidden layer decreases layer by layer to reduce the computational complexity. The number of neurons in each layer is optimized by experiment to ensure that the model can capture enough information without overfitting. Finally, the output layer generates the predicted value, which is the degree of consumer preference. The model architecture is designed as follows.

(1) Input layer. Nodes that contain all consumer characteristics. The number of nodes in the input layer is equal to

the number of features, which are input into the model after normalization.

(2) Hidden layer. Two hidden layers are used, the first containing 128 neurons and the second containing 64 neurons. Each hidden layer is followed by a ReLU activation function to introduce nonlinearity.

(3) Output layer. Outputs the predicted value of consumer preference, using a linear activation function.

The loss function of the model adopts mean square error (MSE), as shown in the following Equation (2).

$$L = \frac{1}{N}\sum_{i=1}^{N}(Y_{true}^{(i)} - Y_{pred}^{(i)})^2 \tag{2}$$

where L is the loss function, N is the number of samples, Y_{true} is the true label, and Y_{pred} is the predicted value of the model.

2.2.3 Algorithm Implementation

The model is implemented using Python's TensorFlow and Keras libraries. These libraries provide efficient neural network implementations and support fast training and evaluation of deep learning models. During the training process, the weights of the model are updated by the backpropagation algorithm, which is based on the gradient descent method and optimizes the network parameters by calculating the gradient of the loss function relative to each weight, and making adjustments. For model training, the Batch Gradient Descent algorithm is adopted to achieve optimization. Each time a small batch of data is input, errors are calculated and weights are updated. The learning rate is an important hyperparameter in model training, and the adjustment of learning rate can directly affect the speed and effect of model training, so it is optimized experimentally. The division of training set, verification set and test set follows the ratio of 70%, 15%, and 15% respectively to ensure sufficient training data and the generalization ability of the model. The algorithm is implemented as follows.

(1) Input data. Consumer demographic data (such as gender, age, income, purchase frequency, etc.).

(2) Model training. Back propagation algorithm and batch gradient descent optimization model are used.

(3) Loss calculation. The mean square error (MSE) is used to calculate the difference between each prediction and the actual value.

(4) Weight update. Weights are adjusted according to gradient descent to reduce losses.

2.2.4 Model Optimization

In order to improve the prediction accuracy of the model and prevent overfitting, the model was optimized in this study. For optimization, the performance of the model is improved by adjusting hyperparameters, using regularization technology and adopting cross-validation. Hyperparameters are adjusted, including the learning rate, batch size, and number of neurons in the hidden layer. Through the cross-validation method, the optimal combination of hyperparameters is selected to ensure that the model performs well on unknown data. When model training, the L2 regularization technique (also known as weight attenuation) is used to limit the excessive value of model parameters and prevent the occurrence of overfitting. To reduce overfitting, this study uses dropout technology in hidden layers, whereby each layer randomly drops a certain percentage of neurons, forcing the model to learn more robust features. For the optimization process, the Adam optimization algorithm is adopted, which is based on the adaptive gradient optimization algorithm, and automatically adjusts the learning rate in different training processes, which is usually more effective than the traditional SGD (random gradient descent) to accelerate convergence. The gradient descent method uses the following Equation (3) to update parameters during the optimization process. This formula adjusts model parameters iteratively based on the gradient of the loss function to minimize prediction error:

$$\theta_{t+1} = \theta_t - \eta\nabla_\theta J(\theta) \tag{3}$$

where θ_t is the current parameter, η is the learning rate, and $\nabla_\theta J(\theta)$ is the gradient of the loss function to the parameter θ.

2.3 Result Analysis and Evaluation

2.3.1 Model Evaluation Index

In order to comprehensively evaluate the performance of the constructed deep learning model in consumer preference analysis, this study selected several commonly used evaluation indicators, including accuracy, precision, recall, F1-score, etc. Through the comprehensive analysis of indicators, the actual effect of the model can be evaluated more objectively, especially in the processing of consumer behavior data, and the model's ability to identify different categories and prediction accuracy can be effectively measured.

Accuracy: represents the proportion of correctly classified samples in the total sample, and is often used to measure the overall classification effect of the model. However, in the case of unbalanced categories, the accuracy may not fully reflect the performance of the model.

Precision: Represents the proportion of a sample classified as positive that is actually positive. The higher the accuracy rate, the stronger the reliability of the model in the positive prediction.

Recall: Represents the proportion of samples that are correctly classified as positive. The higher the recall rate, the stronger the accuracy of the model in detecting positive samples.

F1-score: takes precision and recall into account and is a harmonic average of these two metrics, providing a more comprehensive performance assessment when dealing with unbalanced datasets.

The performance of different models according to evaluation indicators is compared, as shown in Figure 1 below. The optimized MLP neural network model is superior to other

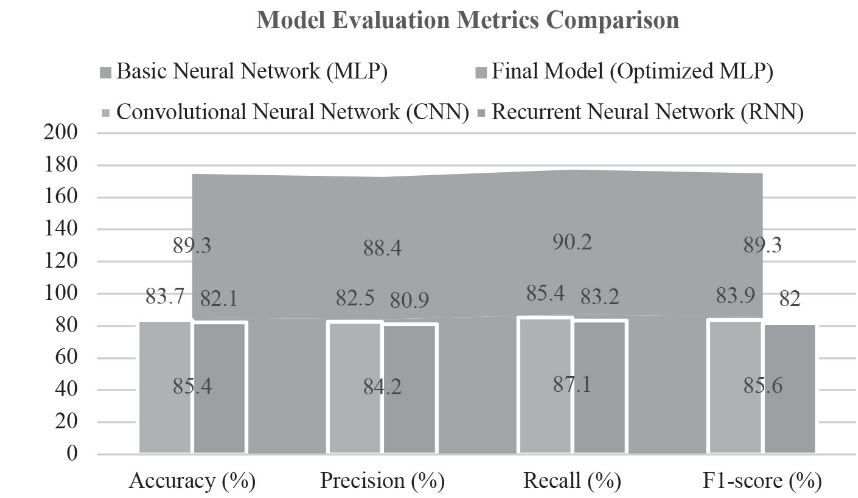

Figure 1 Graph comparing evaluation indicators of different models.

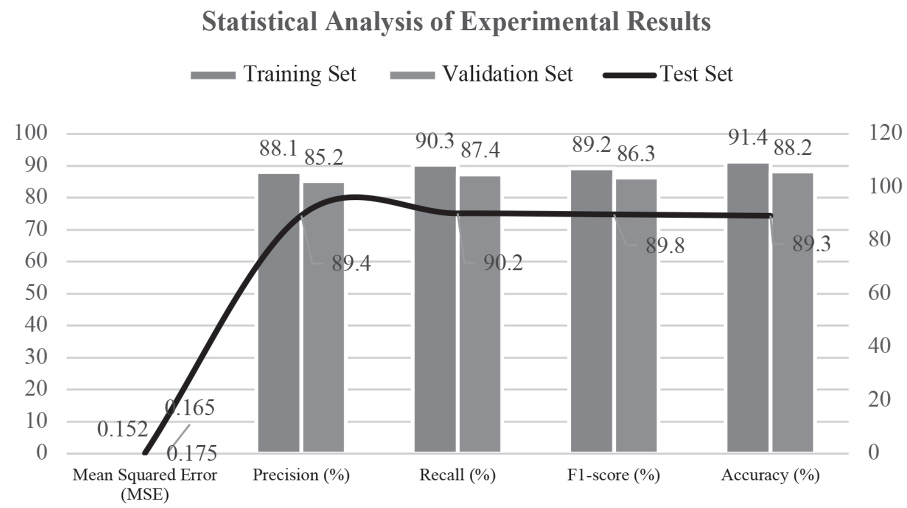

Figure 2 Graph showing statistical analysis of experimental results.

models in terms of accuracy rate, recall rate and F1-score. In terms of recall rate and F1-score, the optimized MLP model performs better, demonstrating that the model is better able to identify and classify positive samples when processing consumer behavior data.

2.3.2 Experimental Design and Data Analysis

The data set was divided into a training set, a validation set, and a test set. The training set was used to train the model, the validation set was used to tune hyperparameters and prevent overfitting, and the test set was used to evaluate the final effect of the model. In the experiment, the model underwent multiple rounds of training on the training set. After each round of training, the model parameters were evaluated on the verification set and timely adjusted to ensure that the model had strong generalization ability.

The dataset was divided into a training set (70%) and a validation set (30%). The training set was used for the training of the model, and the verification set was used for hyperparameter tuning and model performance evaluation. The test set comprised 20% of the total dataset and was used to evaluate the model's performance on unseen data. The error after each training round (such as the mean square error MSE) was calculated, and the error of the training set was compared with that of the verification set to determine any overfitting. The performance of the model on the test set was calculated, and the actual prediction effect of the model was evaluated, including the accuracy rate and other indicators.

As shown in Figure 2, the errors of the training set and the verification set gradually decrease, and the model is continuously optimized during the training process. The accuracy rate, recall rate and F1-score on the test set all perform well, which confirms that the constructed model has strong generalization ability and high prediction accuracy. The accuracy of the model is also consistent on the training set, verification set and test set, which proves the robustness of the model when applied to different datasets.

Through experimental design and data analysis, the actual effect and performance of the constructed model can be clearly demonstrated, and an effective solution for consumer preference analysis is provided. The comprehensive evaluation results show that the optimized MLP neural network model is superior to other models in all evaluation indexes, and has strong forecasting ability in practical application.

2.4 Suggestions and Paths of Marketing Strategies

2.4.1 Marketing Strategies Based on Consumer Preferences

Through in-depth analysis of consumer preferences, the core needs of different consumer groups are identified, and differentiated marketing strategies are tailored for each group. Regarding consumers who prefer environmental protection and green consumption, enterprises can attract such consumers by emphasizing the environmental protection characteristics of green products, energy saving effects and other product features. Businesses can improve the willingness-to-purchase of price-sensitive consumers by applying precise price promotion strategies such as discounts and group buying. Through detailed analysis of data, consumers' behaviors and preferences can be connected with product characteristics to improve the pertinence and effectiveness of marketing.

Marketing programs can be personalized based on consumers' purchase history and interactions. For example, new products or promotions can be recommended to consumers who have bought a certain type of product for a long time. For first-time buyers, businesses can recommend more suitable products or provide certain discounts and coupons to increase the re-purchase rate. Through differentiated marketing, enterprises can effectively improve customer engagement and loyalty, improve sales performance, and increase brand value.

2.4.2 Application of Digital Marketing Tools

The application of big data and AI technology has become an important part of modern marketing strategies. Through big data analysis, enterprises can obtain real-time consumer behavior data and analyze consumers' interests, preferences, purchasing trends and potential demand for certain products or services. By means of big data mining, enterprises can accurately predict market changes and quickly adjust marketing strategies. For example, through data mining, it is possible to identify the products that consumers are most interested in, the most active shopping periods, and the decision path of product purchase. Based on data, enterprises can deliver marketing information to consumers at the most appropriate time and in the most appropriate way to maximize marketing impacts.

The application of AI technology has enhanced the intelligence level of digital marketing. Through machine learning models, businesses can analyze and identify potential high-value customers and design precise marketing strategies to target those customers. For example, based on customer profiling and behavioral analysis, companies can achieve targeted advertising, reduce advertising costs and increase conversion rates. AI technology can also provide automated marketing, such as automated email marketing and social media advertising, which improves the efficiency and response speed of marketing.

2.4.3 Implementation of Personalized Recommendation System

The design of a personalized recommendation system is an indispensable part of modern marketing strategy and has been widely used in e-commerce platforms and content platforms. By analyzing consumers' historical data, browsing behavior, search history and other information, personalized recommendation systema provide tailored recommendation content for each consumer, potentially improving users' purchase conversion rate and satisfaction. According to the needs and preferences of consumers, a recommendation system can achieve accurate product and recommendations, and other functions.

Common recommendation algorithms include the collaborative filtering algorithm and the content-based recommendation algorithm. In collaborative filtering algorithms, the system recommends products by analyzing the similarities of users and the behavior patterns of other users. The algorithm can be divided into user-user collaborative filtering and item-item collaborative filtering. In the content-based recommendation algorithm, the system recommends similar products or content based on the characteristics of the content previously viewed or purchased by the user. The basic calculation of the collaborative filtering algorithm is as Equation (4).

$$R(u,i) = \frac{\sum_{v \in N(u)} sim(u,v) \cdot r(v,i)}{\sum_{v \in N(u)} |sim(u,v)|} \tag{4}$$

where, $R(u,i)$ represents user u's predicted score on item i. $N(u)$ is the set of users similar to user u, $sim(u,v)$ is the similarity between user u and user v, and $r(v,i)$ is user v's actual score on item i.

Through calculation, the system can predict the products that users may be interested in, and recommend them. Personalized recommendation systems enhance the user experience, and increase conversion rates and customer satisfaction. With the continuous increase in the amount of data and the ongoing optimization of algorithms, personalized recommendation systems will become more accurate and efficient, bringing more business value to enterprises.

In the era of digitalization and big data, the marketing strategy based on consumer preference, the application of digital marketing tools and the design of personalized recommendation systems have become the core means whereby modern enterprises can strengthen their competitiveness. Through in-depth analysis of consumer behavior, enterprises can develop more accurate marketing strategies; With big data and AI technology, enterprises can improve the efficiency and effectiveness of marketing. Through the personalized recommendation system, enterprises can provide products and services that are more in line with consumer needs, and enhance user satisfaction and loyalty.

3. RESULTS AND DISCUSSION

3.1 Results

3.1.1 Model Training Results

The loss function in the training process indicates the fitting degree of the model, and the precision represents the performance of the model on the training set. According to the experimental results, the performance of the model in

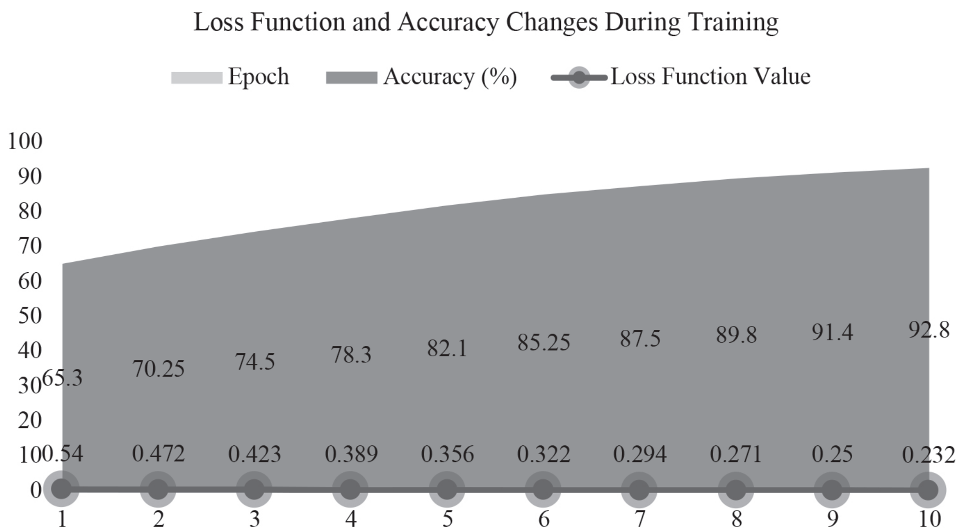

Figure 3 Loss function and precision change during training.

Table 4 Preference characteristics of different consumer groups.

Consumer group	Product type	Sensitivity	Brand loyalty	Purchase frequency (times/month)
Group A	High-end electronics	High	High	3.5
Group B	Health food	Medium	Medium	2.0
Group C	Sports equipment	Low	Low	1.2
Group D	Clothing products	High	Medium	2.8
Group E	Home goods	Low	High	1.5

multiple training rounds has been significantly improved. As the training progresses, the loss function gradually decreases, the precision gradually increases, and the model gradually fits the pattern in the data.

As shown in Figure 3 below, the loss function and precision values change after each round of training. As the training progresses, the loss function decreases gradually and the accuracy rate increases steadily. The stepwise optimization of the training process shows that the deep learning model has good convergence and fitting effect when processing consumer preference data.

3.1.2 Consumer Preference Analysis Results

Consumer preference trends reflect their behavior patterns in regard to different product features, price sensitivity, brand loyalty and so on. Based on consumers' purchase history, browsing history and interaction data, the groups are segmented and the core needs of each group are analyzed in detail.

The preference characteristics of different consumer groups, as shown in Table 4, clearly indicate the different preferences of various consumer groups. Group A has high demand for high-end electronic products, low sensitivity to price, and high purchase frequency; Group C is more sensitive to price, and makes purchases less frequently.

3.1.3 Effect Analysis of Marketing Strategy

According to the afore mentioned analysis of consumer preferences, differentiated marketing strategies are implemented for different groups, and their effects are evaluated. The effects of different marketing strategies on consumers are shown in Figure 4 below. The personalized recommendation strategy has the most significant impact on the purchase conversion rate of consumers. For groups B and C, the increase rate has reached 25%. In addition, the brand recognition of the discount promotion strategy in group A and group D is significantly improved, indicating that this strategy can effectively attract price-sensitive consumers. A loyalty program has the most prominent effect on customer satisfaction, indicating that this strategy can strengthen customer loyalty to the brand.

3.2 Discussion

3.2.1 Problem Summary

This study focuses on the application of deep learning in the analysis of consumer preferences, and uses this technology to model consumer behavior, which can help enterprises optimize marketing strategies in the digital economy. In this study, the deep learning model was built, the consumer data was trained and analyzed, and the accurate identification of consumer preferences was achieved. The analysis results show that different consumer groups show significant differences in terms of preferences, and in their demand for products, prices and brands. Based on the differences, different marketing strategies are developed, and the effectiveness of these strategies is verified by data. Although the study shows relatively satisfactory results, there are still limitations in terms of practical application.

The training and optimization of the model depend on a large amount of high-quality data, and the quality of the

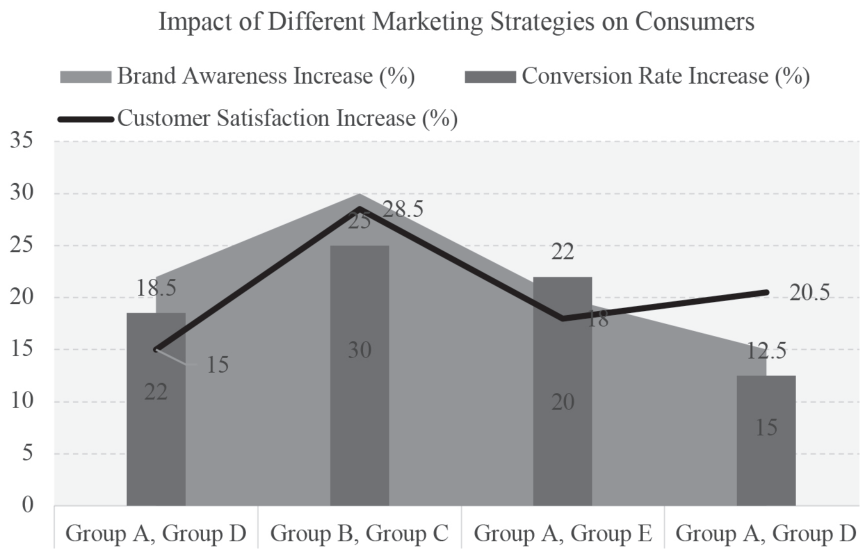

Figure 4 Effects of different marketing strategies on consumers.

data has a direct impact on the accuracy of the results. Data for some consumer groups may be scarce or missing, and the preference analysis of some groups might not be comprehensive enough, which affects the formulation of strategies. Deep learning models show strong learning ability in the face of complex nonlinear relationships, and in the case of abnormal data or more noise, the model may be disturbed, resulting in unstable analysis results. The implementation effect of marketing strategy is also affected by external environmental factors, such as market competition and changes in consumer psychology, which are difficult to predict or model completely through data, thus affecting the final effect of the strategy.

3.2.2 Research Suggestions

In order to improve the stability and accuracy of the model, the data acquisition and preprocessing process should be improved. The quality and comprehensiveness of data are essential for the success of deep learning models. In future studies, the effects of missing data or noise should be minimized to ensure the representation and diversity of training data. Using more diverse data sources (social media, consumer reviews, etc.) can further refine consumer profiles and enhance the accuracy of preference analysis.

Deep learning models have strong learning ability, but there are still limitations in terms of capturing complex nonlinear relationships. Future studies should attempt to combine other advanced machine learning techniques, such as reinforcement learning or generative adversarial networks (GANs), to improve the generalizability and robustness of the model.

In view of the implementation effect of marketing strategy, it is suggested that feedback and adjustment should be carried out continuously during the practical application process. The successful implementation of a marketing strategy depends not only on consumer preferences, but is also closely related to factors such as market dynamics, competitive environment and brand reputation. When implementing a marketing strategy, enterprises should establish a real-time data feedback mechanism, regularly evaluate the effect of the strategy, and timely adjust the strategy according to changes in the market and in consumer behavior. The effectiveness of different marketing strategies can be verified through A/B testing and other methods, and the optimal marketing plan can be found through comparative analysis.

When implementing a personalized recommendation system, it is suggested that multidimensional information on consumers be used to strengthen the mining of data, such as consumers' emotional attitude and social interaction, as these factors have a potential impact on the purchase decision. By taking these factors into account, personalized recommendation systems can push products more accurately, increase conversion rates, and improve customer satisfaction.

4. CONCLUSION

By means of deep learning technology, this study analyzed consumers' preferences in the context of digital economy, and discusses the design of personalized marketing strategies based on consumer preference data. In this study, big data technology was used to closely investigate consumer behavior, and a preference analysis model based on deep learning was constructed. The effectiveness of the model and the implementation effect of various marketing strategies were verified through experiments. Through data analysis, the study provides a comprehensive understanding of consumer group behavior, and provides theoretical support and a practical basis for enterprises wishing to develop more accurate and efficient marketing strategies.

The research results show that the diversity and individuation characteristics of consumer preferences are significant, and the deep learning model can effectively capture the differences among consumer groups, and determine the trending preferences of each group through the processing of large-scale data. It provides data support for enterprises in market segmentation and positioning of target consumer groups. Enterprises can design differentiated marketing strategies according to the needs of different consumer groups to improve the accuracy and effectiveness of marketing.

By evaluating different marketing strategies, the advantages of marketing schemes based on consumer preferences compared with traditional marketing methods are verified. Accurate analysis based on data enables enterprises to implement more personalized and targeted marketing strategies, improve consumer participation and satisfaction, and enhance brand loyalty. The research results also show that digital marketing tools and technologies such as personalized recommendation systems, play an important role in improving marketing effectiveness and optimizing resource allocation. Through technology, companies are able to recommend the most appropriate products to the right consumers at the right time, achieving higher conversion rates and sales.

Although the study achieved satisfactory results, it has several limitations. The training of a deep learning model depends on a large amount of high-quality data, and noisy or missing data may affect the accuracy and stability of the model. The dynamic changes in consumer preferences and the market environment pose challenges for the long-term adaptability and effectiveness of the model. Future research should focus on improving the data acquisition process, the model optimization and the strategy adjustment so as to cope better with the complexity and uncertainty of practical applications.

This research provides an innovative perspective on consumer behavior analysis and marketing strategy development, and offers new directions for the application of deep learning technology in the field of digital marketing. With the development of big data and AI technology, enterprises will be able to understand consumer needs more accurately and provide better services and products in a personalized and intelligent way. It will promote the development of the digital economy and bring greater competitive advantages to enterprises.

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REFERENCES

1. He T., Liu T. Decision support system for human resource management based on big data. Engineering Intelligent Systems. 2025; 33(4): 469–480.
2. Ren P.J., Liu X.D., Zhang W.G. Consumer preference analysis: diverse preference learning with online ratings. Omega. 2024; 125: 103019.
3. Nam Y., Lee S., Lee H. Consumer preferences for unmanned stores: A choice experiment study. Journal of Retailing and Consumer Services. 2025; 82: 104061.
4. Liu W., Han X.Y., Cao X.W., Gao Z.F. Consumers’ heterogeneous preference for organic ginger: a choice experiment. Asia Pacific Journal of Marketing and Logistics. 2024; 36(4): 792–808.
5. Wang F., Wang H.F., Cho J.H. Consumer preference for yogurt packaging design using conjoint analysis. Sustainability. 2022; 14(6): 3463.
6. Liu X.J., Liu X.S., Shi A.N., Li C.W. Agricultural products’ bundled pricing based on consumers’ organic preferences. Sustainability. 2023; 15(17): 13256.
7. Paiva T., Jacinto T.A., Sarraguca M.C., Coutinho P. Beef consumers’ behaviour and preferences - the case of Portugal. Sustainability. 2022; 14(4): 2358.
8. Tomaino G., Wertenbroch K., Walters D.J. Intransitivity of consumer preferences for privacy. Journal of Marketing Research. 2023; 60(3): 489–507.
9. Chen C.W. A feasibility discussion: Is ML suitable for predicting sustainable patterns in consumer product preferences? Sustainability. 2023; 15(5): 3983.
10. Tian Y.R., Peng H., Dong X.X., Li L.W., Zhu W.Q. Consumers’ brand preferences for infant formula: A grounded theory approach. Sustainability. 2022; 14(13): 7600.
11. Liu J.P., Wang Y., Kadzinski M., Mao X.X., Rao Y. A multiple criteria Bayesian hierarchical model for analyzing heterogeneous consumer preferences. Omega. 2024; 128: 103113.
12. Zong L., Wu S.L., Duan S. How social exclusion affects consumers’ color preference. Frontiers in Psychology. 2022; 13: 850086.
13. Wang L., Cao Y., Hu J., Skibniewski M.J. Does digital economy development benefit low-carbon transition: evidence based on urban carbon lock-in. Journal of Environmental Planning and Management. 2024; 271981941.
14. Li Y.J., Chen T.W., Zhang Z.B. Can digital economy development improve the coordination of IFDI and OFDI? Evidence from 246 cities in China. Technology Analysis & Strategic Management. 2024; 271433859.
15. Lou Y.Y., Yang G.L., Guan Z.C. How to leverage the initiative of regional innovation subjects under the digital economy? A study on the mediating effect of innovation environment. Technology Analysis & Strategic Management. 2024; 2372793.
16. Sabli N., Jaafar N.I., Azmi A.C. Discovering the global landscape of digital economy: a two-decade bibliometric review. Technology Analysis & Strategic Management. 2023; 2290153.