Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 26, Issues 3, pp. 1363–1376, DOI 10.12694/scpe.v26i3.4354

DEEP LEARNING AND SUPPLY CHAIN BASED ENTERPRISE STRATEGIC MARKETING OPERATION MANAGEMENT SYSTEM CONSTRUCTION

XIAOTENG MA* AND LIUFENG WANG†

Abstract. The present focus of supply chain management is on how to understand customer information, establish customer segmentation, and make corporate resource allocation rational under restricted resources in order to maintain steady development. This paper explores integrating deep learning with supply chain management to enhance strategic marketing operations. It introduces an evaluation index system using a five-dimensional balanced scorecard and proposes a performance evaluation model based on the LMBP algorithm for efficient network weight calculation and training. Empirical testing with T Mobile demonstrates the model's effectiveness, achieving a 97.29% accuracy rate and over 93% empirical fit accuracy, highlighting its potential for optimizing strategic marketing operations.

Key words: Deep learning; Supply chain management; Corporate strategy; Marketing operations; Business process modeling

1. Introduction. Under the macro market background, enterprises are facing increasingly fierce competition. The comprehensive analysis of the market and the surrounding environment shows that the challenges faced by enterprises mainly come from diverse and personalized customer needs, increasingly high delivery requirements, more and more high-tech use, shorter and shorter product life cycle and globalization of market competition [1]. As a "third party source of profit", the role of operation management in economic activities is becoming more and more obvious, and has gradually become the most important successful competitiveness today [2, 3].

In the competitive market landscape, effective customer segmentation and resource allocation are crucial for gaining a competitive edge. Companies need to leverage data to analyze customer needs, target appropriate customer groups, and focus their supply chain resources to develop effective competitive strategies. However, resource imbalances pose significant challenges, limiting overall operational efficiency and necessitating balanced resource allocation to meet fluctuating customer demands and optimize benefits with minimal resource use.

This paper addresses these challenges by exploring how companies can enhance their strategic marketing operations through optimized resource allocation. It highlights the diversity of enterprise marketing resources, which include human, material, and financial resources, and categorizes them into internal and external resources. The paper emphasizes the importance of balancing tangible resources (such as fixed assets and cash) with intangible ones (such as brand influence and intellectual property).

A key innovation of this study is the application of contemporary marketing theories and data analysis models to improve resource allocation strategies. It proposes using advanced analytical algorithms to address critical issues in marketing information analysis, including product marketing plans, pricing strategies, and cost management. The study aims to provide a comprehensive framework for optimizing resource allocation and enhancing marketing management capabilities, particularly for companies facing rapid market changes and resource constraints.

By establishing a robust product cost information management system and integrating advanced information technology tools, this paper offers practical solutions to enhance strategic marketing operations and achieve stable development in a competitive environment.

In summary, the construction of a strategic marketing operation management system for companies based on deep learning and supply chain has important practical significance.

*College of Information Science and Engineering, Shandong Agricultural University, P.R. China (a8617667122022@163.com)
†Jiaxing Xiuhu School, Jianxing 314000, Zhejiang Province, P.R. China. (Manina202405@163.com).

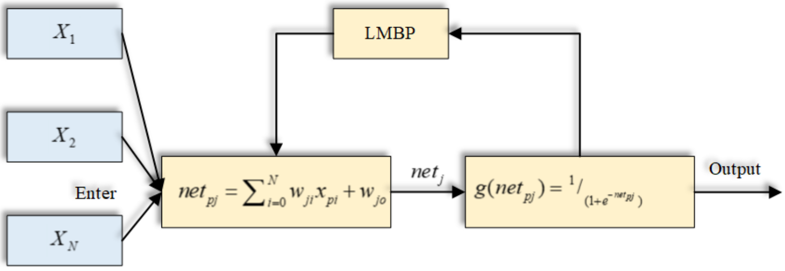

Fig. 2.1: LMBP neural network.

”This article is structured as follows: The Introduction provides an overview of the study’s background and significance. The Data and Methods section outlines the study’s design, participant selection, data collection procedures, and analytical methods. The Results section presents the findings of the study, focusing on the prevalence and impact of cancer-related fatigue, anxiety, and depression in hematologic cancer patients undergoing chemotherapy. Finally, the Discussion interprets the results in the context of existing literature, discusses the implications for clinical practice, and suggests potential areas for future research.”

2. Mathematical model of enterprise strategic marketing operation management algorithm. The improvement and optimization of BP algorithm can be based on the weight adjustment and function change of neural network algorithm, as shown in Figure 2.1.

The sum of the mean squared errors of the network is defined as Eq2.1

$$E = \frac{1}{2} \sum_{P=1}^{N} \sum_{k=1}^{M} (y_{pk} - \hat{y}_{pk}) \tag{2.1}$$

N represents the number of input nodes, M represents the number of output units, Y represents the target output, and $\hat{y}$represents the network output. In the BP network training, the literature uses the fastest descent method and the error function minimization E in the FNN network for the multilayer network containing M hidden layers, the network of strategic marketing operation management system of enterprises is established as Eq2.2-Eq2.5.

$$net_{pj} = \sum\nolimits_{i=0}^{N} w_{ji} x_{pi} + w_{jo} \tag{2.2}$$

$$g(net_j) = {}^{1}\Big/_{(1+e^{-net_{pj}})} \tag{2.3}$$

$$net_{pk} = \sum\nolimits_{j=0}^{M} W_{kj} g(net_{pj}) + W_{ko} \tag{2.4}$$

$$\hat{y}_{pk} = g(net_{pk}) \tag{2.5}$$

where M is the number of hidden layers, W_{kj} is the weight value connecting node j in the hidden layer to node k in the output layer, W_{kD} is the threshold value in layer K , and $\hat{y}_{pk}$ is the target output of the k^{th} . Combining Eq2.5, Eq2.6 and Eq2.7 are derived as:

$$\Delta W_{kj} = -\eta^{\partial E} / \partial W_{kj} \tag{2.6}$$

Table 2.1: Random sample point array of enterprise strategic marketing operation management model.

Serial number	Factor 1	Factor 2
1	0.4295	0.2569
2	0.2572	0.0099
3	0.2975	0.5328
4	0.4248	0.2786
5	0.1193	0.9463
6	0.49527	0.3928
7	0.7065	0.0248
8	0.2437	0.6715
...	...	...

$$\Delta W_{kj} = -[H + \mu I]^{-1} J^T e \tag{2.7}$$

In this study, various resource allocation models and methods are reviewed, each with its strengths and weaknesses. Traditional models often rely on subjective criteria and static parameters, which can lead to inefficiencies in dynamic market conditions. For instance, while linear programming models are useful for optimizing resource allocation under fixed constraints, they may not adapt well to rapid changes in customer demand or supply chain disruptions.

Conversely, advanced methods like the LMBP algorithm used in this study offer significant advantages. The LMBP algorithm enhances training speed and accuracy in neural networks, providing more responsive and adaptive resource allocation. Its strength lies in its ability to quickly adjust network weights based on real-time data, which is crucial for managing dynamic and complex supply chain environments.

However, the LMBP algorithm is not without limitations. It requires substantial computational resources and may not perform optimally with limited data or in highly volatile conditions. Therefore, while it represents a significant advancement over traditional methods, its effectiveness is contingent on the quality and quantity of input data and the specific context of its application.

In this study, the choice of the LMBP algorithm is justified by its superior performance in empirical testing with T Mobile, demonstrating high accuracy and fit. This choice reflects the study's objective to provide a more adaptive and precise resource allocation model that can better handle the complexities of modern supply chains.

By integrating these advanced methods, this study addresses the gaps left by conventional approaches, offering a more robust framework for optimizing strategic marketing operations and resource allocation.

Then, the K-Means clustering algorithm was first applied to conduct a pre-experiment to observe the results of the algorithm operation of the strategic marketing operation management model of the enterprise [13]. 100 sample points with dimension 2 were randomly generated, as shown in Table 2.1 .

Then the program was written in MATLAB R2018a, and the number of simulations was set to 100, and the operating result graphs of each algorithm were obtained, as shown in Fig. 2.2.

It is obvious from Fig. 2.2 that each algorithm is easy to fall into the local optimal solution of the enterprise strategic marketing operation management model, and the results are unstable. In this paper, to address this defect, consider that Clara algorithm can start from K-Mediods algorithm to obtain better clustering center and have higher efficiency, here Clara algorithm is used to optimize K-Means algorithm, and the proposed improvement algorithm is named CK clustering integration algorithm, the principle is shown in Fig. 2.2 and the detailed steps of the improvement algorithm are as follows: first, the input data set c of the improved algorithm is obtained after using the normalization method, and for each attribute j , the following normalization Eq2.8 is executed.

$$C_i(j) = \frac{N_i(j) - \min(N(j))}{\max(N(j)) - \min(N(j))} \tag{2.8}$$

The centers(i) obtained in the pre-run is then used as the clustering centers of the data set, and the clustering results are output and the total error is calculated; the total error is calculated using the Euclidean

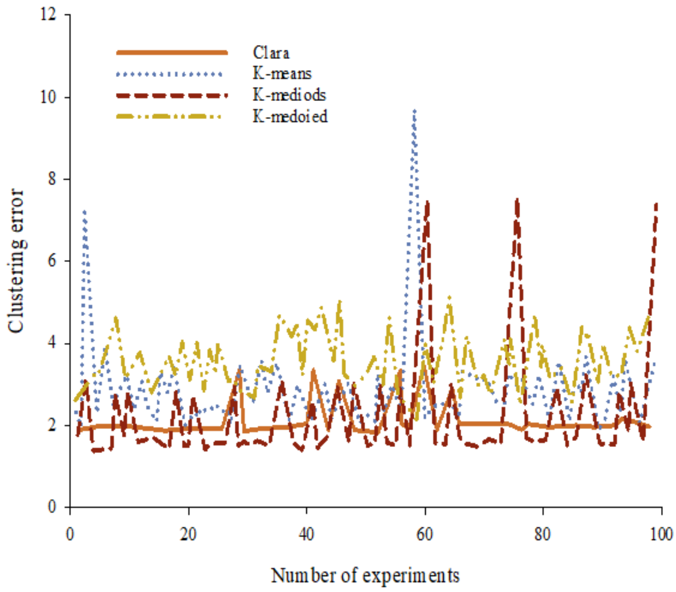

Fig. 2.2: Multiple run graphs of each algorithm.

distance, and the specific Eq2.9 is as follows.

$$dist = \sqrt{\sum_{i=1}^{k}\sum_{j=1}^{km}(C_j - c(i))^2} \tag{2.9}$$

This leads to a mathematical model and a brief procedure for the strategic marketing operations management algorithm of the enterprise, as shown in Fig. 2.3.

3. Method.

3.1. Enterprise strategic marketing resource allocation model and operation. The fundamental purpose of enterprise operation is to pursue profit maximization, and this paper is based on the principle of profit maximization to determine the total amount of marketing resources allocation. From the integration of literature on marketing resources in Chapter 2, it is clear that advertising and promotion account for most of the marketing budget and have a direct impact on sales volume when enterprises actually carry out marketing activities [14]. Promotional and advertising efforts are just as successful in the automobile industry. The primary resources for marketing efforts are financial, human, and material resources. Since dealers represent the majority of SMEs, maintaining the dealer network and growing the market also constitute major marketing costs. Furthermore, one of the biggest costs is after-sales service, which includes setting up an establishment for after-sales service stations, paying salaries to after-sales service staff, etc. All of these things call for coordinated strategic management and resource allocation for marketing inside the company.

First, we define the human resource cost H , which mainly includes the marketing staff salary cost h , travel cost b , annual training cost x , where the quantitative relationship is , and thus the Eq3.1.

$$\begin{cases} H = h + b + x \\ x = \alpha h \quad 0.1 \le \alpha \le 0.2 \end{cases} \tag{3.1}$$

Then, we define the cost of physical resources M , mainly including the cost of marketing staff office hardware equipment m_1 , office space cost m_2 , the constraint relationship for the average depreciation rate of

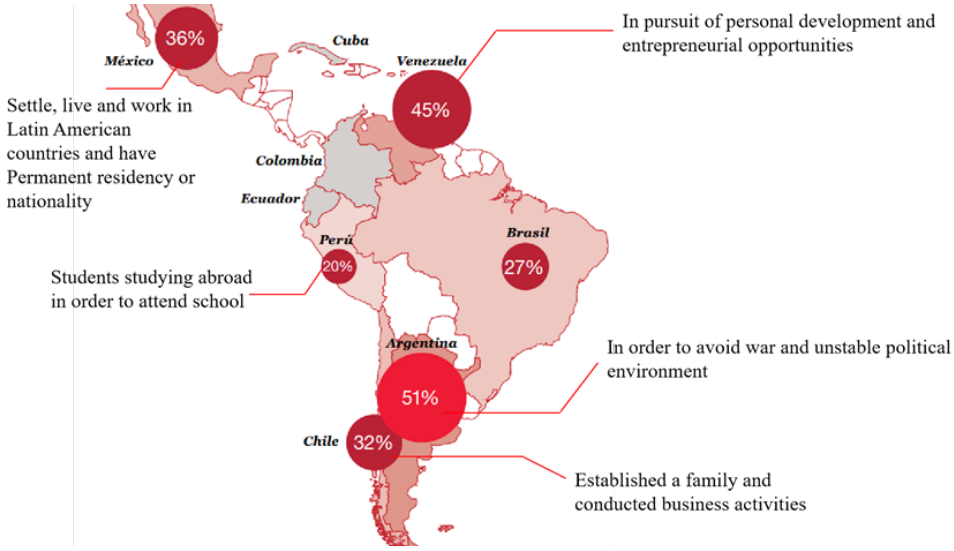

Fig. 2.3: Mathematical model and brief procedure of strategic marketing operations management algorithm for enterprises.

hardware equipment $0.1 < \beta < 0.2$, with Eq3.2.

$$\begin{cases} M = \beta m_1 + m_2 \\ 0.1 \leq \beta \leq 0.2 \end{cases} \tag{3.2}$$

Define the cost of financial resources F , mainly including advertising costs A , market development costs G , office supplies costs d , and business hospitality costs e . Eq3.3 is obtained.

$$\begin{cases} J = j_1 + j_2 \\ J_1 = \theta Q \\ 0.005 \leq \theta \leq 0.01 \end{cases} \tag{3.3}$$

The strategic marketing operations management cost function of the firm under the model was finally determined as Eq3.4.

$$C = f(H, M, F, J, S) = H + M + F + J + S \tag{3.4}$$

Then according to the previous description of the enterprise strategic marketing operation management model, this paper proposes a five-dimensional balanced scorecard-based enterprise strategic marketing operation management and supply chain evaluation model, and its simplified process is shown in Fig. 3.1.

For the model mentioned in this study, its establishment and optimization can be systematically summarized into three stages: data processing, neural network construction and subsequent processing application. The analysis steps are shown in Fig. 3.2.

3.2. Empirical model architecture. In the methodology of this study, Logistic Regression Analysis and K-means Cluster Analysis are employed sequentially, each serving a distinct purpose that contributes to the overall analysis.

Logistic Regression Analysis. This step is utilized first to identify the key predictors or feature variables that significantly influence the outcomes of interest, such as customer purchasing decisions or product demand. By determining the relationships between these variables and the likelihood of certain behaviors (e.g., purchase likelihood), Logistic Regression helps to refine the dataset by highlighting the most relevant factors. This step is critical as it informs the selection of variables that will be used in the subsequent clustering process, ensuring that only the most impactful data is considered.

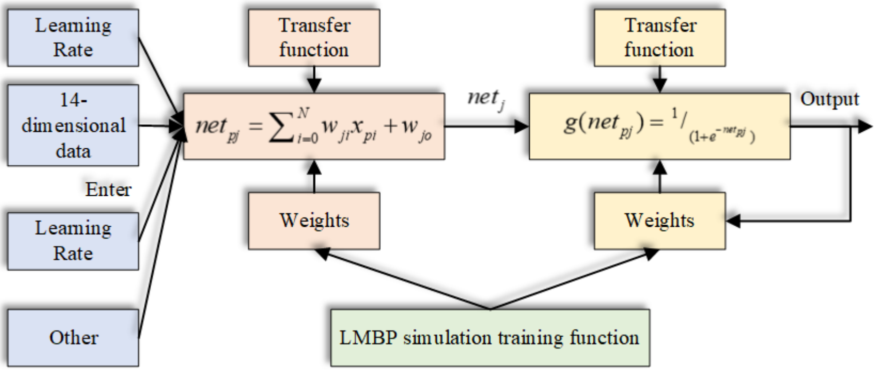

Fig. 3.1: Neural network for strategic marketing operation management of enterprises based on supply chain performance evaluation.

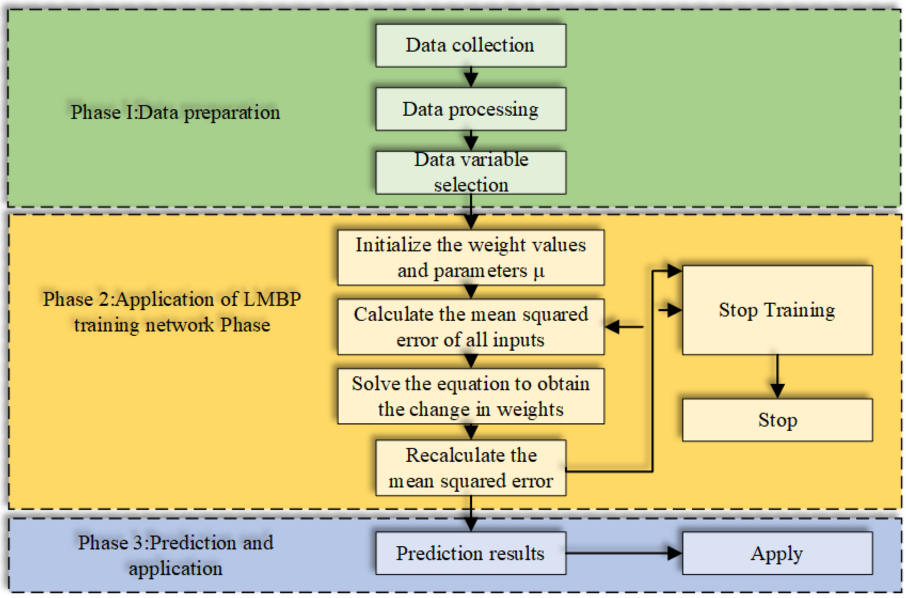

Fig. 3.2: The process of establishing the strategic marketing operation management model of the enterprise.

K-means Cluster Analysis. Following Logistic Regression, K-means Cluster Analysis is applied to the refined dataset. This clustering technique groups similar entities—such as customers or products—based on the significant feature variables identified in the previous step. The purpose of this analysis is to segment the dataset into distinct clusters, each representing a unique group with similar characteristics. This segmentation allows for more targeted marketing strategies and resource allocation, as the clusters represent groups with shared behaviors or needs.

Relationship and Sequence. The sequence of these steps is crucial for effective analysis. Logistic Regression Analysis first identifies which variables are most influential, thereby reducing noise and focusing the dataset on the most relevant information. K-means Cluster Analysis then uses this focused dataset to create meaningful clusters. The effectiveness of the clustering process is enhanced by the prior logistic regression, as it ensures that the clusters are based on variables that truly matter, leading to more actionable insights.

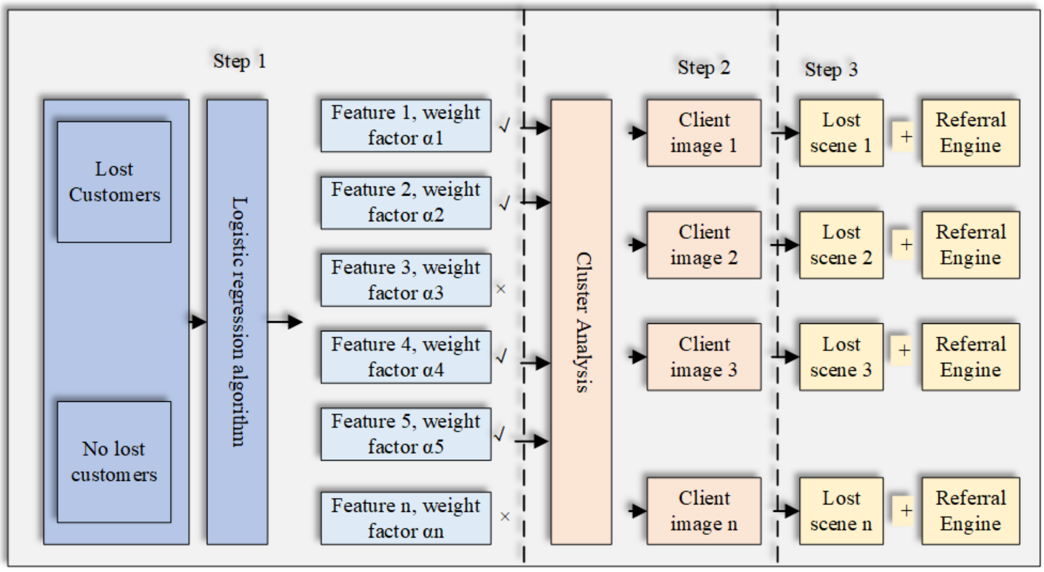

Fig. 3.3: Application ideas of strategic marketing operation management model for enterprises.

By clearly outlining the purpose of each step and their order of precedence, the study ensures that the methodological approach is transparent and logically structured, ultimately enhancing the validity and utility of the findings.

In the enterprise strategic marketing operation management model, the construction is divided into Logistic regression analysis step and K-means algorithm customer portrait clustering analysis step, in which Logistic regression analysis step, the main idea is to build a data mining model by historical lost customers, and use the feature importance analysis ability of Logistic regression algorithm to output each feature variable in In the K-means clustering algorithm stage, after the features that have an important impact on customer churn are selected in the previous step, the clustering analysis is performed on the churned customers based on these feature variables, and the clustering results can be used to cluster potential churned customers [15]. The clustering results can further guide the construction of the churn maintenance operation system. The idea of applying the strategic marketing operation management model is shown in Fig. 3.3.

We have selected T Mobile to be the empirical test object for this study's empirical test phase. This paper uses T Mobile's telephone outbound marketing data from September 2020 to December 2020 in order to ensure that the findings can help with T Mobile's marketing management design, strategic positioning, and customer churn, as well as to ensure the validity and truth of the research data content. However, due to the large number of customers, 228,778 households were randomly selected from them without affecting the model effect marketing data for the study. In order to ensure the accuracy and generalization ability of the model prediction, this study will cover all kinds of behavioral characteristics of users and information characteristics of marketing services as much as possible, and obtain data including users' basic information such as network length, gender and age, business information such as Internet traffic, call length and active days, tariff information such as tariff level and contract bundle, recommended strategy level, recommended strategy traffic expansion capacity and other marketing information. Marketing information, finally involving a total of 125 variables.

The following are the annotations of some fields of the data, such as the annotation of the basic user information field in Table 3.1, which contains information on user's gender, age, length of time in the network, etc. Table 3.2 is the annotation of the user contract information field, which records the subscription characteristics of the user contract bundled products; Table 3.3 is the annotation of the user business behavior information field, which records the information related to the use and activity of the user's Internet behavior and calling behavior; Table 3.4 is the annotation of the subscription information field, which records the information related

Table 3.1: User basic information field comments.

Fields	Note
Serv _ number	Cell phone number
Gender _id	Gender
Age	Age
Join _duration	Length of time in the network (months)
Credit _class _id	Star level
Wb _bind _user_kind	Whether to converge users
Cmasp _asp _type	DM single mobile single extranet extranet operator
Number _ame _id	Number of numbers under the same ID card
User_owned _branch	User belongs to the branch

Table 3.2: User Contract Information Field Comments.

Fields	Note
Serv _ number_ hy	Contract user or not
Contract _ month _ owe	Remaining duration of the contract

Table 3.3: User business behavior information field comments.

Fields	Note
Minimum _ contract _ spending	Minimum monthly consumption of terminal contract

Table 3.4: User tariff subscription information field comments.

Fields	Note
Inner _ gprs _ pct	Current Month Traffic Saturation
Inner _ gsm _ pct	Voice saturation for the month
M _ gprs _ bill _ flux _ dtal	Current month billed traffic usage
Avg _ jf_ dou _ 3mon	Average monthly billed traffic usage in the past three months
R _ jf _ dou _ 3mon	Monthly average billed traffic usage volatility in the past three months
Dou	Current Month DOU
Dir _ dou	Monthly targeted traffic usage
Cur _ mon _ voice _ days	Number of call days in the month
If _ flux _ ct	Whether the current month traffic over-set users
If _ gsm _ ct	Whether the current month is a voice over-set user
If _ off _ flux _ ct	Whether it is a frequent traffic over-set user
If_ off _ gsm _ ct	Whether it is a frequent traffic voice user
Cur _ mon _ flux _ days	Number of days of traffic use in the month

to the user's current subscription tariff service and the content of the tariff service; Table 3.5 is the annotation of the customer marketing information field, which records the service information of the recommended strategy when actively marketing to the customer and the service expansion information relative to the user's current subscription tariff, etc.

4. Case study.

4.1. Model optimization validation. The data set of retail customer orders is processed using Python, and the final segmentation variables for 36763 customers are shown in Fig. 4.1, Fig. 4.2, and Fig. 4.3.

The algorithm program is written in MATLAB R2018a, and finally the algorithm performance is verified

Table 3.5: Customer Marketing Information Field Comments.

Fields	Note
Mkt_user_group_desc	Operation Strategy
If_success_deal	Whether the operation is successful
Discnt_type	Strategy offer combination type
Strategy_type	Strategy Type
Inclu_flu	Strategy information_contains preferential traffic
Inclu_dur	Strategy information_contains preferential voice
Inclu_dir_flu	Strategy information_includes preferential targeted traffic
Fee_front Policy Information_Phase 1	Price After Discount
Fee_after Policy Info_Phase 2	Discounted Price
Period front Policy Info_Phase 1	Discount Length
Period after Policy_Phase 2	Discounted hours

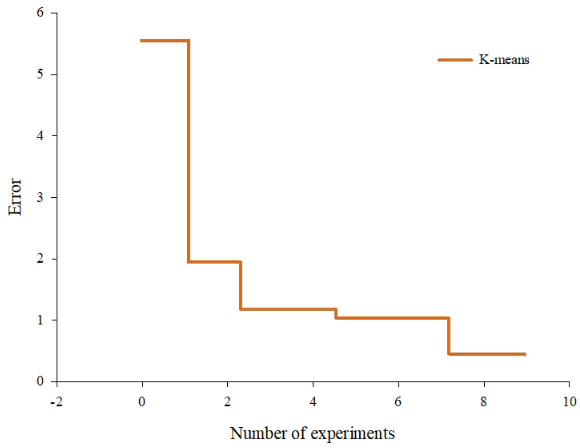

Fig. 4.1: Iteration curve of K-Means algorithm.

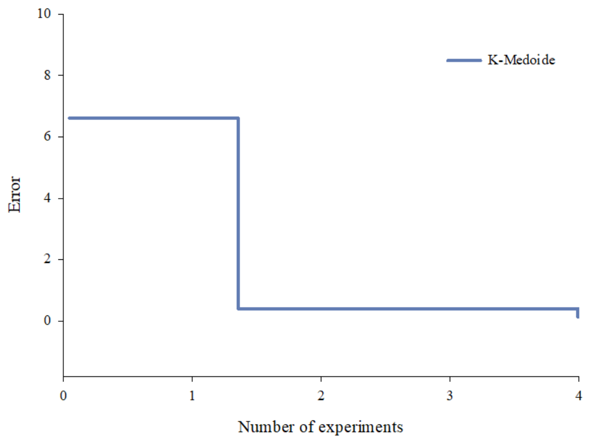

Fig. 4.2: Iteration curve of K-Medoide algorithm.

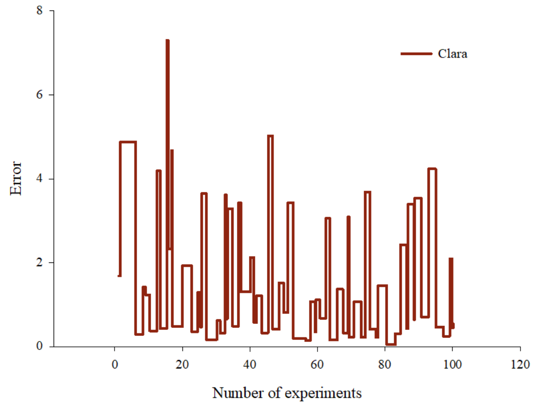

Fig. 4.3: Clara algorithm iteration curve.

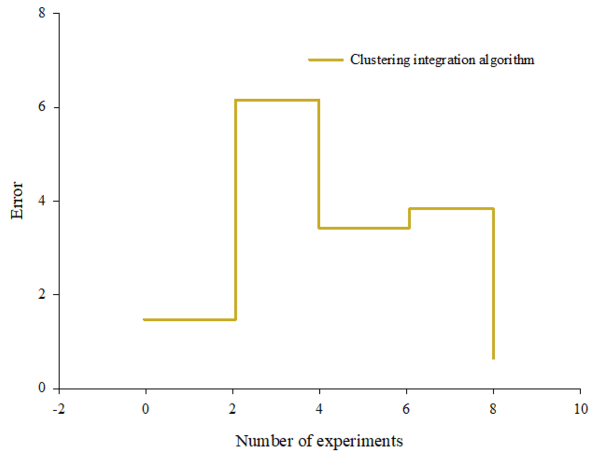

Fig. 4.4: Comparison of total error before and after algorithm optimization.

by using algorithm comparison in the case of algorithm validation. The running iteration curve obtained by using the customer clustering factors as the input data of the algorithm is shown in Fig. 4.4, which shows that the improved CK clustering integration completes the iteration in the 8th round, and the iteration speed is more blocky when compared with K-Means algorithm, K-Medoide algorithm, K-Mediods algorithm, and Clara algorithm. To verify the performance of the CK clustering integration algorithm with the remaining algorithms, the optimization resulted in a significant 13% reduction in system error, as shown in Fig. 4.4.

Based on the prediction results of the model on the test set, the model prediction effect evaluation index is obtained.

The check accuracy rate is:

$$\Pr ecision = \frac{TP}{TP+FP} = 97.29\% \tag{4.1}$$

According to the prediction results, it can be seen that the logistic regression model established for churn customer prediction has a good prediction effect, so the weight coefficients of each feature variable output from the model can be used as a basis for judging the importance of the features. Based on the results of the run, we generally consider the features with P-values less than 0.05 to be significant for model prediction, and Table

Table 4.1: Results of the program run to calculate the weight coefficients of the characteristic variables.

if_ct_cur_day	Whether the current month is over set	-1.444621180	0.603648488	-2.393148752	0.0016803322
if_jmb_cur_day	Is there a reduction package in the current month	0.887794131	0.290237359	3.058854421	0.002312845
if_jmb_end_cur_mon	Whether the current month reduction package expires	-1.354896755	0.403436820	-3.358378352	0.000782988
if_order_wb	Whether to subscribe to broadband	1.790728519	0.794705835	2.253341623	0.025227831
if_bensheng_user	Is it a user in this province	-0.202891716	0.094718683	-2.1420544607	0.032279722
is_tj	Whether the last month is closed	-1.624844361	0.287323465	-5.649205523	0.000000015
is_wb_bind_user	Is the broadband bundle users	2.327311892	0.729575326	3.189952778	0.001422855
is_wb_bind_user_lst1	Whether broadband users last month	3.297398250	0.132989531	2.910351629	0.003510239
is_wb_bind_user _Ist2	Whether the last month is broadband users	-3.4207775	1.089823560	-3.167923325	0.001525373
is_pre_prd_chng_down	Is the package downgrade users	2.675488950	1.222509216	2.188533576	0.027521566
effect_date	Length of time on the network	0.281032752	0.107003748	-3.552268892	0.008520032
last_voice_to_now	Duration of last call to current	-0.152847928	0.043026947	2.8869788769	0.000381687
cur_mon_voice_days	Number of days of voice communication	0.439566140	0.1522583219	2.9732159823	0.003789592
slnt_days	Number of days of silence in the current month	0.17419289	0.058577137	2.973690351	0.002932427

4.1 shows all the variables with P-values less than 0.05 among the results obtained from this program run.

In the above results, Estimate is the estimated value of the importance coefficient of each characteristic variable, Std.Error is the standard error of the coefficient estimate, z value is the z statistic, $\Pr(> |z|)$ is the estimated p value of the characteristic variable, and the smaller p value means the more important to the outcome variable, it can be seen that the model proposed in this study has a better fit both in terms of accuracy optimization and empirical testing.

4.2. Analysis of empirical results. Based on the model calculated in Chapter 4 on the training sample set, the ROC plot shown in Fig. 4.5 is obtained after validation on the test sample set.

As can be seen from the figure, the AUC value of the model calculated based on the above parameters is 80.1%. In a general classifier, the ideal classifier does not produce any prediction errors, i.e., the model can achieve a 100% true positive rate before producing any false positives, at which point the AUC value is 1. In a random classifier, each correct prediction is followed by an incorrect prediction the next time, at which point the AUC value is 0.5. So, however, from the ROC curve, a model with an AUC > 0.8 classifies effect is quite good. Another way to determine whether the final trained model is reasonable is to observe the importance of each feature variable in the XGBoost model calculation, and the top 10 important features according to the function calculation are listed in Table 4.2.

From Table 4.3, it can be seen that whether the user for marketing recommendation strategy, mainly affected by the following aspects: the level of preferential recommendation strategy. In general, the sales price of the recommended product in a marketing recommendation is essentially the same as the user's current stable consumption level; that is, the higher the recommended strategy traffic expansion capacity, the more affordable it is for the user. These two characteristics of importance, the recommended strategy traffic expansion capacity and the type of discount reduction, both represent the level of benefits to the user marketing recommendation strategy. as well as the kind of discount decrease, which describes the union of tariff strategy, discount duration, and The tariff strategy combination's kind of preference length is referred to as the type of preference reduction, includes 12 months, 24 months, "3+9", "6+6", "12+12" and other types of preference length combinations, and

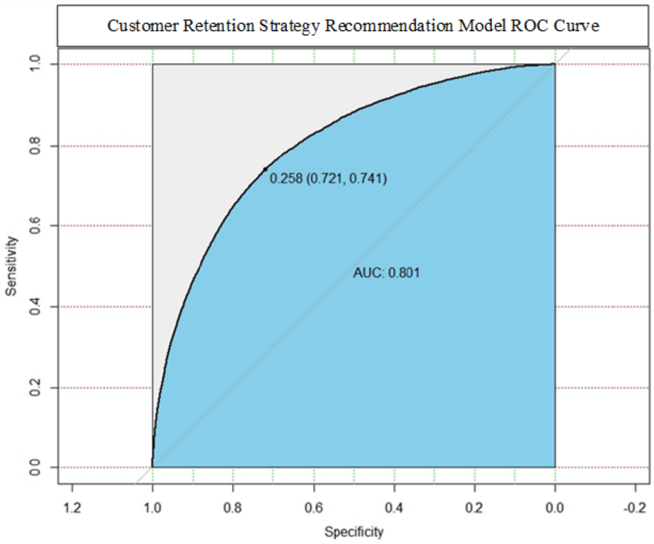

Fig. 4.5: ROC curve of the recommended model of customer retention strategy based on strategic marketing operation management of the company.

Table 4.2: XGBoost Output Feature Importance.

Feature Name	Chinese Comments	Feature Importance
Inclu_flh_up	Recommended strategy traffic expansion capacity	0.0469
Period_type	Preference reduction type	0.0422
If_wary	Whether King's Glory Preferred User	0.0340
Inner_gsm_pct	In-suite voice saturation	0.0333
Lasti1_dou	Last month's Internet traffic	0.0330
M_gprs_bil_flux_dtal	The amount of billed traffic usage for the month	0.0309
Credit_class_id	Star Rating	0.0309
If_contract_terminal	Whether the current terminal is a contract terminal	0.0267
Join_duration	Length of time on the network	0.0276
Incr_data_gprs_fee	Data traffic charge for the month	0.0230

Table 4.3: Comparison of prediction effects of different algorithms.

Models	TP	TN	EP	FN
CART	4789	2907	8611	3247
Logistic Regression	4362	2892	9035	2852
Random Forest	5165	2912	8239	3126
XGBOOST	1225	3183	2169	2638

users' concern about the type of preference reduction also It also shows that the level of recommendation strategy offer plays an important role in the success of marketing recommendation.

Based on the above ideas, we subjected the test set to model validation by running three prediction models, CART decision tree, logistic regression, and random forest, respectively, and obtained the confusion matrix metrics for each type of model, and the results are shown in Table 4.3.

A bar graph based on the above data is shown in Fig. 4.6.

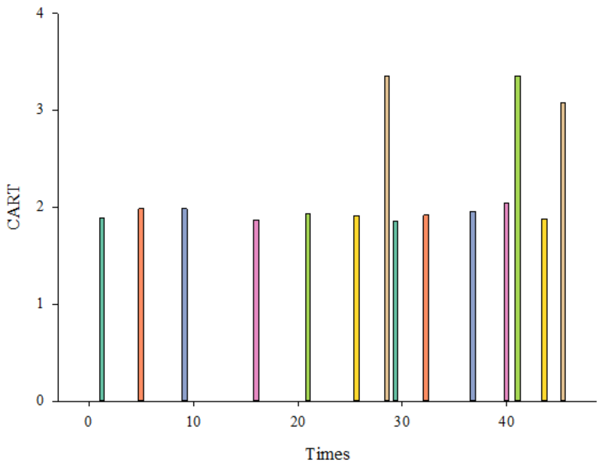

Fig. 4.6: Comparison of prediction effectiveness of different algorithms.

Table 4.4: Comparison of evaluation indexes of different algorithms.

Models / Evaluation Metrics	Accuracy Rate/%	Accuracy/%	Completeness/%	F1-score/%
CART	74.11	35.69	59.55	44.68
Logistic Regression	74.08	32.58	60.38	42.29
Random Forest	75.23	38.49	62.37	47.57
XGBOOST	93.79	83.68	94.55	88.81

Of course, it is rather thin to compare the good or bad prediction effect of various algorithms only by the value of confusion matrix, so four secondary indicators are also proposed on the separate mathematical addition method, and the results are shown in Table 4.4.

It can be seen that the accuracy of this model reaches more than 93%. By analyzing the recommendation probability of the recommendation strategy relative to the user, we can classify the strategy recommendation probability into four different levels, less than 0.2, 0.2-0.5, 0.5-0.8, and more than 0.8. When the probability of recommending a policy to a user is less than 0.2, it means that the user does not prefer the recommended policy and may have a high probability of rejecting it. When the recommendation probability of the user recommendation strategy is 0.2-0.5, it means that the user has a relative preference for the recommendation strategy, but further marketing recommendation is needed before the user can handle it. When the recommendation probability of the user recommendation strategy is 0.5-0.8, it means that the user has a high preference for this recommendation strategy, and the operator may recommend it successfully with a simple recommendation. When the recommendation strategy to the user is above 0.8, it means that the user has a very high preference for the strategy, and at this time, the high-cost outbound marketing channel can be considered to be converted into a low-cost SMS distribution channel for marketing, as expected from the empirical results.

5. Conclusion. This paper first analyzes the basic situation of enterprise strategic marketing operation management system based on deep learning and supply chain, and takes T mobile company as an empirical model, extracts historical customer marketing data of stock customers, builds a recommendation model for customer strategy preference by using classification algorithms such as XGBoost, and then analyzes the portrait characteristics of historical lost customers of T mobile company based on K-means clustering algorithm. The experimental results prove that the check accuracy of the enterprise strategic marketing operation management optimization model proposed in this study is 97.29%, the empirical fitting accuracy is higher than 93%.

Data Availability. The experimental data used to support the findings of this study are available from the corresponding author upon request.

Funding Statement. There is no specific funding to support this research.

REFERENCES

[1] Kumar, T. S.*Data mining based marketing decision support system using hybrid machine learning algorithm.* Journal of Artificial Intelligence, (2020) 2(03), 185-193.

[2] Abbas, K., Afaq, M., Ahmed Khan, T., & Song, W. C.*A blockchain and machine learning-based drug supply chain management and recommendation system for smart pharmaceutical industry.* Electronics,(2020). 9(5), 852.

[3] Kamble, S. S., Gunasekaran, A., Kumar, V., Belhadi, A., & Foropon, C. *A machine learning based approach for predicting blockchain adoption in supply Chain.* Technological Forecasting and Social Change, (2021).163, 120465.

[4] Perevozova, I., Horal, L., Mokhnenko, A., Hrechanyk, N., Ustenko, A., Malynka, O., & Mykhailyshyn, L.*Integration of the supply chain management and development of the marketing system.* International Journal of Supply Chain Management,(2020). 9(3), 496-507.

[5] Valaskova, K., Ward, P., & Svabova, L.*Deep learning-assisted smart process planning, cognitive automation, and industrial big data analytics in sustainable cyber-physical production systems.* Journal of Self-Governance and Management Economics,(2021). 9(2), 9-20.

[6] Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., ... & Machtynger, L.*Artificial intelligence (AI) in strategic marketing decision-making: a research agenda.* The Bottom Line,(2020). 33(2), 183-200.

[7] Brintrup, A., Pak, J., Ratiney, D., Pearce, T., Wichmann, P., Woodall, P., & McFarlane, D.*Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing.* International Journal of Production Research, 58(11), 3330-3341.

[8] Helo, P., & Hao, Y.*Artificial intelligence in operations management and supply chain management: An exploratory case study.* Production Planning & Control, (2022). 33(16), 1573-1590.

[9] SINGH, Arpit, et al.*Identifying issues in adoption of AI practices in construction supply chains: towards managing sustainability.* Operations Management Research, 2023, 16.4: 1667-1683.

[10] Huang, M. H., & Rust, R. T. *A strategic framework for artificial intelligence in marketing.* Journal of the Academy of Marketing Science,(2021). 49(1), 30-50.

[11] Hair Jr, J. F., & Sarstedt, M.*Data, measurement, and causal inferences in machine learning: opportunities and challenges for marketing.* Journal of Marketing Theory and Practice,(2021). 29(1), 65-77.

[12] Kim, A., Yang, Y., Lessmann, S., Ma, T., Sung, M. C., & Johnson, J. E.*Can deep learning predict risky retail investors, A case study in financial risk behavior forecasting.* European Journal of Operational Research, (2020). 283(1), 217-234.

[13] Wu, X., Chen, H., Wang, J., Troiano, L., Loia, V., & Fujita, H.*Adaptive stock trading strategies with deep reinforcement learning methods.* Information Sciences, (2020).538, 142-158.

[14] LIU, Bochao.*Integration of novel uncertainty model construction of green supply chain management for small and medium-sized enterprises using artificial intelligence.* Optik, 2023, 273: 170411.

[15] HOSSEINNIA SHAVAKI, Fahimeh; EBRAHIMI GHAHNAVIEH, Ali.*Applications of deep learning into supply chain management: a systematic literature review and a framework for future research.* Artificial Intelligence Review, 2023, 56.5: 4447-4489.

Edited by: Bradha Madhavan
Special issue on: High-performance Computing Algorithms for Material Sciences
Received: Jul 24, 2024
Accepted: Sep 6, 2024