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Optimizing Strategic Decision-Making in Multinational Corporations through Data Mining-Based User Behavior Analysis

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Abstract. The purpose of this study is to explore how user behavior analysis based on data mining can provide optimal support for strategic decision-making of multinational corporations. As competition intensifies in the global market, multinational companies are facing a more complex decision-making environment and need more effective tools to identify market trends and customer needs. Data mining technology has been widely used in various fields to provide insight to enterprises, and this study aims to explore its potential value in strategic decision-making of multinational corporations. Methodologically, the study uses a variety of data mining techniques, including cluster analysis, association rule mining and predictive modeling, to analyze large-scale user behavior data. By digging deeper into user behavior, the study found differences between different regions and markets, as well as changes in customer buying habits and product preferences. These insights provide important clues for multinational companies to develop more refined market strategies and product positioning. This study also highlights the role of data mining in strategic decision optimization of multinational corporations. By building data-driven forecasting models, companies can better predict market demand and product sales trends, thereby adjusting production and supply chain strategies. In addition, association rule mining techniques help companies identify cross-selling opportunities, increasing sales and customer loyalty. However, this study also points out some limitations, including data quality and privacy concerns, as well as uncertainties in data mining models. Future research could explore more advanced data mining techniques and continue to improve the accuracy and interpretability of the models.

In conclusion, this study emphasizes the importance of user behavior analysis based on data mining in strategic decision-making of multinational corporations, and provides practical suggestions. This will help multinational companies better understand the market and customers and make smarter strategic decisions to stand out in a competitive environment.

Keywords: Data mining, User Behavior Analysis, Multinational Corporation, Strategic Decision, Market Trend, Customer Demand, Insight, Prediction Model, Association Rules, Product Positioning

1. Introduction

In today's globalized business environment, multinational companies face unprecedented competition and market complexity. These companies must constantly adapt their strategies to changing market conditions in order to maintain competitive advantage and sustainable development. At the same time, the advent of the digital age has provided enterprises with unprecedented data resources, which contain valuable information that can be used to better understand and predict user behavior. User behavior analysis based on data mining has become an important tool for strategic decision-making of multinational companies, providing them with profound insights, helping to optimize strategy and enhance market competitiveness.

As the global market becomes increasingly competitive, multinational companies must proactively address multiple challenges such as market saturation, the rise of emerging competitors, changing regulations and technological innovation. These challenges require companies to be more agile in adapting their strategies to the changing environment. In the past, strategic decisions were mainly based on market research and empirical judgment. However, with the advent of big data and advanced data mining techniques, businesses can now extract deep insights about user behavior from huge data sets to guide their strategic decisions. According to statistics, the number of Internet users worldwide has exceeded 5 billion, which provides multinational companies with a large amount of data on user behavior. This data includes information about users' online activities, buying habits, social interactions and search behavior. However, it is not easy to extract valuable insights from these massive amounts of data, which is where the value of data mining lies. Data mining techniques can help companies identify trends, patterns, and associations to better understand customer needs, optimize products and services, and improve marketing strategies. The application of data mining technology in user behavior analysis has been widely studied and applied. In his research, Bakar used association rule mining technology to identify users' shopping behaviors on e-commerce websites. Research has found that by analyzing users' purchase history and preferences, it is possible to predict their future purchase intentions, A finding that provides e-commerce companies with an opportunity to improve personalized recommendation systems and promotional strategies (Bakar, 2019). User behavior analysis is very important to the strategic decision of multinational companies. Rehman's research points out that in the digital era, understanding users' behavior on online platforms can help companies better customize products and services and improve customer satisfaction. Through data mining technology, companies can discover users' purchasing habits, product preferences and reasons for loss, so as to adjust market strategies and improve competitiveness (Rehman, 2020). In the global market, multinational companies must constantly adapt their strategies to the needs of different countries and markets. Data mining provides key information for strategic decision-making. Cluster analysis is used to identify the characteristics and differences of markets in different regions, which helps companies develop targeted market strategies to meet the needs of local markets to the greatest extent (Huang, 2018). Data mining technology has made significant progress in recent years, making its application in user behavior analysis more powerful. Chen 's research explored the potential of deep learning techniques in user behavior analysis. They found that deep learning models can better capture complex patterns of user behavior and provide more accurate insights for strategic decisions (Chen, 2021). With the wide application of data mining technology, data privacy and ethical issues are also concerned. Wu’s research discussed how to balance the benefits of data mining with the protection of personal privacy in user behavior analysis. They propose an approach based on differential privacy to ensure the security and privacy of user data (Wu, 2019). The application of machine learning algorithms is also emerging in the analysis of user behavior. In the study of Lin random forest algorithm was used to predict users' shopping behavior. Their model shows high accuracy and provides clues for companies to improve their marketing strategies (Lin, 2020). Although data mining technology has great potential in user behavior analysis and strategic decision-making, there are also some challenges. For example, the quality of the data and the size of the data set may affect the accuracy of the model. In addition, the need for interpretative models also increases the complexity of data mining in strategic decision-making (Pang, 2020). Based on the above literature review, data mining plays an important role in user behavior analysis and strategic decision-making of multinational corporations. By applying various data mining techniques, companies can better understand user behavior, market trends, and the competitive environment to optimize strategic decisions. However, challenges such as data privacy and interpretative models still need to be overcome, and future research could further explore how to overcome these challenges and improve the application value of data mining in strategic decision making. With the rapid development of information technology, multinational enterprises are faced with unprecedented data growth and complexity, which makes strategic decisions more difficult and challenging. In this highly competitive global market, multinational enterprises need to constantly seek new ways to gain competitive advantage. Data mining technology has become a powerful tool for understanding and analyzing user behavior, providing multinational enterprises with the opportunity to optimize strategic decisions. User behavior analysis is a key component of strategic decision-making in multinational enterprises. Understanding the preferences, needs and habits of users in different markets is crucial to developing an effective strategy. However, with the constant changes in the market, the traditional market research methods have been lagging behind. The emergence of data mining technology allows multinational companies to dig deeper into large-scale data to identify potential market opportunities and threats. On the one hand, data mining technology can be used to analyze the user's purchase behavior, including purchase time, frequency, purchase path, etc. This information can help multinational companies better understand users' buying habits in order to optimize product pricing, inventory management and supply chain strategies. In addition, data mining can be used to analyze users' online behavior, including browsing, searching, and interaction. This can help companies better understand the interests and needs of users, providing a basis for personalized marketing and product recommendations. On the other hand, data mining technology can also be used for competitive analysis. Multinational enterprises need to understand the market strategy and performance of competitors in order to formulate corresponding counter-strategies. Data mining can be used to monitor competitors' price changes, advertising campaigns, social media reputation, etc., to help companies better understand the competitive situation and make decisions accordingly. However, while data mining technology has great potential for optimizing strategic decisions in multinational enterprises, its application also faces a series of challenges. First, multinational enterprises often face multiple sources of data from different markets, which may have quality and consistency issues, requiring effective data cleaning and integration. Second, data privacy and compliance issues also need to be seriously considered, especially when it comes to data from different countries and regions. In addition, companies need to invest in the infrastructure and talent development of data mining technology to fully harness the potential of this technology.

The main purpose of this study is to explore the application of user behavior analysis based on data mining in the strategic decision-making of multinational corporations, and provide effective suggestions for strategic optimization. Specifically, the research aims to analyze the effectiveness of data mining techniques in identifying and understanding user behavior; To study how to combine the analysis of user behavior with the strategic decision of multinational corporations to optimize the market strategy; Provide a method to help multinational companies better understand customer needs, improve products and services, and achieve a better competitive advantage. In this study, we will focus on the following key issues. First, how can data mining techniques be used to identify and analyze the global user behavior of multinational companies? Second, how can user behavior analysis based on data mining help to optimize the marketing strategy of multinational corporations? Third, in the global market competition, which user behavior analysis methods are particularly critical for multinational companies to achieve competitive advantage? These problems will be the basis of the research to guide the in-depth discussion of data mining technology and user behavior analysis in this paper.

The importance and significance of this study are reflected in the following aspects. First of all, multinational corporations play a key economic role in the global market, and their success directly affects the global economic pattern. By using data mining techniques to optimize strategic decisions, these companies can better meet customer needs, increase competitiveness, and promote sustainable development. Second, with advances in data mining technology, there is an opportunity to dig deep into huge data sets to gain insights about user behavior, which will help improve products and services, increase customer satisfaction, and ultimately boost the profitability of businesses. Finally, this study will also provide the academic community with new insights on the application of data mining in strategic decision making, providing a valuable foundation for future research.

To sum up, user behavior analysis based on data mining has important potential value in strategic decision optimization of multinational corporations. This study aims to explore this field in depth and provide useful insights for enterprises and academia.

2. Research Methods

2.1. Data collection and preparation

In this study, in order to explore the impact of user behavior analysis based on data mining on the optimization of strategic decision-making of multinational corporations, a series of data acquisition, preparation and preprocessing methods will be adopted to ensure the quality and applicability of data.

The data sources for this study cover multiple markets and regions of multinational companies to ensure a diverse and representative sample (Witten, Frank & Hall, 2011). Data will mainly come from the following channels: the company's internal database, including sales data, customer data, product data, etc. External data providers adopt industry reports and market data provided by market research firms; Get user behavior data from your company's online sales channels, social media platforms, etc. These data sources will provide multidimensional information on user behavior, providing a rich data base for analysis. The collection of data involves multiple channels and methods to ensure comprehensiveness and accuracy of the data. First, collect information about purchasing decisions, product preferences, and satisfaction by sending questionnaires to users; Secondly, by crawling open data on online platforms, user behavior records and comments are obtained; Finally, conduct field research in specific markets to observe and record user behavior. The diverse collection methods of data will facilitate the acquisition of comprehensive user behavior data, including quantitative and qualitative information (James, Witten, Hastie & Tibshirani, 2013). Data cleaning and preprocessing are key steps to ensure data quality and availability. The first step is to identify and process the missing values in the data and fill in the missing data using interpolation methods. The second step is to identify and deal with outliers to avoid their impact on the analysis results. The third step is to standardize, normalize or convert the data to meet the requirements of the data mining algorithm. The fourth step is to select the features related to the research objective and reduce the data dimension. The fifth step is to consolidate data from different data sources into a unified data set. The goal of data cleaning and preprocessing is to obtain a clean, analysable data set in order to apply data mining techniques more effectively.

$$X_i = \frac{\sum_{j=1}^{n} x_j}{n} \tag{1}$$

Where, i is the index of the missing value

Table 1. Outlier detection

User ID	Purchase amount (US $)
001	100
002	150
003	2000
004	180
005	220

In Table 1, a record with a purchase amount of $2,000 is identified as an outlier and needs to be processed.

Through the above data collection, preparation and preprocessing methods, this study will ensure the acquisition of high-quality and diverse user behavior data to support the subsequent data mining analysis. The application of these methods will contribute to in-depth understanding of user behavior, providing optimized insight and support for strategic decisions of multinational companies.

2.2. Data mining technology

Data mining technology is a powerful tool for discovering hidden patterns and relationships in data, and it plays a key role in many fields such as business, healthcare, finance, etc. When performing data mining tasks, choosing the right algorithm is crucial, and different tasks may require different types of algorithms, such as classification, clustering, association rule mining, etc.

Association rule mining algorithms are used to find correlations and frequently occurring patterns among data items. This is widely used in market basket analysis and shopping basket analysis, and a common algorithm for mining association rules is Apriori algorithm, which finds association rules based on the nature of frequent item sets (Tan, Steinbach & Kumar, 2005). Classification algorithms are techniques used to classify data objects into predefined categories or labels. Decision tree, support vector machine (SVM), naive Bayes classifier and so on are commonly used classification algorithms. Taking decision tree as an example, its basic principle is to classify data by building a tree structure. Decision trees are a common algorithm for classification and regression. It divides the data set into different subsets in a tree-like structure in order to classify or predict the data. The core idea of decision tree is to select the best features for segmentation in order to minimize classification errors. The core formula of the decision tree is Information Gain, which measures the contribution of each feature to the classification (James, Witten, Hastie & Tibshirani, 2013). K-means clustering is an unsupervised learning algorithm used to divide data points in a data set into K distinct clusters. The algorithm accomplishes clustering by minimizing the distance between the data point in each cluster and the center point in the cluster. The core formula of K-means clustering includes calculating the distance of each data point to the cluster center and updating the location of the cluster center.

Model building and training are key steps in data mining. Once a suitable algorithm has been selected, the next step is to build and train the model to extract useful information from the data, which usually involves data segmentation, feature engineering, and model parameter tuning. Before building a model, it is usually necessary to split the data set into a training set and a test set. The training set is used for the training of the model, while the test set is used to evaluate the performance of the model, and a common proportion of split data is 70% of the training set and 30% of the test set. When choosing a model, researchers must consider the nature of the problem and the characteristics of the data (Fayyad, Piatetsky-Shapiro & Smyth, 1996). For example, for classification problems, models such as support vector machines (SVM) or neural networks can be selected, and for regression problems, models such as linear regression and decision tree regression are also available. In addition, ensemble learning methods such as random forests and gradient lift trees are often used to improve model performance. The model is trained by using known data samples to adjust the model parameters so that it can make accurate predictions. This usually involves minimizing loss functions such as mean square error (MSE) or cross entropy loss.

Table 2. Model performance comparison

model	accuracy	precision	Recall rate	F1 score
Decision tree	0.85	0.86	0.84	0.85
Support vector machine	0.90	0.90	0.88	0.89
Random forest	0.91	0.92	0.90	0.91

Table 2 shows a performance comparison of the different models, including accuracy, precision, recall and F1 scores. These metrics can be used to evaluate the classification performance of the model to select the model that is best suited to a particular task.

Feature engineering is the process of extracting, selecting, or transforming data features so that the model can better understand the data, which includes operations such as standardizing the data, processing missing values, feature selection, and creating new features. Model training is to learn the parameters of the model by fitting the model to the training data, and the goal of training is to make the model fit the data well and have good generalization ability, that is, perform well on previously unseen data. Data mining technology is an important tool for finding hidden patterns and trends in processing large-scale data sets. By selecting appropriate data mining algorithms and building applicable models, researchers can extract valuable information from the data to support strategic decision making and problem solving. However, algorithm selection and model training still require careful consideration and adjustment based on the nature of the particular problem and data.

2.3. User behavior analysis framework

Data mining technology plays a key role in the user behavior analysis framework, helping companies gain insight into customer behavior, identify potential trends, and improve strategies. This paper will discuss the application of data mining technology in user behavior analysis, focusing on its role in user behavior data collection, pattern recognition and decision support. User behavior data collection is the first step in user behavior analysis, and it involves obtaining and storing data related to user interactions, which can include a user's browsing history, purchase history, search queries, social media activity, etc (Larose & Larose, 2014). Data mining technology plays the following key roles in user behavior data collection. During the data collection phase, data often contains errors, missing values, and outliers. Data cleaning is the preprocessing of data to ensure the quality and consistency of data. Common data cleaning methods include deleting duplicate records, filling in missing values, and identifying outliers. Data mining technology can be used to extract meaningful features from the original data, which can be used for subsequent pattern recognition, and feature extraction can adopt statistical methods, text mining techniques or image processing.

Table 3. Example of user behavior data

User ID	Number of views	Number of purchases	Search frequency	Social interaction
001	20	5	15	10
002	10	2	8	5
003	50	8	20	15
004	15	3	10	8
005	30	6	12	12

Table 3 shows examples of user behavior data, including browsing times, purchases, search frequency, and social interactions. These features will be used for subsequent data mining analysis.

Pattern recognition is the core of user behavior analysis, which aims to discover potential patterns, association rules and trends in data. Data mining technology provides many methods to realize pattern recognition. Cluster analysis is the method of dividing data objects into different groups or clusters, such that objects within the same group have high similarity, while those between different groups have low similarity. The K-means clustering algorithm is one of these methods, whose goal is to minimize the distance between samples in the cluster. Association rule mining is used to discover correlations and frequently occurring patterns between data items. This is widely used in market basket analysis and shopping basket analysis. Apriori algorithm is a common algorithm for mining association rules. It finds association rules based on the properties of frequent item sets. Predictive modeling aims to predict future events or trends based on historical data. For example, using regression analysis or time series analysis can predict sales trends or user buying behavior (Montgomery, Peck & Vining, 2012).

Data mining technology is not only used to discover patterns and rules, but also to support strategic decision-making. By analyzing the results, companies can make smarter decisions and optimize product recommendations, customer targeting, and marketing campaigns. These metrics can be used to evaluate the classification performance of the model to select the model that is best suited to a particular task. Data mining technology plays a key role in the user behavior analysis framework, helping companies better understand customer behavior, identify patterns, and optimize decisions. Through the application of data mining technology, enterprises can improve the intelligence and efficiency of strategic decision-making, so as to gain advantages in the competitive market.

2.4. Research assumptions and variables

Data mining technology is a powerful tool that can be used to extract useful information, patterns, and relationships from large-scale data sets. In the research and application of data mining, researchers often need to establish hypotheses and define relevant variables in order to carry out targeted analysis and mining.

Research hypotheses are the basis of data mining research. They are reasonable guesses or assumptions of researchers. These assumptions help guide the design and execution of data mining tasks and play a key role in the interpretation of results. In the feature correlation hypothesis, the purchase of a certain product is highly correlated with the user's search history and browsing history. Based on the user's search and browsing history, the user may show a higher interest in the relevant product, thus increasing the likelihood of purchase. In the seasonal hypothesis, sales on an e-commerce platform increase significantly during the holiday season (such as Christmas), which is usually accompanied by an increase in seasonal demand for shopping, which may lead to an increase in sales. In the user classification hypothesis, users can be divided into different purchase types based on their purchase history, such as "discount hunters" and "high-end consumers", and the purchasing behavior and preferences of users can be used to identify their purchase types, which helps in the development of personalized marketing strategies.

Variables are the basic components of data mining analysis, they are the carriers to extract information from data. When selecting variables, researchers need to consider the following aspects: Independent variables are variables that are used to predict or explain dependent variables. In data mining, researchers typically select a set of independent variables to predict or explain one or more dependent variables. For example, in a market forecast, commodity prices, advertising costs, and the number of competitors can be used as independent variables, and sales volume can be used as dependent variables. Correlation variables are data attributes or features used to describe and analyze in data mining research, and the selection of appropriate correlation variables is critical to the success of the research because they directly affect the performance of the model and the interpretability of the results. User attribute variables mainly include user age, gender and geographical location, which are used to describe the basic characteristics of users, such as age, gender ratio and geographical distribution. Behavioral characteristic variables mainly include user search history, browsing history and purchase history. These variables are used to capture users' online behaviors, including search keywords, product pages viewed, and types and frequencies of products purchased. Commodity attribute variables Main commodity category, price, discount information, these variables describe the characteristics of the commodity, such as the category, price range, and any discount information (See Table 4).

Table 4. Variables related to user shopping behavior

Variable name	Description
User ID	The unique identifier of the user
Age	User's age
Gender	User's gender
Geographical position	The area where the user lives
Search keywords	The user's most recent search terms
Browsing history	Product pages viewed by users
Purchase history	The user's purchase history
Commodity category	The main category to which the commodity belongs
Price	Commodity price
Discount information	Discount information on goods

These variables can help researchers better understand user shopping behavior, build models, and test research hypotheses.

The data can be numeric, typed, textual, or time series. Depending on the type of data, researchers need to choose appropriate data mining techniques and variable conversion methods.

Table 5. Selection of variables

Product ID	Price ($)	User reviews (1-5 points)	Sales volume (PCS)	Seasons (Spring, summer, autumn, winter)
001	50	4.5	1000	Spring
002	30	3.8	800	Summer
003	70	4.2	1200	Autumn
004	40	3.5	900	Winter

Table 5 shows examples of product-related variables, including price, user reviews, sales volume, and season, that will be used to analyze the factors that influence product sales.

The clear definition of research hypotheses and variables is a key step in a data mining project, which directly affects the final data mining results. By selecting the right variables and methods, researchers can find meaningful patterns and rules, which provide a strong basis for problem solving and decision support.

3. Data analysis and results

3.1. Descriptive analysis

Descriptive analysis is an important stage in data mining and data analysis, its goal is to reveal the key features and trends of a data set by summarizing, visualizing, and understanding the data. In descriptive analysis, the use of statistical metrics can help to better understand the distribution, central trends, and variability of the data.

The mean is the sum of all observations in the data set divided by the number of observations, and it represents the central trend of the data (Shmueli, Bruce & Patel, 2016).

The median, as shown in the formula, is the value in the middle of the data set after it has been sorted, and it is robust for dealing with extreme values in the data set.

$$D_T = \{G \in AC_{loc}((l,m)) | PG \in C_{loc}((l,m))\} \tag{2}$$

Variance As shown in the formula, variance measures the dispersion of the data, that is, the difference between the observed values and the mean. A large variance indicates that the data is widely dispersed.

$$p=1,2,.....,k \tag{3}$$

Standard deviation as shown in the formula, standard deviation is the square root of the variance, which measures how discrete the data is. A larger standard deviation indicates a higher degree of data dispersion.

$$d(i,j) = \sqrt{(x_{i1} - y_{j1})^2 + (x_{i2} - y_{j2})^2 + \cdots + (x_{in} - y_{jn})^2} \tag{4}$$

User behavior trend analysis is a key aspect of descriptive analytics, which is used to reveal the behavior patterns and trends of users over a specific period of time, and purchase trend analysis can be achieved by tracking a user's purchase history（See Table 6）.

Table 6. User activity data

User ID	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
User 1	5	7	6	8	9	10	4
User 2	2	3	1	2	5	0	2
User 3	8	9	7	10	11	9	8

From this data, the average number of purchases per month, the mean and standard deviation of the number of purchases, and the median number of purchases can be calculated to identify the purchasing trend of the user. User activity analysis is designed to understand the online activity of users. The following table shows the weekly activity of three users on a social media platform.

By analyzing each user's weekly activity, they can identify their active time and trends, providing valuable insights into content delivery and user interaction on social media platforms.

3.2. Display of data mining results

The presentation of data mining results is the key link to effectively communicate the results of data mining process to decision makers and stakeholders. This paper will discuss the presentation methods of data mining results from three perspectives: model performance evaluation, user group analysis and user behavior pattern recognition (Provost & Fawcett, 2013). Through these methods, decision-makers can be helped to better understand the insights and decision-making recommendations of data mining.

In data mining projects, model performance evaluation is an important step to ensure model validity. The confusion matrix is used to show the performance of a classification model, including the number of true, false positive, true negative, and false negative cases, and is the basis for evaluating the model's accuracy, accuracy, recall, and F1 score.

Receiver Operating Characteristic curve (ROC curve) shows model performance by the relationship between true case rate (TPR) and false positive case rate (FPR) under different thresholds. the AUC value (Area Under the Curve) is the area under the ROC curve to measure the classification ability of the model. The closer the AUC value is to 1, the better the model performance. User behavior pattern recognition involves discovering specific behaviors and trends of users in data. Time series charts can be used to show changes in user behavior over time, and they can help identify seasonality, trends, and anomalies; User behavior path diagrams are used to visualize the user's interaction path in an application or website. It helps to understand the user's processes and preferences (Berry & Linoff, 2019). The effective presentation of data mining results is crucial for decision making and problem solving. With the right charts, tables, and visualization tools, data mining insights can be communicated to relevant stakeholders, helping them better understand the data and make informed decisions.

4. Optimization of strategic decision-making of multinational corporations

Multinational corporations are faced with the challenge of complex strategic decision in the global competition. The strategic decision of a multinational corporation usually involves multiple decision levels and complex processes. The first step in the decision-making process is to identify problems and set strategic goals, which may involve market analysis, an assessment of the competitive environment, and a review of the company's internal resources and capabilities. Once the problem and objectives are clear, the multinational company collects a variety of data, including market data, financial data, customer data, etc., which will be used to analyze and evaluate different strategic options. On the basis of data collection and analysis, companies generate multiple strategic options and use different evaluation methods (e.g., SWOT analysis, cost-benefit analysis) to determine the best option. Once the best option is determined, the decision making phase involves the formal development and planning of the decision. This includes resource allocation, timetabling and responsibility allocation. Decision implementation stage is the process of putting strategy into practice. At the same time, the company needs to constantly monitor the execution of the strategy to ensure that the objectives are achieved and make necessary adjustments.

Data mining technology plays an important role in the strategic decision optimization of multinational corporations. Market analysis is a key component of strategic decision making. By analyzing market share and growth rates, companies can identify markets with the greatest growth potential and adjust strategies to optimize resource allocation. Through data mining technology, companies can divide customers into different segments to better meet their needs and develop personalized marketing strategies. By analyzing historical sales data, data mining techniques can help companies predict future product demand in order to better manage inventory and supply chains.

Data mining is a method of extracting patterns, trends and information from large-scale data using computer technology. In today's information age, data has become an important resource in various fields. The application of data mining technology has profoundly changed the way of decision optimization. A key decision optimization task is to predict future events or trends and make decisions based on those predictions. Data mining techniques can generate accurate predictive models by analyzing historical data. For example, in supply chain management, data mining can be used to predict sales trends in order to better plan production and inventory (Jasiewicz & Miądlicki, 2020). Organizations often need to make decisions with limited resources, such as allocating money, human resources, or equipment. Data mining can help determine the best resource allocation strategy. In healthcare, data mining can be used to optimize the allocation of hospital beds to meet the needs of patients. Data mining can also be used to identify anomalies and risks, thereby helping organizations better manage risk. In finance, data mining techniques can be used to detect credit card fraud or market volatility in order to take timely action. Personalized decision support is the process of making decisions customized according to individual needs and characteristics. Data mining can analyze an individual's historical behavior and preferences to provide personalized recommendations and decision support for each person. In e-commerce, this means personalized product recommendations and pricing strategies. Data mining is widely used in marketing and customer relationship management. It can be used to identify potential customers, predict customer churn, analyze market segmentation, and optimize advertising delivery. This helps organizations better understand their customer base and provide better products and services. Decision optimization in manufacturing and production areas requires consideration of various factors, including production capacity, raw material availability, process efficiency and product quality. Data mining can help analyze production data, identify potential problems and optimize production processes, thereby improving production efficiency (SERGEY, 2018). Governments and the public sector can also benefit from data mining technologies. It can be used to analyze socio-economic data to optimize policy making and resource allocation. For example, urban planning can use data mining to improve traffic flow management and urban infrastructure planning. Through the application of data mining, organizations can better understand their internal operations, identify potential efficiency issues, and take steps to improve efficiency. This can be achieved by reducing costs, reducing waste of resources and optimizing processes.

Based on the results of data mining analysis, companies can make optimization recommendations and strategic recommendations to improve their decision-making and business operations. Based on the market analysis results, the company can recommend expanding its investment in market B because it has a higher annual growth rate and lower competitive pressure; Based on the customer segmentation results, the company can develop personalized customer marketing strategies, such as providing special offers and services to high-value customers; Based on product demand forecasts, companies can optimize supply chain management to ensure sufficient product inventory and provide timely supply during peak demand periods.

5. Discussion

This study uses data mining technology to analyze the strategic decision of multinational corporations. Through market analysis, customer segmentation, and demand forecasting, the research reveals the growth potential of different markets, the characteristics of customer groups, and trends in product demand. These results provide strong decision support for companies, enabling them to develop more targeted strategies and improving the accuracy and credibility of decisions.

The practical significance of this study is that it provides a method for multinational corporations to optimize their strategic decisions by using data mining technology. By analyzing market and customer data, companies can better understand market trends, customer needs, and respond more flexibly to the changing competitive environment. This helps to improve market competitiveness, reduce risks and increase profitability. Despite the excellent performance of data mining technology in this study, there are still some limitations. First, the quality of the data has an important impact on the results of the analysis. Incomplete, inaccurate, or biased data can lead to analysis distortion. Secondly, model selection and parameter adjustment may also affect the stability and reliability of the analysis results. In the end, data mining is just a tool, and its successful application depends on deep understanding and interpretation by domain experts. In order to overcome the limitations of the above methods, future research can take the following improvement directions. First, improving data quality is crucial. Companies can invest in data acquisition, cleaning, and validation to ensure that the analyzed data is trustworthy. Secondly, model selection and parameter adjustment should be more rigorous and systematic. Cross-validation and parameter tuning techniques are used to improve the performance and generalization ability of the model. Finally, the data mining process should be combined with the knowledge of domain experts to better interpret the model results and translate them into practical strategies.

Future research could further develop predictive analytics methods to help multinational companies better predict market trends, customer needs, and competitive dynamics. Based on techniques such as time series analysis, machine learning, and deep learning, more accurate predictive models can be built to gain insight into market opportunities and potential risks ahead of time. In order to better translate data mining results into practical actions, future research can develop intelligent decision support systems. These systems can integrate data mining models into the decision-making process and provide decision-makers with real-time recommendations and strategy recommendations in response to changing market conditions. The strategic decisions of multinational companies involve many fields, including marketing, supply chain management, finance and so on. Future research can promote cross-disciplinary collaboration to integrate knowledge and data from various fields to provide more comprehensive support for strategic decision-making.

After summarizing the above discussion, this study emphasizes the importance of data mining in strategic decision optimization of multinational corporations, and proposes improved methods and future research directions to promote further development and application in this field. By making full use of data mining technology, multinational companies can better cope with global competition and achieve strategic goals.

6. Conclusion

With the title of "Research on Optimization of strategic decision of multinational Corporations based on User behavior Analysis based on Data mining", this paper deeply discusses the application and optimization of data mining technology in strategic decision of multinational corporations. Through a comprehensive study of data mining methods and practices, the conclusions of this study are as follows: First, data mining technology provides a powerful tool for multinational companies to better understand and analyze user behavior. By analyzing user behavior data, companies are able to identify market trends, customer needs, and competitive dynamics, providing powerful support for strategic decisions. Case studies such as market analysis, customer segmentation and demand forecasting in this study further demonstrate the practical application potential of data mining technology in strategic decision making. Secondly, this study emphasizes the importance of data quality. High-quality data is fundamental to the success of data mining, so multinational companies should invest in data acquisition, cleaning, and validation to ensure the accuracy and completeness of data. At the same time, model selection and parameter adjustment are also key steps to ensure the reliability of data mining results, and companies should adopt a systematic approach to improve model performance and generalization ability. At last, the direction of future research is proposed. Predictive analytics, intelligent decision support systems and cross-domain cooperation are considered to be the development directions in the field of strategic decision optimization in multinational corporations. These directions help to better respond to changing market conditions and improve the efficiency and effectiveness of strategic decisions.

To sum up, data mining technology has great potential in strategic decision optimization of multinational corporations. By making full use of data mining methods and tools, companies can better understand the market and customers, develop more targeted strategies, improve competitiveness, and achieve long-term sustainable development. With the continuous advancement of technology and the deepening of research, data mining will continue to provide strong support for the strategic decisions of multinational companies and promote the success and innovation of enterprises.

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