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Research Article

Enterprise Precision Marketing Effectiveness Model Based on Data Mining Technology

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Due to the explosive growth of massive consumption data, the traditional marketing model of enterprises has become stretched. The rapid advancement of data mining technology has given new impetus to the innovation of the marketing strategies of enterprises, promoting the progressive transformation of enterprises from traditional passive marketing to precise and refined marketing. Data mining technology's basic task is to analyze data, acquire insight into cause and effect, and then predict the future. As a result, the technology is coupled with the enterprises' marketing activities, and a precise marketing model is built using big data consumption. This will aid in the comprehensive and three-dimensional description of customers, as well as the analysis of potential customers' attributes, to give a scientific basis for the formulation and implementation of precise data-driven decision-making for enterprises. As a result, our study enhances and optimizes the *K*-means algorithm in combination with the artificial bee colony algorithm aiming at fixing the issue that the *K*-means algorithm is sensitive to cluster center initialization and improving the enterprise precision marketing model's clustering performance. In the precise marketing scenario of the telecom business, the improved K-means clustering model is utilized to realize the analysis and prediction of telecom customers, as well as to carry out precise marketing based on the predicted findings. Finally, the optimized K-means clustering algorithm can objectively and comprehensively reflect the characteristics of telecom customer value segmentation, efficiently mining future clients and preventing blind marketing by enterprises, based on the model's actual verification results. Simultaneously, it provides substantial data support for telecom enterprises' resource planning, as well as pointing out the next step in increasing market share.

1. Introduction

Currently, with the spanking rise of e-commerce platforms relying on Internet technology, online shopping has gradually become a new fashion. It can be said that e-commerce has grown in importance as a means of conducting business between enterprises, between enterprises and customers, and between customers and customers [1]. Furthermore, as the extent of e-commerce in our country has grown rapidly, enterprises' marketing activities have become increasingly reliant on information. In the traditional sense, targetless and passive marketing approaches have struggled to match the development needs of modern enterprises, particularly in the Internet-based e-commerce industry. Precision marketing follows the path of enterprise marketing, which is gradually evolving towards precision. Following that, major corporations throughout the world immediately adjusted their strategies, and precision marketing models became widespread [2, 3]. Big data technology has played a significant role in several fields, as seen by recent developments [4–6]. E-commerce enterprises have a unique big data application environment that provides the raw ingredients for precision marketing. Customers' daily consuming behaviors must generate vast amounts of data for each platform. Customers' purchasing intentions and demands are recorded in these data, as are their consumption habits. Big data can be argued to offer new tools and perspectives for precision marketing. The driving core of the big data-led precision marketing concept is technology, as opposed to the traditional marketing notion. It collects and analyzes large amounts of data to develop precise marketing strategies and deliver personalized ads to specific customers.

Therefore, in the face of new opportunities and challenges, enterprises should be adept at assessing and designing marketing strategies that fully utilize data mining technology. It can extract valuable information from Internet data, obtain customers' consumption needs promptly, and then achieve precise positioning and marketing, providing strong support for improving corporate marketing strategies, thanks to its data collection, processing, and analysis capabilities. In recent years, data mining technology has grown in popularity in other nations, and it is now fashionable to use data mining techniques in the field of precision marketing [7]. Many studies have found that using precision marketing strategies based on data mining techniques may elevate marketing to a new level of effectiveness [8]. Literature [9] focuses on real estate enterprises and integrates big data technologies with precision marketing. It elaborates and analyzes the platform's construction measures, implementation impacts, existing challenges, and improvement suggestions, using specific examples, so that the significance of big data precision marketing in real estate enterprises can be fully realized. Literature [10] studies the role and specific measures of data mining technology in enterprise precision marketing and further improves the direct marketing theory. Precision marketing based on data mining technologies, according to the study, can comprehend customers' preferences and habits in real-time and then supply them with targeted and personalized product promotions. The applications of data mining technologies in enterprise precision marketing were discussed in depth in Literature [11] and Literature [12]. They are based on Internet platform user data, which is subsequently analyzed and processed using data mining algorithms. Finally, it gives data support for precise enterprise marketing depending on the mining results. According to the literature [13], the traditional marketing strategy has been unable to fulfill the development needs of e-commerce, and the development of big data precision marketing will be the general trend. It's a "mirror" mapping of the real environment that serves as a link between the virtual and real worlds. According to the literature [14], In the context of an intelligent network, enterprises should grab the opportunity, fully utilize modern information technology, and shift from a product-centered marketing model to a customer-centered precision marketing model. Provide customers with personalized products and services to accurately locate them. Literature [15] uses the telecoms industry as an example of how to apply data mining technologies to accurately identify enterprise customers to increase enterprise customer value. Literature [16] highlights the importance of big data in corporate marketing activities and anticipates the future application and development of data mining in precision marketing.

Although the current research results on precision marketing and data mining are relatively rich and perfect, they have some practical significance for encouraging the development of enterprises, according to the above research findings. There are still some flaws and gaps. For example, most current research is theoretical, and there are few studies on how to apply data mining technology to extract the information hidden behind the data and use that information to direct precision marketing. Precision marketing mixed with the use of big data by enterprises, in particular, has received less attention and requires further study. As a response, this paper focuses on telecom operators' university business, merges cluster analysis technology with enterprise marketing activities, and builds a precise marketing model based on consuming big data. In this way, a full and three-dimensional picture of telecom customers can be created, and then the characteristics of potential customers can be studied, resulting in a scientific foundation for the formulation and implementation of accurate data-driven decision-making for enterprises. The following is the specific innovation work:

(1) First, systematically introduce and analyze related concepts and technologies, including the theory and process of data mining, the concept of precision marketing, and the application of data mining technology in precision marketing, to offer a theoretical foundation for future study.

(2) Secondly, from the perspective of K-means algorithm optimization, this research offers a K-means clustering algorithm based on an artificial bee colony algorithm to address the limitation of the traditional K-means algorithm in the initialization of the center point and improve its clustering performance. And the improved clustering algorithm is used in the actual business's precise marketing situation, where it creates a precise marketing effect model, conducts customer analysis and prediction, and executes precise marketing activities based on the predicted results.

(3) Finally, the target customer data set is generated and selected using the characteristics of the telecommunications industry, and the developed model is applied to the business scenario of a university's telecommunications product marketing. The model's clustering result not only confirms the improved algorithm's superiority but also demonstrates that the optimized model can objectively and comprehensively reflect the segmentation characteristics of telecom customer value, allowing for effective customer acquisition and avoidance of blind marketing.

2. Related Concepts and Technologies

2.1. Data Mining Theory and Process. How to mine meaningful potential information from the huge data stored on the Internet platform is a challenging issue in light of the present data boom. The rapid advancement of data mining technologies offers technical support in resolving this issue. In a summary, data mining is the process of extracting potentially valuable information from a vast volume of unprocessed, noisy data using appropriate mining algorithms and applying it to multiple areas [17, 18]. As shown in Figures 1 and 2, data mining can be accomplished using a

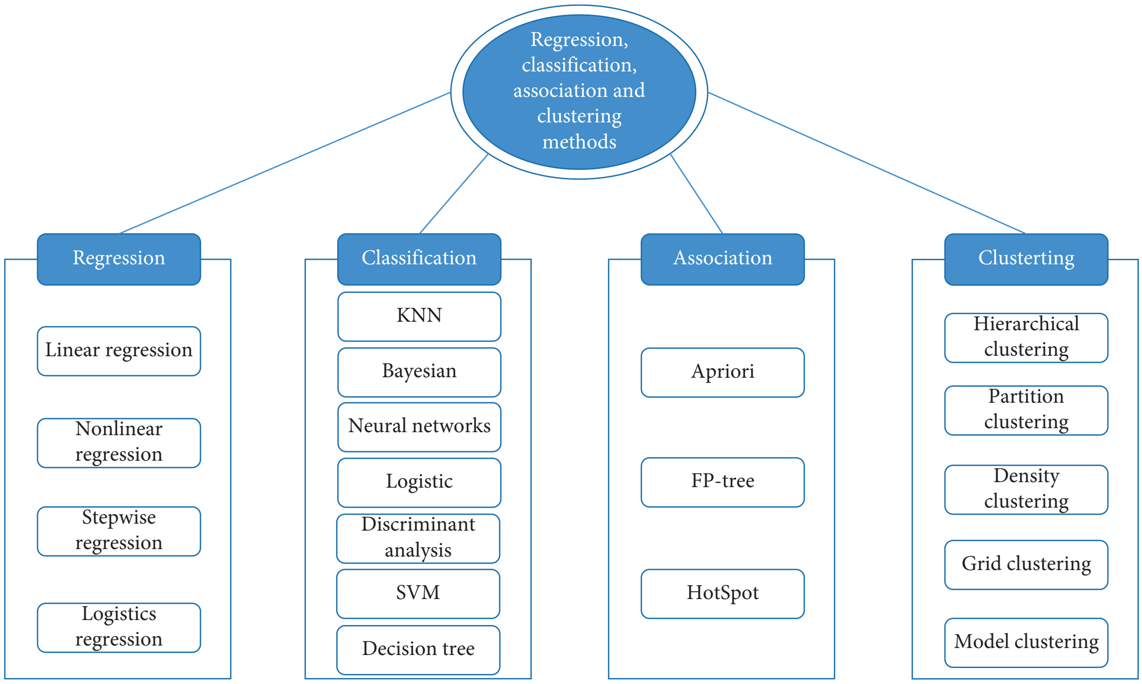

Figure 1: Methods of regression, classification, association, and clustering.

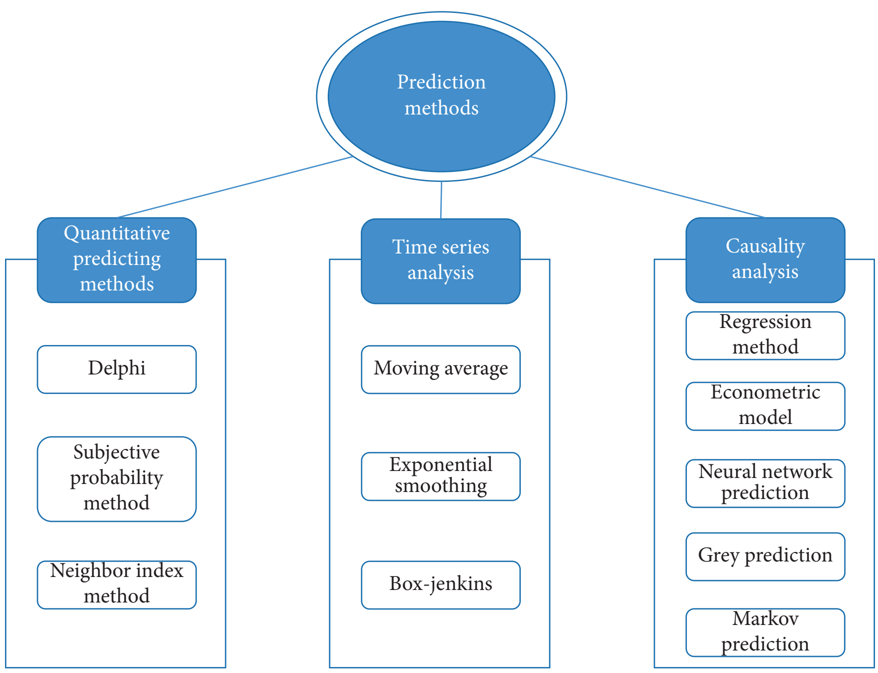

Figure 2: Prediction methods.

variety of techniques. Examples include regression, classification, affinity grouping or association rules, clustering, prediction, and so on.

Typically, appropriate data mining algorithms are adopted for data analysis and processing based on the type of mining tasks in actual business requirements, to guarantee that the algorithms' advantages are properly utilized. In this research, clustering algorithms are applied to application scenarios. Clustering, the most popular data mining technique, divides a huge number of data objects or data sets into separate groups of data objects, referred to as clusters, in an unsupervised manner. Data objects have the greatest similarity within a cluster. The similarity between objects in different clusters is poor or nonexistent.

Data mining is usually broken down into three stages: data preparation, implementation of data mining-related algorithms, and result evaluation. The general method of data mining is depicted in Figure 3.

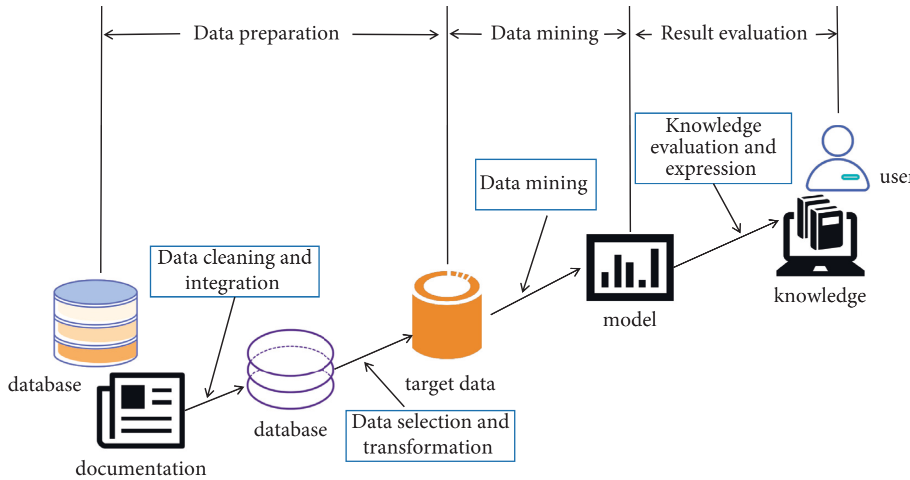

Figure 3: The general process of data mining.

Combined with Figure 3, the specific information in the mining process is as follows: (1) data cleaning and integration: To overcome difficulties like missing values, aberrant parameters, and erroneous data, standardize the collected sample data. Then, on the processed multi-faceted data sources, perform the necessary integration operations and integrate them into the new data warehouse. (2) Data selection and transformation: the data in the data warehouse is refiltered according to the task's actual demands. Then, using the filtered valid data, create data patterns that satisfy the mining criteria. (3) Data mining: apply appropriate mining algorithms to extract various pieces of information from the target data. (4) Knowledge evaluation and expression: Refer to specific parameters to determine the specific expression of knowledge, and then carry out corresponding data mining operations for users.

2.2. Precision Marketing. A scholar in the United States was the first to suggest the concept of "precision marketing." He stated that we may get insight into customer behavior, precisely segment the market, and then start focused marketing activities to fulfill the enterprise's expected goals using scientific management methods or procedures [19]. Professor Philip Kotler, the "father of contemporary marketing," initially proposed the precision marketing hypothesis in 2005 [20]. He believes that both actions and results are critical if an enterprise wants to stand out in the competitive marketplace. First, use marketing communications that are more specific, measurable, and have a high return on investment. Second, develop a marketing strategy based on results. Finally, the importance of target customers' communication input must be emphasized further. Later, through their research, some experts defined the concept of precision marketing. Precision marketing, they explained, indicates that enterprises should fully reflect "right" and "appropriate" in the four aspects of channels, time, target customers, and information to meet the goal of encouraging target customer purchase [21]. Following that, as Internet technology advances, precision marketing is increasingly combined with information technology. As a result, we define precision marketing in this study as a business built on precise market positioning, with customers at the center, and employing advanced technical tools to create an efficient, scientific, and individualized service system for customers, so that it can achieve measurable, low-cost, and long-term development. To put it another way, precision marketing has four characteristics: (1) The selectivity of customer objects. (2) The effectiveness of communication strategies. (3) The economy of communication behavior. (4) The measurability of marketing results. Figure 4 shows the complete model of precision marketing.

Precision marketing, as seen in Figure 4, focuses on precision, has the advantage of controllability, and can be analyzed and quantified, as opposed to traditional marketing strategies. Customers must always be considered marketing breakthroughs, and enterprises must pay close attention to customer needs while utilizing various modern information technologies to ensure that their products, advertisements, and marketing activities reach customers in need via appropriate methods and carriers at the appropriate time and place. It can drive customers' enthusiasm for consumption and encourage them to actively comprehend products and consultations while attracting potential customers. Finally, a specific and detailed marketing strategy is developed based on the analysis results to promote the enterprise's economic benefits and meet the predicted goals.

2.3. Application of Data Mining in Enterprise Precision Marketing. Data mining technology is used in the enterprise marketing process to analyze enormous consumption records created by customers on various Internet platforms [22]. Enterprises can process and analyze customers' purchasing behavior, frequency, transaction data, and other data to find out the law of changes using data mining technologies such as cluster analysis, association rules, and classification analysis. Simultaneously, it is also inseparable from the help of huge data from different platforms in the process of precision marketing based on data mining. The

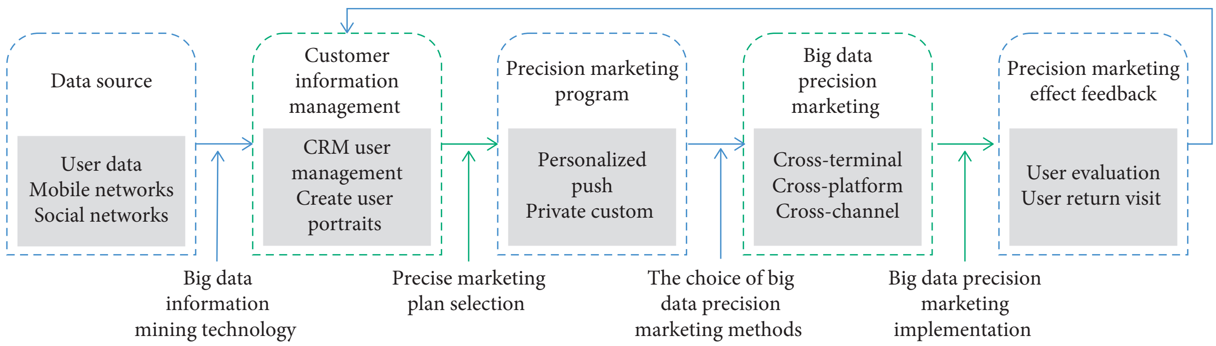

Figure 4: The precision marketing model.

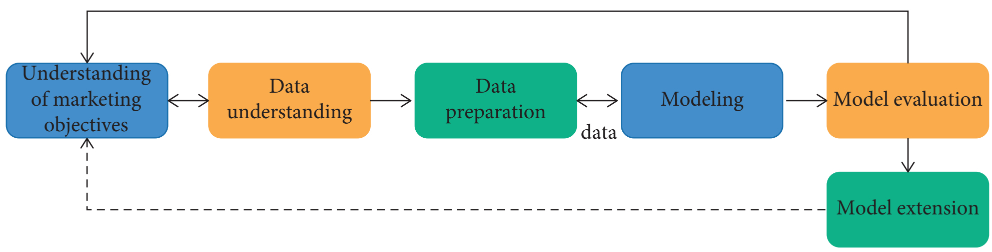

Figure 5: The flow chart of data mining technology in enterprise marketing.

customer groups and values are then classified depending on the mining results to correctly locate the target customers. Then, based on the demands of target customers, enhance customer value and give customized services to them. Potential customers can be attracted to buy enterprise products promptly in this way, and precision marketing can be accomplished [23]. As a result of using data mining technologies, enterprises' marketing activities are transformed from passive and fixed procedures to measurable and controllable activities. This will aid in improving the marketing effect, achieving the enterprises' profit aim, and eventually improving the enterprises' market competitiveness. Meanwhile, data mining technology is increasingly being used to conduct precise marketing of enterprise products. Figure 5 depicts the data mining procedure in the enterprise marketing process.

As can be seen from Figure 5, the data mining process in the enterprise marketing process mainly covers several steps of marketing target understanding, data understanding, data preparation, modeling, model evaluation, and model expansion. The understanding of marketing goals is the premise. This link realizes the conversion between marketing goals and data mining goals, that is, transforming a knowledge definition into a problem definition in data mining. There can be multiple cycles between data understanding and marketing goal understanding. Then, based on data understanding, sampling, filtering, and other operations are performed on the massive enterprise data to construct the corresponding data set. The entire procedure revolves around modeling. The corresponding algorithm is utilized for modeling to realize the effect of data mining by aiming at the target data. Then assess and analyze the mining results to see if the marketing requirements are fulfilled. The model expansion step begins once the target requirements have been met. If not, go back to the stage of understanding marketing objectives and continue the process until the requirements are met. The stages above are interconnected and interact with one another, allowing enterprises to extract important information from huge data, provide a scientific decision-making foundation for precision marketing, and eventually improve their economic benefits.

3. K-Means Clustering Model Based on Artificial Bee Colony Algorithm

To locate potential customers more effectively, divide customer groups based on customer attributes and collect key factors that determine customer intentions. Clustering algorithms are a popular way to solve problems like group partitioning. This research uses this information to combine marketing theory with the K-means algorithm to increase the algorithm's clustering performance. On this foundation, a data mining-based marketing and optimization system model is built, bringing fresh ideas and kinetic energy to the development of enterprises. Figure 6 depicts a data mining-based marketing and optimization system model.

Synthesizing Figure 6, the model's business process consists mostly of the following components: (1) Information collection and processing. This link is primarily used to record all types of data necessary by the real marketing link, as well as to generate and transfer supporting data samples into the warehouse. (2) Marketing and optimization system. To fix the existing errors and deviation parameters, the obtained data is classified into the general warehouse, and the associated preprocessing operations are carried out concerning the mining parameter requirements. Finally, collect valuable information to aid relevant topics in their decision-making. (3) Data mining. The operation of

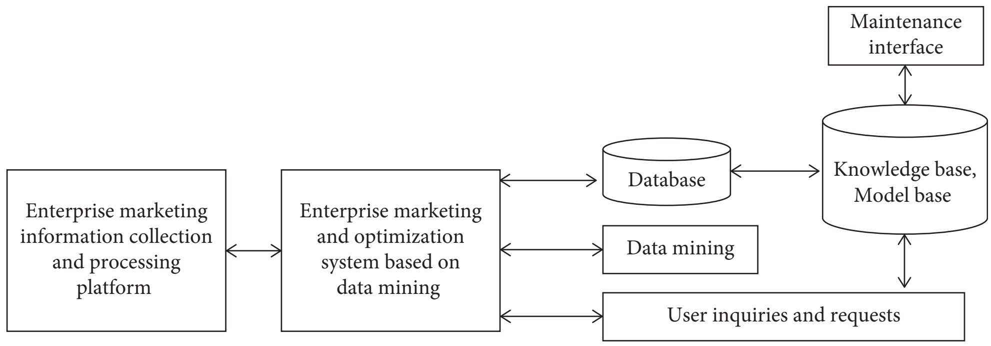

Figure 6: The architecture of the enterprise marketing model is based on data mining.

supporting simplification and conversion is carried out according to the decision-making needs, and the K-means clustering algorithm based on an artificial bee colony is used to mine and analyze these data, and then obtain effective information. This session can provide decision-makers with a wealth of information. (4) Knowledge base. Covers the infrastructure and functions of the data warehouse. (5) Maintenance interface. Relevant developers rely on this interface to carry out maintenance to ensure that the system has good stability. (6) Data warehouse.Stores data about various aspects of businesses and customers.

3.1. K-Means. As one of the representative algorithms in the data mining field, the K-means clustering technique is very popular in certain areas of life [24]. The algorithm's core principle is to assume that clusters are made up of samples with similar distances, then repeatedly update the center of each cluster based on the position of the samples in the cluster until the total of the distances within the cluster is minimized. In a summary, the K-means algorithm uses sample distance as an indicator of whether or not samples are related and then classifies the collection's samples without labels into K clusters. Suppose the set $X = \{x_1, x_2, \ldots, x_M\}$ contains M samples. Clustering is the process of dividing M samples into K clusters, represented by $C = \{c_1, c_2, \ldots, c_K\}$. During the clustering process, when the samples in each cluster change, the center of the cluster needs to be recalculated and updated, as shown in the following formula:

$$c_j' = \frac{1}{M_j} \sum_{x \in X_j} x, \quad (1)$$

where M_j denotes the number of samples in cluster X_j, c_j' denotes the center of the updated j-th cluster. Then, Algorithm 1 illustrates the explanation of the K-means clustering algorithm.

The K-means clustering algorithm is simple in principle and easy to execute, as shown by the algorithm described in Algorithm 1. The key step is to preset the value of clusters K and the cluster center. However, it is worth mentioning that in the traditional method, the value of K must be artificially set in advance and has some randomness. The algorithm's clustering effectiveness will be affected if the setting is unreasonable. As a result, the K-means algorithm has limitations, including poor stability and sensitivity to noise and outliers.

3.2. Artificial Bee Colony Algorithm. Research has proven that the artificial bee colony algorithm offers a viable solution to the K-means algorithm's cluster head initialization problem[25]. The four elements of the algorithm are Source, Leader, Scouter, and Follower. It differs from other swarm intelligence algorithms such as the leapfrog and particle swarm algorithms. It seeks high-quality sources through the role switching of Leader, Follower, and Scouter and group collaboration.

It is assumed that the dimension of the solution space is K. Then the position of the Source can be expressed by formula (2):

$$s_i = [s_{i1}, s_{i2}, \ldots, s_{iK}]. \quad (2)$$

The initialization method of Source I is

$$s_{id} = A_{\min} + \lambda (A_{\max} - A_{\min}), \quad (3)$$

where $\lambda = \text{rand}(0,1)$, $A_{\min} \le x_{ik} \le A_{\max}$, $A_{\min}$, and $A_{\max}$ denote the minimum and maximum value of the solution space. S_{id} represents the value of the d-th dimension space of the i-th bee source.

The Leader creates a new Source i around Source in the beginning, as shown in formula (4):

$$n_{ik} = x_{ik} + u\left(x_{ik} - x_{jk}\right), \quad (i \ne j, u \in [-1, 1]), \quad (4)$$

where u obeys a random distribution, and n_{ik} represents the value of the k-th solution space of the i-th bootstrap peak. Then the newly generated i-th Source is expressed as formula (5):

$$n_i = [n_{i1}, n_{i2}, \ldots, n_{iK}]. \quad (5)$$

Then, its fitness is denoted as $F(c_i)$. The calculation method of $F(c_i)$ is determined by the specific problem. Taking the minimization problem as an example, if $F(n_i)$ <F(s_i), use n_i instead of s_i according to the greedy selection mechanism, otherwise keep s_i. After all, Leaders are updated according to formula (4), Followers will calculate the updated probability according to formula (6):

(a) Randomly initialize the centers of K clusters, that is, select K samples x1, x2,..., xK in the set X as the initial cluster centers.
(b) Traverse the remaining M-K samples, calculate the distance from the sample to the center of each cluster, and divide the sample into the cluster of the center with the closest distance.
(c) Calculate and update the center of the cluster according to formula (1).
(d) If $c_j' \neq c_j\,(j = 1, 2 \ldots, K)$, return to step b). Otherwise, output the clustering result.

Algorithm 1: Description of K-means clustering algorithm.

(a) Set the parameter *tem*, the number of solution spaces P, the solution dimension K, and the maximum number of iterations T, and initialize the source s_i.
(b) To create a new source n_i, attach a leader for every source s_i and search using formula (3).
(c) Fitness calculation using the greedy approach to assess whether the source should be kept.
(d) According to formula (5), judge whether s_i is retained and whether the leader is converted to scounter.
(e) Follower searches using formula (6) and uses the greedy technique to decide whether or not to preserve the source.
(f) Decide whether or not to quit s_i. If "use", convert leader to scounter. If "not", go to step (h).
(g) Create a new source based on formula (7).
(h) Check to see if the number of loops exceeds T. If "yes," stop the iteration and show the best result. If "not," return to step (b).

Algorithm 2: Description of artificial bee colony algorithm.

(a) Initialize the total number of samples is M, and the number of clusters is K.
(b) Initialize source according to formula (2).
(c) Based on the cluster center in step b), select a plan, and assign another M-K noncluster center sample to K clusters, so that the sum of the distances between each sample and the cluster center is minimized.
(d) Use the K-means method to update the cluster center nodes. Calculate the fitness value of each source according to formula (1).
(e) Follow the new source according to the artificial bee colony algorithm described in Section 3.2.

Algorithm 3: Description of K-means clustering algorithm based on artificial bee colony.

$$p_i = \frac{F(s_i)}{\sum_i F(s_i)}. \tag{6}$$

Then, $r_i \in [0,1]$ are randomly generated. If $r_i > p_i$, a new Source based on the formula (3) is created.

If Source s_i does not identify a superior Source after T iterations, it'll be dropped throughout the search process. Its equivalent Leader takes on the duty of Scounter. As illustrated in formula (7), Scounter produces a new Source at random within the data set:

$$s_i^{t+1} = \begin{cases} A_{\min} + \lambda\left(A_{\max} - A_{\min}\right)\varepsilon \geq \text{tem}, \\ s_i^t \varepsilon < \text{tem}, \end{cases} \tag{7}$$

where ε is the number of attempts and *tem* is the maximum number of attempts.

To sum up, the procedures of the artificial bee colony algorithm are shown in Algorithm 2.

It is easy for the artificial bee colony algorithm to jump out of the local optimal solution and optimize in a global scope since it uses a role-switching mechanism. It has better global search capability and higher convergence precision.

3.3. K-Means Clustering Model Based on Artificial Bee Colony Algorithm. The swarm intelligence algorithm can effectively tackle multi-modal and nonlinear np-hard problems due to its high robustness. Therefore, the artificial bee colony algorithm is introduced into the cluster center initialization process of the K-means clustering algorithm to solve the shortage of K-means in the selection of the initial cluster center. The steps are shown in Algorithm 3 below.

4. Performance Test of Clustering Model in Enterprise Precision Marketing

The precision marketing model combined with an optimized K-means clustering algorithm is utilized to mine and evaluate the operators' big data, which aims to clearly describe the characteristics of each cluster and the key factors influencing customer consumption behavior, thus providing powerful data support for precision telecommunications marketing. This study uses the university market business of a telecom operator as an example to test the model's performance in real-world scenarios.

4.1. Data Acquisition and Processing. This paper randomly selects the relevant data of 10,000 customers in a telecom university market from January to December 2021 from the Vertica database to obtain the basic attributes and consumption behavior of these customers. The collected sample

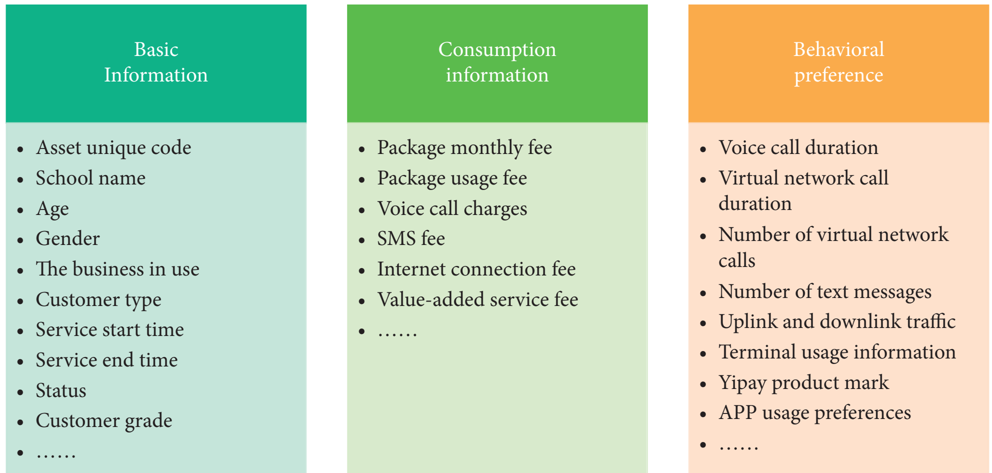

Figure 7: Three types of attributes of customer data.

data was processed and classified into three types of attributes to facilitate research: basic information, consumption information, and behavioral preferences.Figure 7 depicts the details of the three types of attributes.

As illustrated in Figure 7, since the initial sample often has a huge quantity of data and complex data types, it also contains some abnormal data, missing values, invalid data, inconsistent data types, etc. Therefore, it is necessary to perform data cleaning on the collected sample data of 10,000 customers. We eliminated some data that did not meet the requirements, and finally screened out 9,862 valid student customer data. Then, according to the needs of the experiment, the data samples were further screened to determine the type of school, gender, age, the package in use, the total annual usage fee of the package, the related business expenses beyond the package, the usage of uplink and downlink traffic, terminal usage, APP usage preferences, and other data types together form the database required for the experiment.

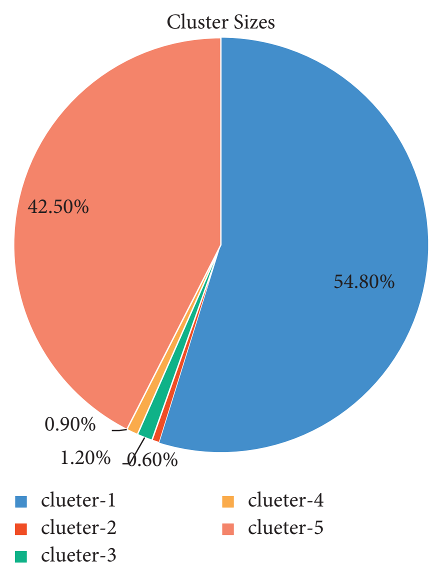

Figure 8: Clustering result graph when $K = 5$.

4.2. Experimental Verification and Analysis. To evaluate the precision marketing model's success in telecommunications marketing activities in colleges and universities, it is utilized to cluster and assess the processed data. First, according to different indicators, the number of clusters of customers is defined as 5. The clustering results obtained by the model are shown in Figure 8.

Observing the clustering results in Figure 8, it can be seen that when the number of clusters of customers is defined as 5, the clustering effect obtained by the model is general. Among them, cluster-1 contains the largest number of student customers, accounting for 54.8%. Cluster-2 has the smallest number of student customers, accounting for only 0.6% of the total. Cluster-5 has a somewhat lower percentage of student customers than cluster-1, at 42.5%. Cluster-4 and cluster-3 also clustered relatively fewer student customers, slightly higher than cluster-2. The three clusters accounted for only 2.7% of the total. Therefore, combined with the above analysis, we redefine the number of clusters of customers and set it to 3 by default. A new clustering result is obtained as shown in Figure 9.

The clustering findings in Figure 9 show that when the number of clusters is 3, the model's clustering results are much better than those in Figure 8. All student customers were separated into three clusters, with each cluster accounting for 54.8%, 36.2%, and 9% of all student customers, respectively. A more realistic clustering result was progressively produced after changing the model parameters and performing multiple clustering. In the end, 43.6%, 38.1%, and 18.3% of student customers in each group were combined. The market customers of a telecommunications firm at colleges and universities are then grouped based on the clustering results. Table 1 contains the detailed results.

Relying on the prior clustering results and the data in Table 1, customers of a telecom business in the university market could be classified into three groups. These three types of customers can be classified as high-value customers,

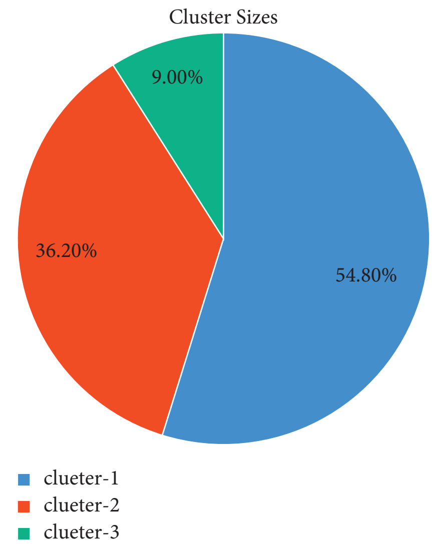

Figure 9: Clustering result graph when $K = 3$.

Table 1: The grouping result of university market customers.

Group	Number of customers	Percentage (%)	ARPU (Yuan/m)	Voice usage fee (Yuan/m)	Internet usage (G/m)	The proportion of all Netcom usage (%)
Group 1	4300	43.6	60.2	3.73	24.63	91.43
Group 2	3757	38.1	41.4	1.15	16.57	85.27
Group 3	1805	18.3	20.8	0.58	7.16	78.68

medium-value customers, and low-value customers based on their ARPU value. The three types of customers had average ARPU values of 60.2 yuan/month, 41.4 yuan/month, and 20.8 yuan/month, respectively. High-value customer groups account for 43.6% of these three types of student customer groups, while medium-value customer groups and low-value customer groups account for 56.4%. This is also valid in the current state of affairs. To capture school market share, telecom providers frequently offer low-cost business packages to students in an attempt to attract them to apply for packages, while neglecting the profitability indication.

To summarize, the clustering results divide existing university market customers into high-value student customers, traffic-oriented student customers, and low-use student customers. Then, when combined with the current situation, enterprises can summarize and analyze the characteristics of these three groups' consumption behavior to identify the key factors that influence customer consumption behavior and provide a decision-making basis for enterprises to conduct precision marketing in the future.

5. Conclusion

The application of precision marketing in the field of e-commerce enterprises is the general trend in the current big data era, and the future looks good. It gives fresh support and backing for precision marketing of enterprises, as well as new prospects for enterprise transformation and development, particularly with the use of intelligent technologies such as data mining and cloud computing. To mine valuable information contained in vast consumption data, enterprises should actively build "big data thinking" and deeply combine advanced data mining technology with marketing. At the same time, it serves as a scientific resource for enterprises to use when making marketing decisions. This study enhances and optimizes the K-means algorithm by combining it with the artificial bee colony algorithm to improve clustering performance. The improved clustering algorithm is then used in telecom enterprises' business marketing situations, and a precision marketing effectiveness analysis model is built to determine the key factors that influence customers' use of telecom services. Finally, the real verification results demonstrate the worth and benefits of the optimized K-means clustering model in telecommunication precision marketing efforts. It aids in the achievement of the goals of increasing customer value, identifying potential customer needs, and accurately advertising business, hence raising the marketing effectiveness of enterprises. The paper's problem is that, in the presence of a complex and changing Internet environment, the measurement indicators used in the tests are very simplistic and cannot effectively reflect customer behavior and habits. Therefore, in the future, it will be necessary to further enrich the clustering model, select a variety of measurement indicators and user behavior data, and continuously optimize the parameters and indicators of the model, to carry out more in-depth mining and analysis for different customer characteristics, and enhance the generalization ability of the model.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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