

Transformation of New Quality Productivity in Enterprise Management Empowered by AI: Evolution from Automation to Intelligent Decision Making

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Abstract: In modern enterprise management, the application of AI (Artificial Intelligence) technology is rapidly driving the transformation of productivity from traditional automation to intelligent decision-making. This article explored the background, current situation, and future development direction of this transformation, analyzed the current problems, and introduced new methods and specific cases of AI empowerment to achieve intelligent decision-making. This article studied the application effect of XGBoost algorithm in enterprise management, with a focus on evaluating its performance in improving production efficiency, decision accuracy, reducing operating costs, and improving customer satisfaction. After applying the XGBoost algorithm, the average production efficiency increased to 60 pieces, an increase of 20%; the average decision accuracy increased to 0.92; the monthly average operating cost decreased to \$80000, a decrease of 20%; the quarterly average customer satisfaction score increased to 4.2 points, an increase of about 20%. From the data conclusion, it can be seen that the XGBoost algorithm has a significant efficiency improvement effect in intelligent decision support systems, providing strong technical support for the intelligent transformation of enterprise management.

Keywords: Artificial Intelligence; Enterprise Management; XGBoost Algorithm; Productivity Transformation; Intelligent Decision-making.

1. Introduction

In modern enterprise management, although traditional automation technology has been widely applied, its limitations are becoming increasingly apparent. Automation technology mainly improves the efficiency of repetitive tasks, but its performance is not satisfactory when facing complex decisions and dynamic environments. With the increasingly fierce market competition and the constantly changing external environment, the demand for efficient decision-making and flexible response by enterprises has become increasingly urgent. In this context, the application of XGBoost algorithm can effectively compensate for the shortcomings of traditional automation technology and help enterprises achieve a comprehensive transformation from simple automation to intelligent decision-making.

This article explores the specific application of XGBoost algorithm in enterprise management and verifies its significant effects in multiple aspects. The experimental results show that the XGBoost algorithm can significantly improve production efficiency, enhance decision-making accuracy, reduce operating costs, and enhance customer satisfaction. These results demonstrate the effectiveness of XGBoost algorithm in intelligent decision support systems, providing solid theoretical and practical support for the transformation of enterprise management towards intelligence.

This article first introduces the research background, importance of the research, and a review of existing literature

in the introduction section. The method stage introduces data collection and preprocessing, model training and optimization, natural language processing applications, and integration with intelligent decision-making systems. The actual effectiveness of XGBoost algorithm is evaluated through experiments in four aspects: production efficiency, decision accuracy, operating costs, and customer satisfaction. Finally, the experimental results are discussed, and the main contributions of the research and future research directions are summarized.

2. Related Works

Many scholars have conducted in-depth research on the application of AI in enterprise management. For example, the application of AI in mechanical design, manufacturing, and automation is becoming increasingly widespread. Hua Jiayi believed that by applying AI technology, enterprises can improve production efficiency, reduce costs, and enhance product quality and competitiveness [1]. Industrial Internet, as a new industrial ecology deeply integrated with the new generation of information technology and industrial manufacturing, is of great significance in improving the operating efficiency of enterprises and promoting the high-quality development of manufacturing industry. Therefore, Wang Kangzhou comprehensively analyzed the relevant literature on operation management under the industrial Internet scenario [2]. The integration of AI analysis provides the potential for transformation in optimizing the manufacturing supply chain. Mahi R used a qualitative case

study method to explore specific ways in which manufacturers utilize artificial intelligence solutions in demand forecasting, inventory management, logistics planning, and predictive maintenance [3]. Helo P provided an overview of the concepts of artificial intelligence and supply chain management, followed by a timely and critical analysis of AI-driven supply chain research and applications [4]. Many companies are currently investing in artificial intelligence because it has the potential to improve customer satisfaction or financial performance. Therefore, Monod E discussed the impact of differentiation and power transfer on theory and practice after applying artificial intelligence systems to support customer relationship management [5]. AI has gradually been applied into various industries, but research on customer attitudes and behaviors towards using artificial intelligence is still in its early stages. Nguyen T M examined the impact of artificial intelligence on traffic customer experience, customer brand recognition, and customer promotion based on traffic theory and social identity theory [6]. Cheng Y's research aimed to explore the role of AI-driven chatbot marketing activities in establishing relationships between brands and their customers, and to expand the connection between relationship marketing and online consumer behavioral intentions [7]. However, most of these studies have focused on the application of AI technology in specific fields, and there is a lack of comprehensive exploration on how to systematically achieve intelligent decision-making transformation in enterprise management.

To address the above issues, some researchers have attempted to improve enterprise management efficiency by integrating different AI technologies and management methods. Inventory cost control is an important factor in supply chain management. If the supplier's inventory is insufficient, the opportunity to trade products can decrease. The main purpose of Govindasamy C was to utilize

blockchain technology to achieve intelligent inventory management in the cloud domain [8]. Cuartas C proposed a hybrid algorithm based on reinforcement learning and inventory management methods to determine the optimal time and required quantity to purchase a certain product [9]. With the rapid development of technology, people are increasingly using AI and machine learning technologies in their daily lives. Yin X discussed the ethical dilemmas faced when using natural language processing techniques and machine learning methods for internal communication in auditing [10]. However, these methods still face high technical complexity and implementation costs in practical applications, making it difficult to promote them in small and medium-sized enterprises. This article proposed a comprehensive management solution based on XGBoost algorithm technology, aiming to overcome the shortcomings of existing research and provide a highly operable and cost-effective solution.

3. Methods

3.1. Data Collection and Preprocessing

This article carries out detailed planning and implementation in data collection and preprocessing to ensure the quality and consistency of the data used, laying a solid foundation for subsequent model training and optimization. Firstly, various data related to production, operations, and customers are comprehensively collected from the enterprise's ERP (Enterprise Resource Planning) system, sensor network, and external market data sources. These data cover multiple dimensions such as production efficiency, operating costs, and customer feedback, providing a rich source of information for building a comprehensive intelligent decision support system. The specific customer dataset is shown in Table 1:

Table 1. Customer dataset

Customer ID	Age	Annual Income	Satisfaction Score	Purchase Frequency	Loyalty Years	Complaints
1	34	94537	3	15	4	1
2	67	135814	4	22	7	0
3	25	45623	2	8	2	3
...
1000	53	78056	5	30	6	1

During the data collection process, standardized data collection interfaces and protocols are implemented for the data in Table 1 to ensure real-time and accurate data. In order to process data from different sources, a unified data format and storage structure are designed, enabling seamless integration of data into the enterprise's data management system.

After the data collection is completed, detailed data cleaning and preprocessing work is carried out. Due to the possibility of missing, duplicate, and outliers in the data, basic statistical analysis is first conducted to identify and address these issues. For missing data, multiple interpolation methods are used, and methods such as mean interpolation, linear interpolation, or interpolation prediction are selected according to specific situations for processing. For mean interpolation, Formula (1) can be used to represent:

$$x_i = \frac{1}{n} \sum_{j=1}^n x_j \quad (1)$$

Among them, in Formula (1), x_i is the missing value; x_j

represents all non missing values in the dataset; n is the number of non missing values.

For duplicate data, deduplication is performed to ensure the uniqueness and representativeness of each data. For outliers, statistical methods such as box plot analysis and standard deviation method are used to identify them, and reasonable corrections or elimination are made according to the actual situation. The determination of outliers can be represented by Formula (2):

$$Z = \frac{x - \mu}{\sigma} \quad (2)$$

In Formula (2), Z is the standard score; x is the data point; μ is the mean of the data; σ is the standard deviation of the data. When $|Z| > 3$, the data point is considered an outlier.

In addition, the data is standardized to eliminate dimensional differences between different features, making subsequent model training more stable and efficient. Specifically, numerical data is normalized and mapped to the $[0,1]$ interval; for categorical data, a unique hot encoding

method is used to convert it into a numerical format that can be used in machine learning models.

To ensure the timeliness and representativeness of the data, two key technologies are adopted: temporal analysis and feature engineering. Firstly, through time series analysis, the trend, seasonal, and periodic features of the data are successfully extracted. These features provide important information about time dependence for the model, making predictions more accurate.

Next, various derived features are constructed through feature engineering based on business requirements and the uniqueness of data. For example, by combining historical sales data and holiday information, a "holiday sales increment" feature is developed, which helps the model predict a surge in sales during holidays.

Overall, data collection and preprocessing constitute the core part of this study. The high quality and consistency of data are ensured through a series of strict processes and diverse technical means. These carefully prepared data provide a solid foundation for subsequent XGBoost algorithm training and the construction of an intelligent decision support system [11].

3.2. Model Training and Optimization

The XGBoost model was initially mainly used in industries, pharmaceuticals, transportation, and other fields. In recent years, it has been applied in economic fields such as housing price prediction, business information prediction, and stock selection, and has performed well. However, there is no literature using it for predicting corporate credit ratings. This article optimizes the XGBoost algorithm based on the existing external ratings of enterprises, using rated enterprise information as a sample to predict the credit rating of unrated enterprises. Compared to neural network models, XGBoost performs better in processing structured data, with low computational requirements and lower requirements for data volume and hardware [12].

This study chooses XGBoost to construct a credit rating prediction model, combined with Bayesian optimization algorithm parameter tuning, and finds the global optimal solution through Gaussian process regression to improve the accuracy of credit rating prediction. In cross validation, a subset is used for validation and the remaining subsets are used for training. The calculation formula for cross validation can be represented by Formula (3):

$$CV_{error} = \frac{1}{k} \sum_{i=1}^k Error(S_i) \quad (3)$$

Among them, in Formula (3), k is the fold of cross validation, and $Error(S_i)$ is the error of the i -th fold.

During the model training process, multiple hyperparameters of the XGBoost algorithm are optimized, including learning rate, maximum depth, subsampling rate, and column sampling rate. The learning rate controls the magnitude of weight adjustment of the tree in each iteration; the maximum depth determines the complexity of each tree; the sub sampling rate and column sampling rate are used for randomly sampling data and features to prevent overfitting. By combining grid search and random search, the optimal combination of these hyperparameters can be found. During each parameter tuning process, the training error and validation error of the model are recorded, and the parameter combination with the smallest validation error is selected as the final model parameter.

In order to further improve the performance of the model, the early stop method is adopted to prevent overfitting.

During the training process, if the validation error does not significantly decrease within several consecutive rounds, the training is terminated in advance. This not only improves the generalization ability of the model, but also reduces training time.

After completing the training and tuning of the XGBoost model, an independent test set is used for XGBoost model evaluation in this article. To ensure the wide applicability of the evaluation results, key performance indicators such as accuracy, precision, recall, and F1 value are selected to comprehensively evaluate the performance of the model.

In the data analysis phase, the XGBoost's feature importance analysis tool is also extensively utilized to identify the factors that have the greatest impact on the model's prediction, including customer age, annual income, purchase frequency, and satisfaction score. For example, analysis shows that customers with high annual income are more inclined to purchase high priced products, which provides an important basis for the market strategy.

After conducting these operations, not only does the effectiveness of the XGBoost model be validated, but valuable insights are also provided for enterprise management.

3.3. Natural Language Processing Applications

Early NLP technology is based on the study of linguistics and tended to be rule driven. The rule-based NLP technology abstracts contract risk into a set of syntax rules, specifying that the input and output results of a set of data conform to the "If-Then" logic to determine whether the target corpus meets the preset risk rules. Common rule-based NLP methods include If-Then expert systems, regular expressions, etc.

Data preprocessing includes steps such as word segmentation, part of speech tagging, and removing stop words to help structure text data and facilitate subsequent analysis. When processing multilingual text, using a multilingual model ensures accuracy.

The NLP techniques such as sentiment analysis, topic modeling, and keyword extraction are applied to extract information from text. Emotional analysis evaluates the emotional tendencies of customer and employee feedback; topic modeling identifies the main discussion topics in the text; keywords are extracted to identify the most important vocabulary in the text. These technologies collectively support the decision-making process of enterprises.

In terms of sentiment analysis, a deep learning-based BERT (Bidirectional Encoder Representations from Transformers) model is used, which is a pre trained language model that can capture contextual information of text, thereby improving the accuracy of sentiment classification. Among them, the mathematical expression of emotion classification can be achieved through the softmax function, as shown in Formula (4):

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (4)$$

Among them, z_i is the output vector of the model. The experimental results indicate that the BERT model performs well in sentiment analysis tasks and can accurately identify emotional tendencies in customer and employee feedback. In terms of topic modeling, the LDA (Latent Dirichlet Allocation) model is adopted to identify the main themes in the text data through iterative optimization. The results of the LDA model reveal the main issues that customers are concerned about, such as product quality, after-sales service, and price, providing important basis for enterprises to take improvement

measures.

In addition, a visualization tool is developed to present NLP analysis results to management and decision-makers in the form of charts and reports. Through this tool, enterprise managers can intuitively see the emotional trends, main concerns, and potential issues feedback from customers and employees, thus making wiser decisions.

The NLP technology provides powerful tools for enterprises to extract and analyze information from textual data. Through techniques such as sentiment analysis, topic modeling, and keyword extraction, it is possible to better understand the needs and feedback of customers and employees, thereby improving the management level and decision-making quality of enterprises. In the future, with the continuous development of NLP technology, its application prospects in enterprise management can be broader, providing more possibilities for further optimization and innovation of intelligent decision support systems [13].

3.4. Integration of Intelligent Decision-making Systems

After completing data collection, preprocessing, model training and optimization, as well as natural language processing applications, the integration stage of intelligent decision-making systems is entered. System integration is the organic combination of various independent modules to form a unified, coordinated, and efficient intelligent decision support platform, in order to achieve data-driven enterprise management.

Firstly, the preprocessed data and trained model are integrated into the enterprise's management information system. For this purpose, using API based middleware can achieve data exchange and seamless integration between different systems. Through this middleware, data from various modules can be transmitted and shared in real-time, ensuring the overall coordination and consistency of the system.

In order to accelerate the system's response speed and improve processing capabilities, a distributed computing architecture is adopted. The system improves processing efficiency and enhances system scalability and reliability by processing data analysis and model prediction tasks in parallel through computing nodes on multiple servers. In terms of data storage, a high-performance relational database and MySQL are combined to ensure structured storage of data, while also supporting the processing of semi-structured and unstructured data.

In user interface design, the ease of use and intuitiveness of the system are emphasized. A visual dashboard is developed, allowing managers to easily view key performance indicators such as production efficiency and customer satisfaction. The dashboard also has interactive functions such as data filtering, chart switching, and trend analysis, supporting users to conduct detailed analysis and decision support according to their needs. At the same time, an automatic refresh mechanism is designed to ensure real-time updates of data and analysis results.

The system has also developed various warning and recommendation functions, which automatically identify and warn of abnormal situations, such as abnormal production efficiency or significant decrease in customer satisfaction, through real-time monitoring data analysis. Based on the prediction results of the XGBoost model, the system can also provide optimization suggestions to managers, such as

adjusting production plans, optimizing resource allocation, etc., further improving the practicality and intelligence level of the system.

In terms of security, multiple measures are taken to ensure the security and privacy of data. The system integrates identity authentication and access control mechanisms, ensuring that only authorized users can access sensitive data and functional modules. Meanwhile, all data transmission adopts encryption technology to prevent data leakage and tampering during transmission. Security audits and risk assessments are regularly conducted to promptly identify and eliminate potential security risks. The encryption algorithm used in the data transmission process can be represented by Formula (5):

$$C = E(k, P) \quad (5)$$

Among them, in Formula (5), C is the encrypted ciphertext; E represents the encryption algorithm; k represents the key; the clear text is represented as P in the formula.

In summary, the integration of intelligent decision-making systems is an important aspect of this study. By organically combining various modules such as data processing, model application, and user interface, a powerful, easy to operate, and highly intelligent decision support platform is constructed. This platform not only improves the management efficiency and decision-making quality of enterprises, but also provides solid technical support and guarantee for the intelligent transformation of enterprises.

4. Results and Discussion

4.1. Production Efficiency Improvement Evaluation Experiment

The production efficiency improvement experiment evaluates the effectiveness of XGBoost algorithm in improving enterprise production efficiency in intelligent decision support systems. The experiment compares and analyzes the production efficiency changes of two sets of data within 100 days, as shown in Figure 1:

From Figure 1, it can be seen that the average production efficiency under traditional automation systems is 50 products per hour, while the intelligent decision support system optimized by XGBoost algorithm improves the average production efficiency to 60 products per hour, an increase of 20%. From the data conclusion, it can be seen that the application of XGBoost algorithm in intelligent decision-making has greatly improved production efficiency, which also provides strong support for the transformation of enterprises from automation to intelligent decision-making.

4.2. Decision Rate Evaluation Experiment

The decision rate evaluation experiment evaluates the decision accuracy of XGBoost algorithm in intelligent decision support systems. Ten iterative experiments are conducted in the experiment, and the decision accuracy in different iterations is recorded.

From Figure 2, it can be seen that in the ten iterations of the experiment, the average decision accuracy of XGBoost algorithm in intelligent decision support systems is 0.92; the average decision accuracy of the random forest algorithm is 0.88; the average decision accuracy of the logistic regression algorithm is 0.81. From the data conclusion, it can be seen that the XGBoost algorithm performs well in each iteration, and its application in enterprise management can significantly

improve decision accuracy, providing reliable technical support for the transformation of enterprises from automation

to intelligent decision-making, as shown in Figure 2:

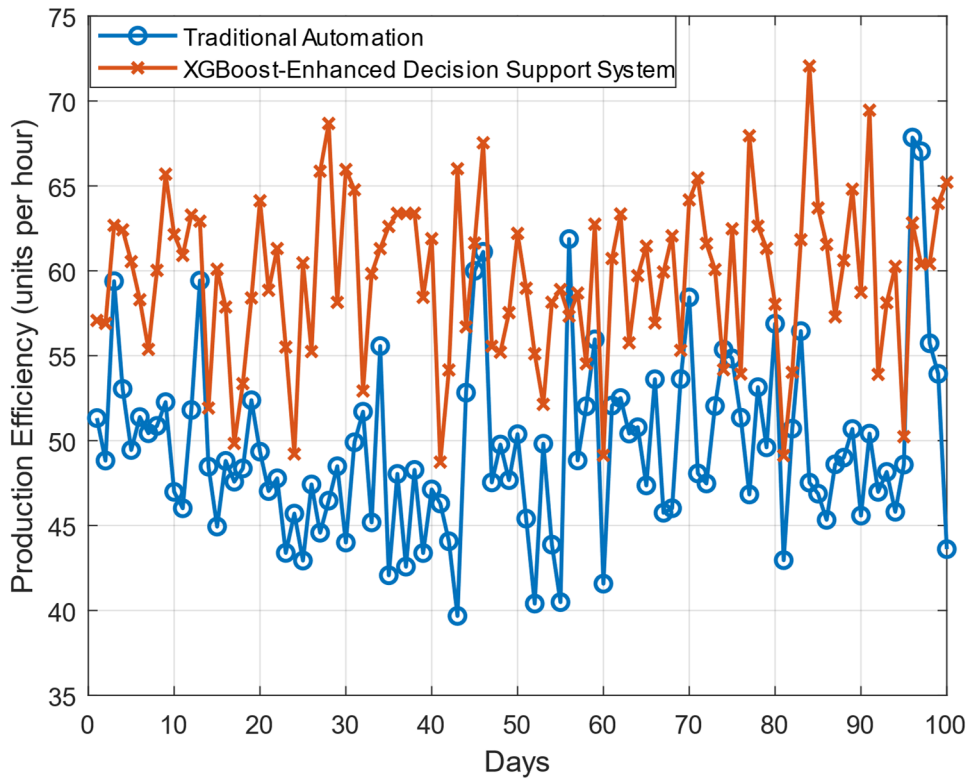


Figure 1. Evaluation of production efficiency improvement

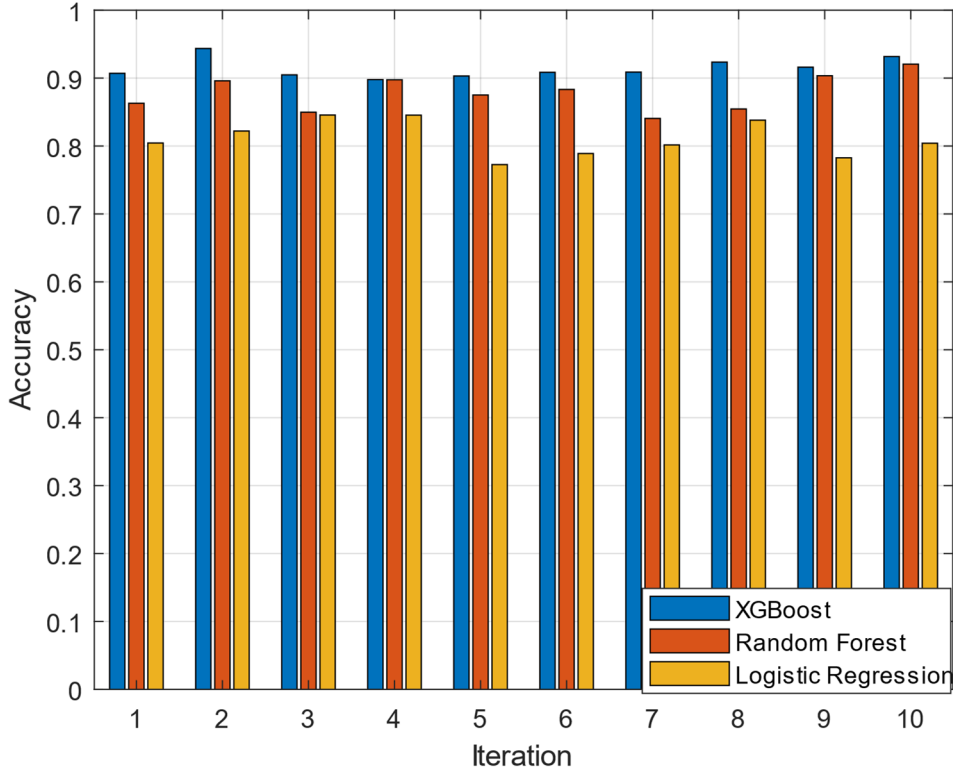


Figure 2. Evaluation of decision accuracy

4.3. Cost Reduction Evaluation Experiment

In the cost reduction experiment, the effectiveness of XGBoost algorithm in reducing operational costs of enterprises in intelligent decision support systems is

evaluated. The experiment records the operating cost situation, with one representing the monthly operating cost in a traditional management environment and the other representing the monthly operating cost after applying the XGBoost algorithm. The changes in operating costs within 12

months are shown in Figure 3:

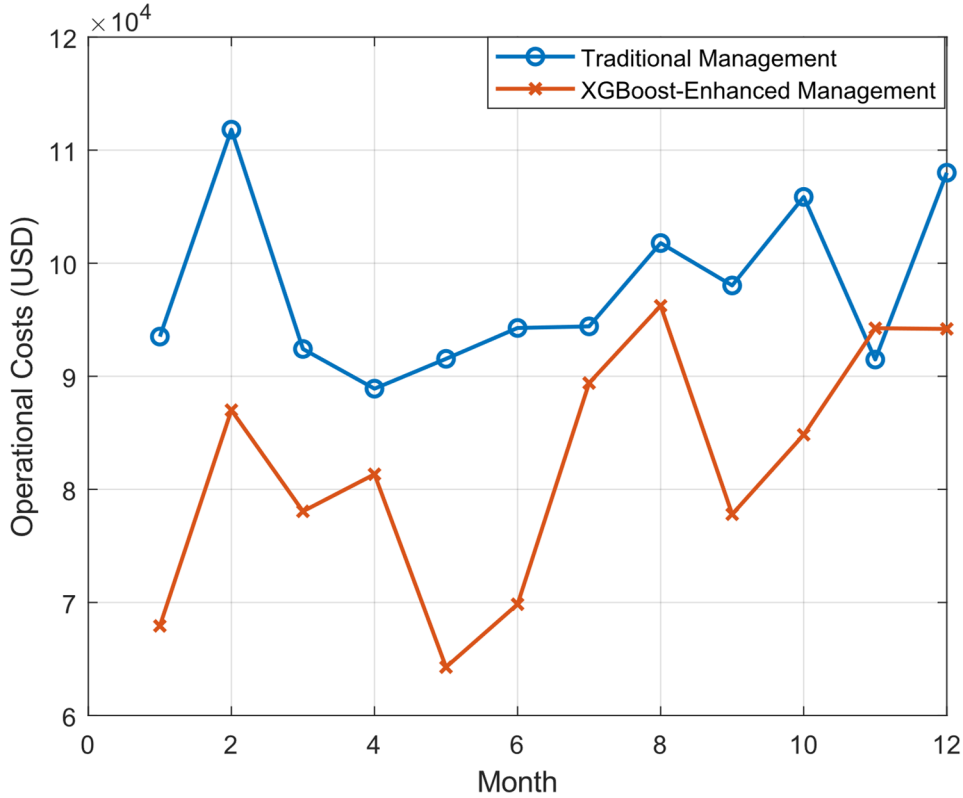


Figure 3. Cost reduction analysis

From Figure 3, it can be seen that in a traditional management environment, the average monthly operating cost is \$100000. However, after using the XGBoost algorithm, the average monthly operating cost decreases to \$80000, a decrease of 20%. From the data conclusion, it can be seen that the application of XGBoost algorithm in intelligent decision support systems can effectively reduce the operating costs of enterprises, improve resource utilization efficiency, and provide significant economic benefits and competitive advantages for enterprises in fierce market competition.

4.4. User Experience Evaluation Experiment

The user experience evaluation experiment evaluates the effectiveness of XGBoost algorithm in improving customer satisfaction in intelligent decision support systems. The experiment records changes in customer satisfaction over four quarters, and the specific data details are shown in Table 2:

Table 2. User experience evaluation

Quarter	Traditional_Management	XGBoost_Enhanced_Management
1	3.1	3.9
2	4.1	4.3
3	3.1	4.4
4	3.7	4.2

In Table 2, under the traditional management environment, the quarterly average customer satisfaction score is 3.5, while using the XGBoost algorithm, the quarterly average customer satisfaction score increases to 4.2. From the data in Table 2, it can be seen that the application of XGBoost algorithm in intelligent decision-making can effectively improve customer satisfaction and provide enterprises with better service and customer experience.

5. Conclusion

In the study, the application of XGBoost algorithm in enterprise management was deeply explored by implementing it in multiple enterprises. By collaborating with local small and medium-sized enterprises and applying an XGBoost-driven intelligent decision support system, a comprehensive implementation framework was constructed, covering data collection, preprocessing, model training, optimization, and natural language processing applications. During the execution process, challenges such as inconsistent data quality and insufficient resource allocation were encountered. However, through close collaboration with enterprise technical personnel, a process was developed for data cleaning and validation, significantly improving the availability of data. The experimental results showed that the carefully optimized XGBoost model significantly improved production efficiency and decision accuracy. However, this study mainly used simulated data for preliminary validation, and the complexity and uncertainty in the actual environment may lead to different results. Future research should further validate the applicability of the method proposed in this article in different enterprise environments, explore more simplified and efficient algorithm optimization solutions, and consider the diversity and complexity of practical applications, in order to promote the XGBoost algorithm more widely and support the intelligent transformation of enterprise management.

References

- [1] Hua Jiayi. The Practice of Artificial Intelligence in Mechanical Design, Manufacturing and Automation [J]. Engineering Research and Practice, 2024, 5 (10): 64-66.

- [2] Wang Kangzhou, Wang Dongdong, Dou Lei, et al. Overview of operation management research in the industrial Internet scenario [J]. *Industrial Engineering*, 2024, 27 (2): 1-12.
- [3] Mahi R. Optimizing supply chain efficiency in the manufacturing sector through ai-powered analytics[J]. *International Journal of Management Information Systems and Data Science*, 2024, 1(1): 41-50.
- [4] Helo P, Hao Y. Artificial intelligence in operations management and supply chain management: An exploratory case study [J]. *Production Planning & Control*, 2022, 33(16): 1573-1590.
- [5] Monod E, Lissillour R, Köster A, et al. Does AI control or support? Power shifts after AI system implementation in customer relationship management[J]. *Journal of Decision Systems*, 2023, 32(3): 542-565.
- [6] Nguyen T M, Quach S, Thaichon P. The effect of AI quality on customer experience and brand relationship[J]. *Journal of Consumer Behaviour*, 2022, 21(3): 481-493.
- [7] Cheng Y, Jiang H. Customer–brand relationship in the era of artificial intelligence: understanding the role of chatbot marketing efforts[J]. *Journal of Product & Brand Management*, 2022, 31(2): 252-264.
- [8] Govindasamy C, Antonidoss A. Enhanced inventory management using blockchain technology under cloud sector enabled by hybrid multi-verse with whale optimization algorithm[J]. *International Journal of Information Technology & Decision Making*, 2022, 21(02): 577-614.
- [9] Cuartas C, Aguilar J. Hybrid algorithm based on reinforcement learning for smart inventory management[J]. *Journal of intelligent manufacturing*, 2023, 34(1): 123-149.
- [10] Yin X. Ethical dilemma of using Natural Language Processing (NLP) machine learning method in auditing company internal communication[J]. *International Journal of New Developments in Engineering and Society*, 2023, 7(3): 16-20.
- [11] Kaggwa S, Eleogu T F, Okonkwo F, et al. AI in decision making: transforming business strategies[J]. *International Journal of Research and Scientific Innovation*, 2024, 10(12): 423-444.
- [12] Han Y, Sun H, Liu X, et al. Study on the Impact Factors of Digital Intelligence Empowerment on Organizational Quality Change in Smart Manufacturing Enterprises[J]. *Industrial Engineering and Innovation Management*, 2023, 6(3): 36-42.
- [13] Javaid M, Haleem A, Singh R P, et al. Artificial intelligence applications for industry 4.0: A literature-based study[J]. *Journal of Industrial Integration and Management*, 2022, 7(01): 83-111.