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Application of artificial intelligence and Big Data in financial Management

Jinyi Yang[1*]

[1]Chengdu Foreign languages school, Chengdu, 610000, China

Abstract. As artificial intelligence and big data technologies are rapidly changing the face of financial management. This paper delves into the application of artificial intelligence (AI) and big data technologies in modern financial management, revealing how these two technologies can reshape the financial management process, improve management efficiency and decision-making quality, and create greater economic value for enterprises. The core of the study focuses on the specific applications of AI and big data in financial data processing, risk identification and assessment, predictive analytics, and intelligent decision support, as well as how these applications can contribute to the intelligence, precision, and efficiency of financial management.The significance of this study lies in the fact that it provides new ideas and methods for enterprise financial management practices and promotes the intelligent transformation of financial management. By deeply analysing the application cases and effects of AI and big data in financial management, this paper provides valuable references and lessons on how enterprises can effectively use these technologies to improve their financial management.

1 Introduction

1.1 Research Background

With the rapid evolution of information technology, from manual operation to mechanical auxiliary, to the transformation of comprehensive automation, the wave of digital economy, especially "big wisdom move cloud" (big data, intelligent technology, mobile Internet, cloud computing, Internet of things) the rise of emerging technologies and depth fusion, for financial management to intelligent transformation to build a solid foundation.However, navigating through its landscape is noteasy.To do so, researchers such as Arner et al.(2015) follow a fintech timeline that starts before the 1970's.In particular, the authors explain that the transition from analogue to digital services (Fintech 1.0: 1886 – 1967) is the first manifestation of fintech principles [1].In the new era of digital economy, enterprise management has become more refined, operational efficiency has been significantly improved, the cost structure has been continuously optimized, and at the same time, the competition among enterprises has become more intense. In order to meet the urgent needs

* Corresponding author: yjyyjy7777777@163.com

of the company's business expansion, keep up with the pace of efficient operation and strong competition, and fully highlight the core role of finance in enterprise management, the intelligent transformation of financial management has become an irreversible trend.

The traditional financial management mode mostly focuses on the role of "accounting room", and a lot of time and energy is spent on the record of daily business activities and the preparation of financial statements. Due to the lack of intelligent tools, the basic accounting work has occupied the core task of financial personnel for a long time, which limits their ability to deeply participate in the company's strategic planning and production and operation decision-making. With the advancement of the wave of information technology, financial management has also experienced a profound change from manual account books to financial software assistance, and then to automatic accounting processing and intelligent finance. However, the traditional model focuses on financial accounting and post-hoc analysis, which is slightly insufficient in enabling business and creating value. Only with manual statistical statements or standard analysis statements, it is difficult to effectively support the strategic decisions of enterprises, and even more difficult to actively contribute to the value creation of enterprises.

The construction and operation of the financial sharing center not only optimized the financial organizational structure, standardized the business process, improved the work efficiency and processing quality, but also accelerated the pace of enterprise informatization, promoted the transformation of the thinking mode of financial personnel, and laid a solid talent, organization, data and technology foundation for the transformation of financial intelligence. With the advent of the era of digital economy, the new generation of information technology represented by artificial intelligence and big data is increasingly popularized and deepened, which will further strengthen the financial function. Relying on the good ecology built by the financial sharing center, the enterprise finance will accelerate the progress to the intelligence, and truly realize the core driving role of finance in the enterprise value creation [2].

1.2 Study Purpose and Significance

In the face of the profound changes in the era of digital intelligence, enterprises are in urgent need to explore and innovate financial management paths to cope with new work challenges and market environment. The application of artificial intelligence and big data technology in the field of financial management aims to improve the efficiency and accuracy of decision-making, optimize the financial operation process, strengthen the risk prevention and control ability, and stimulate the sustainable development and innovation vitality of enterprises. The purpose of this study is to explore how these emerging technologies help the transformation and upgrading of financial management, which has far-reaching practical significance and practical value for modern enterprises to maintain the leading position in the competitive market environment and realize the innovation and breakthrough of financial management mode.

1.3 Study Methods

1.3.1 Literature research method

Through the research of intelligent financial management and digital transformation related literature, we can understand the development of intelligent financial management at home and abroad, the role of intelligent financial management, and clarify the relationship between intelligent financial management and digital transformation. Through the research of related literature of artificial intelligence and big data, we understand the development in financial management, the path of artificial intelligence and big data in financial management, and clarify the research direction of the paper. It provides theoretical support for the current application of artificial intelligence and big data in financial management, and provides ideas for the exploration of digital transformation.

1.4 Relevant Concepts and Theoretical Basis

1.4.1 Digital transformation

Companies use modern technology and communication methods to change the way they create value for their customers. This process involves not only the upgrading and transformation of IT systems, but also a comprehensive redefinition of organizational activities, processes, business models, and employee capabilities. Specifically, digital transformation is a process based on data, a new means of production, with online and intelligent features as the core features, and to better meet customer needs through innovative business models.

1.4.2 Data analysis

Financial data analysis is an indispensable part of modern enterprise management, it through a variety of methods and tools for in-depth analysis of enterprise financial data, in order to reveal the business conditions, financial health level and potential risks and opportunities. Through the analysis of financial data, analyze the traditional data analysis and calculation methods, and study the advantages of the statistical new machine learning algorithms and data mining technology.

1.4.3 Risk management

It is an important means of modern financial risk management to conduct credit risk and market risk analysis through prediction model and risk assessment algorithm. Can effectively identify and control the potential uncertainties and negative factors. In terms of credit risk, banks usually adopt user credit risk prediction models based on big data, such as Logistic regression and random forest methods. These models can predict the possibility of default based on customer data and information, helping banks avoid risks and reduce losses. In terms of market risk, the common methods include SWOT analysis method, PEST analysis method and competitive environment analysis method. These methods are useful to assessing the uncertainty of the market environment and its impact on corporate goals and strategies. Comprehensive, effective and flexible analysis and control of market risks is the key to ensure the sustainable development of enterprises [3].

1.4.4 Decision support system

Using AI-driven decision models and optimization algorithms can significantly support financial decisions. AI technology can provide intelligent financial decision support by analyzing a large amount of historical data and assessing the risks and rewards of different decision schemes. In addition, AI has also played an important role in automating financial reporting, accounting processing, and financial forecasting and analysis, improving work efficiency and reducing human error. The application of these technologies not only improves the efficiency and accuracy of financial management, but also brings more business opportunities and competitive advantages to enterprises.

2 Data Analysis

With the advent of the era of big data, the amount of financial data of enterprises has increased sharply, and the traditional financial data analysis methods have been difficult to meet the needs of enterprises for in-depth mining and accurate analysis of data. Therefore, machine learning algorithms and data mining technology have gradually become important tools for financial data analysis.

2.1 Study Methods

Machine learning is an automatic learning method based on data and experience. Through the construction of mathematical models and algorithms, the computer can automatically extract laws and knowledge from the data. In financial data analysis, machine learning algorithms can provide more accurate financial analysis results and predictions for enterprises by learning from a large amount of historical financial data. The three most useful categories are financial risk forecasting, financial fraud detection, and investment decision support. They are all ways to solve the difficulties and problems facing many enterprises and try to avoid the various risks that may occur.

Data mining technology is an efficient data analysis method that can discover useful information and knowledge from large data sets. In practical applications, data mining techniques are often used to solve various problems, such as predicting trends, identifying patterns, classifying data, etc. For data mining, analysts will need to use various technical tools. Among them, the database management system is used to store and manage large amounts of data to ensure the security and consistency of data. Data preprocessing tools are used to clean and integrate raw data and improve the quality of data. The data mining algorithm library is the core of the mining process, including the Pearson algorithm and the ARIMA model, which are used to discover the rules and patterns in the data [4].

Data mining technology can also be applied to financial risk early warning. By building models, such as CNN-LSTM-SW model, mining historical multi-period financial data to realize financial risk early warning. In addition, data mining technology can also be used to dynamically monitor and evaluate the financial situation of enterprises, to find out potential risks in time and take corresponding measures.

Table 1. Specific introduction of machine learning algorithm and data mining technology

Technology / Algorithm	description	Application examples
Machine learning algorithm		
1. linear regression	Models investigating the linear relationships between independent and dependent variables, used to predict continuous values.	Forecast of future sales, cost forecast, etc.
2. Logic regression	Although it is called "regression", it is used for classification problems, especially for dichotomy problems.	Assess the credit risk, predict whether the customer will default, etc.

3. decision tree	By constructing a tree structure to perform classification or regression, the algorithm is easy to understand and interpret.	Identify fraudulent transactions and classify customers with different income levels, etc.
4. random forest	Integrated learning methods based on multiple decision trees to improve prediction accuracy and stability.	Credit risk score, sales forecast, etc.
5. support vector machine (SVM)	Algorithms for classification or regression by finding optimal hyperplanes in a high-dimensional space.	Fraud detection, customer segmentation, etc.
6. neural network	Complex networks that mimic neuronal connectivity in the human brain, suitable for handling nonlinear relationships.	Predict stock prices, credit scores, etc.
Data mining		
1. cluster analysis	Dividing data into groups or clusters makes high data similarity within the same cluster and low data similarity among different clusters.	Customer segmentation, market segmentation, etc.
2. Association rule mining	Find associations between data items, such as "customers who buy A goods also tend to buy B goods".	Shopping basket analysis, cross-selling recommendations, etc.
3. Sequence-based pattern mining	Find time series relationships between data items, such as "the customer buys B item for A period of time after purchasing A item".	Customer behavior prediction, inventory management, etc.
4. anomaly detection	Identify outliers or abnormal patterns in the data that may indicate fraud, error, or special circumstances.	Fraud detection, error identification, etc.

2.2 Major Achievements

It realizes the real-time financial statement generation and financial abnormality detection, and greatly improves the speed and accuracy of data processing. These technologies enable automated data analysis and model building, reduce the workload and cost of manual processing, and make financial analysis more intelligent.

2.3 Current Limitations

Data privacy issues and high cost are the main challenges, and how to use data efficiently while ensuring data security still needs to be further studied. Financial data is often very large and complex, and may contain problems such as deletions, anomalies and duplications, which can affect the results of data mining and visualization. Moreover, transaction data may contain noise and missing values, which can also affect the accuracy of machine learning models. Transaction data changes over time, so the model needs to adapt to changes in the market. However, instead of developing and testing frameworks specifically for AI and machine learning, many companies use the same common framework as traditional algorithms, preventing them from coping with the rapidly changing market.

3 Risk Management

Credit risk and market risk analysis are conducted through the prediction model and the risk assessment algorithm.

3.1 Credit Risk

Credit risk analysis Credit risk refers to the risk that the borrower or the debtor fails to perform its debts or credit obligations in the manner agreed in the contract, causing losses to the creditor. In credit risk analysis, prediction models and risk assessment algorithms are mainly used to evaluate the default rate and credit status of borrowers [5].

3.1.1 Prediction model

Logistic regression model: Logistic Regression is a classic classification model used to predict the borrower's default probability. It estimates the probability of the default event through a feature variable, and the output result is a probability value representing the default likelihood [6].

Decision tree model: The decision tree model forms a tree structure through a series of judgment branches (nodes), and finally obtains the classification results. In credit scores, decision trees are easy to understand and interpret, but may have too appropriate problems and need to be pruned [7].

Support Vector Machine (SVM): The SVM classifies different categories of data points by finding the maximum interval between the data points, which is suitable for processing high-dimensional data and non-linear data. In terms of credit score, SVM can effectively classify borrowers into default and non-default categories [8].

Neural networks: Neural networks process data by simulating the basic structure of the human brain, and are able to handle complex nonlinear relationships. Neural networks perform well in credit risk prediction, but training costs and require significant computational resources and time.

3.1.2 Risk assessment algorithm

The financial liquidity, operating position, profitability and financial status are evaluated by analyzing the balance sheet, income statement and statement of cash flow.

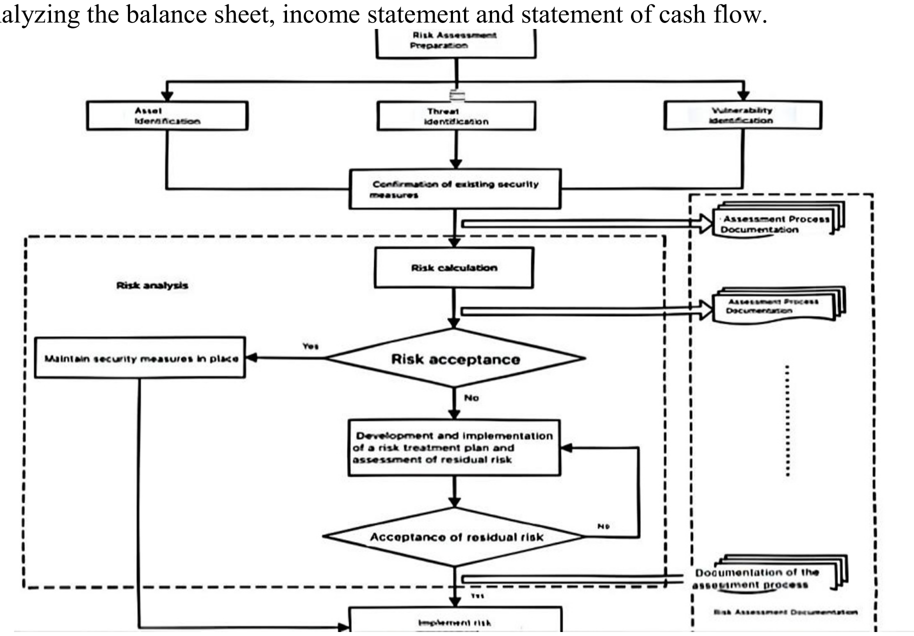

Figure 1. Overview of the risk assessment process diagram

3.2 Market risk

3.2.1 Prediction model

Linear regression model: used to analyze historical data to identify significant factors affecting market risk and to predict future market risk levels. Linear regression models are easy to understand but may not capture complex nonlinear relationships.

Time series analysis: a statistical analysis method used to study the patterns and trends of data changes over time. It involves the process of modeling, predicting, and analyzing a series of data points arranged in chronological order. It aims to reveal the patterns, trends and periodicity behind the data and to make future predictions and decisions based on these patterns and trends. The goal of time series analysis is to extract information from observed time series data to make predictions, analyze trends and patterns and make decision making [9].

Machine learning algorithms: such as decision tree, random forest, support vector machine and neural network, can automatically learn and improve from large amounts of data model performance, capturing complex market dynamics and non-linear relationships [10].

3.2.2 Risk assessment algorithm

Sensitivity analysis: it is a method to evaluate the influence of the model input parameters change on the output results. It is widely used in finance, engineering, climate model and other fields. The main purpose is to determine which input variables are most critical to the model or decision-making process and to help identify and manage risk.

Stress test: simulates the risk a portfolio or financial institution may face in extreme market conditions. Historical scenario analysis or hypothetical scenario analysis were used [11].

VaR (value of risk) model: is a used to measure the financial portfolio or exposure may face the biggest loss, it aims to provide a risk management tool to help financial institutions and investors to assess and control the risk level of the portfolio, accurately reflect the financial assets or portfolio risk measure [12].

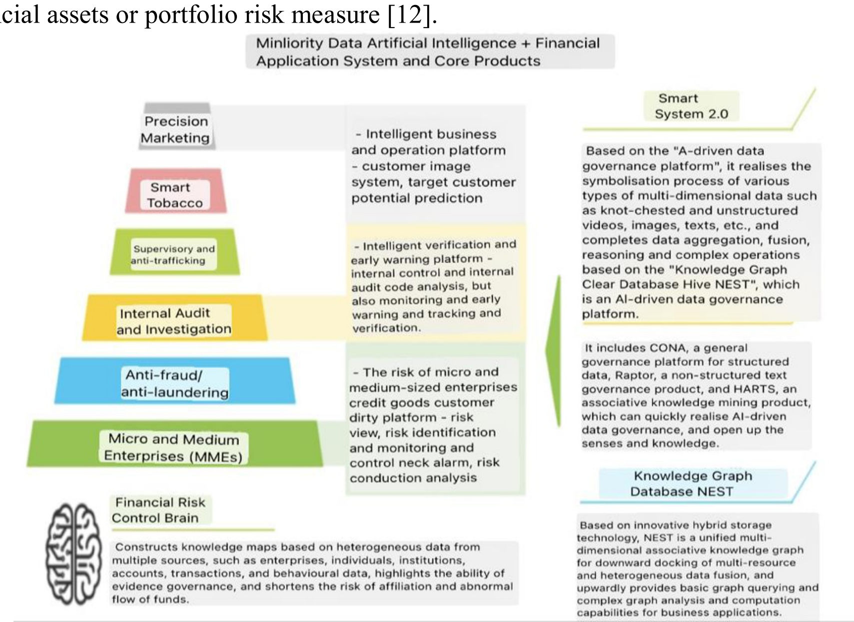

Figure 2. Financial risk control

Table 2. Specific introduction of credit risk analysis and market risk analysis

The field of analysis	Predictive model / risk assessment algorithm	Description	Application examples
Credit risk analysis			
1. Credit score model	Logical regression, decision tree, random forest, neural network, etc	Assess the risk of default of individuals or businesses and generate a credit score.	The financial institution evaluates the credit risk of the loan applicant and decides whether to approve the loan and the loan amount.
2. The survival analysis model	The Cox proportional hazards model, Junyao Li. Cox proportional hazards model with time lag covariates [D]. Lanzhou University, 2023.	Forecast the probability of customer default over a period of time, considering the time factor.	Evaluate the risk of credit card users will default over some time and adjust credit lines or collection strategies.
3. Machine learning integration method	Stacking, Boosting (eg. XGBoost, LightGBM)	Combining the prediction results of multiple single models to improve the overall prediction accuracy.	Financial institutions use integrated models to improve the accuracy and stability of credit scores and reduce credit losses.
Market risk analysis			
1. Time-series analysis	ARIMA, GARCH, LSTM, Li Jiarui, Yang Min. Hierarchical prediction method of tobacco storage / sales ratio based on the LSTM-LightGBM model [J]. Journal of Yantai University (Natural Science and Engineering Edition), 2024,37(03):256-261.	Forecast the future trend of market indicators such as asset prices and volatility.	Financial institutions predict the future changes of market variables such as stock prices, exchange rates and interest rates to guide investment strategies.
2. Risk management model	VaR (in risk value), CVaR Li Wenyu. Study on the risk measurement of CSI 500 stock index futures based on EGARCH-M-CVaR model [J]. The China market, the 2024,(21):38-42.	Quantifies the maximum loss a portfolio can suffer at a certain level of confidence.	Financial institutions use the VaR model to assess the market risk of the portfolio and develop risk management strategies.
3. Pressure test	Scenario analysis, historical simulation, Monte Carlo simulation, etc	Assess portfolio performance and potential losses in extreme market conditions.	Financial institutions conduct stress tests to assess their ability to withstand market shocks and ensure business continuity.
4. Association analysis	Covariance, correlation coefficient, factor model, etc	Analyze the correlation between different assets or markets, and evaluate the diversification effect of the portfolio.	Investment institutions use correlation analysis to optimize asset allocation and reduce the overall risk.

3.2.3 Major achievement

Significant progress has been made in credit risk analysis and market risk prediction, and risk early warning and management capabilities have been improved.

3.2.4 Current limitations

Problems of model accuracy and reliability remain, and more data and optimization algorithms are needed to improve the model performance. Both credit risk and market risk analysis need to consider various factors, and use a variety of prediction models and risk assessment algorithms for comprehensive evaluation. These models and algorithms have different advantages and disadvantages, and the most appropriate method should be selected according to the actual situation. At the same time, any prediction model and risk assessment algorithm have certain limitations and uncertainties. Investors and decision makers need to make comprehensive judgment combined with their own investment objectives and risk tolerance when using it.

Overall, prediction models and risk assessment algorithms play an important role in credit risk and market risk analysis, and help investors and decision makers to better understand and respond to risk.

4 Decision Support System

4.1 Study Methods

The use of AI-driven decision models and optimization algorithms to support financial decisions can significantly improve the efficiency and accuracy of corporate financial management. Artificial intelligence technology can quickly process and analyze large amounts of financial data, identify key patterns and trends, and provide accurate information for decision-makers. By automating data collection, collation, and analysis, AI can simplify the financial reporting process, reduce human error, and improve efficiency [13].

AI plays an important role in financial forecasting and budgeting. Learn historical financial data and market trends through the deep learning model, and generate new data samples for decision support such as financial forecasting, investment advice and risk assessment. Moreover, AI can use big data and predictive analytics algorithms to forecast markets, optimize procurement and production plans, and ensure accurate accounting and auditing [14].

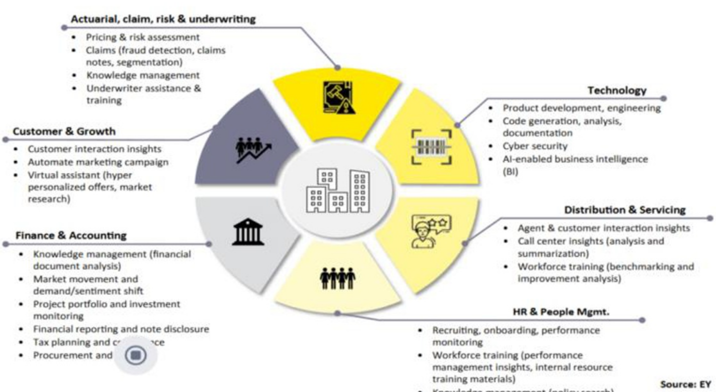

Figure 3. The application of artificial intelligence in financial management as examples

Below is a tabular overview of using AI-driven decision models and optimization algorithms to support financial decisions, covering different stages from problem analysis to in-depth research.

Table 3. AI-driven decision models and optimization algorithms support financial decisions

Stage	Activity	Description
Problem analysis		
1.1	Problem definition	Define the specific needs and objectives of financial decisions, such as budget planning, cost control, investment optimization, etc.
1.2	Identify key indicators	Determine the key factors and indicators that affect financial decisions, such as sales, profit margin, cash flow, etc.
1.3	Evaluate the data availability	Check the quantity, quality, and integrity of the existing data to determine if data cleaning and preprocessing is required.
The whole network search		
2.1	Search for existing technology	Use resources such as search engines, professional databases and academic papers to understand the current development of current AI-driven financial decision models and optimization algorithms.
2.2	Collect case studies	Find and collect cases of successful application of AI in financial decisions, and analyze their application scenarios, technology selection and effect evaluation.
2.3	Identify technical challenges	Summarize the technical difficulties and limitations that may be encountered in the application of AI to the financial decision-making process.
Preliminary investigation		
3.1	Select the appropriate algorithm	According to the problem definition and data analysis results, appropriate AI algorithms (such as machine learning, deep learning, optimization algorithms, etc.) are selected for preliminary testing.
3.2	Data preparation	The raw data were cleaned, transformed, and pre-processed to meet the requirements of the algorithm input.
3.3	Model construction and training	The processed data was used to build AI decision models or optimization algorithms and trained to learn patterns and patterns in the data.
3.4	Preliminary evaluation	The performance of the model, including accuracy, stability and generalization ability, and its applicability is preliminarily judged.
Deep research		
4.1	Model optimization	According to the preliminary evaluation results, the model is optimized, such as adjusting parameters, improving feature selection, and trying different combinations of algorithms.
4.2	Cross validation	Cross-validation techniques were used to further validate the model stability and reliability, avoiding overfitting or underfitting problems.
4.3	Integrated learning and integration	Explore the integrated learning methods (such as random forest, gradient lifting tree, etc.), and the integration with

		other financial tools (such as ERP system, BI tools, etc.), to improve the decision-making effect.
4.4	Sensitivity analysis and risk assessment	Conduct sensitivity analysis on the model to evaluate the influence of different input variables on the output results, evaluate the potential risks of the model in practical application and propose countermeasures.
4.5	Deployment and monitoring	Deploy the optimized model into the actual financial decision process, establish a monitoring mechanism to track the performance of the model, and continuously optimize based on feedback.

This table provides an overview of the phases from question analysis to in-depth study, and the key activities and tasks to be undertaken at each stage. Through this process, companies can more systematically use AI-driven decision models and optimization algorithms to support their financial decision-making process and improve the scientificity, accuracy and efficiency of their decisions.

4.2 Major Achievements

Automated financial decision system and intelligent investment advisory system are developed to help enterprises make more scientific financial decisions. Artificial intelligence technology enables in-depth analysis of historical financial data and combines it with market dynamics and internal enterprise information to produce more accurate predictions. By applying machine learning and big data technologies, AI can efficiently process and analyze large amounts of financial data to provide reliable predictions of future financial conditions.

AI technology can provide intelligent financial decision support. By analyzing and simulating different financial scenarios and decision options, intelligent algorithms can evaluate the risks and returns of various decisions and help enterprises make more scientific decisions. In addition, application scenarios based on generative AI can be further subdivided into predicted financial data, optimized tax planning, etc., all of which can help companies remain competitive in a complex market environment.

4.3 Current limitations

(1) The complexity of technology implementation and the limitations of application scenarios make the application of these systems challenging in practice, which requires further improvement and promotion.

(2) Ai requires a lot of data to learn and predict, but these data often contain sensitive information about individuals and businesses. To protect the privacy and security of data, strict data encryption, access control and authentication measures need to be implemented.

(3) The algorithms of artificial intelligence are usually complex black-box models, and it is difficult to intuitively explain the reasons and process of their decisions. To improve transparency and interpretability, research and development of interpretable AI technologies need to be developed to better understand and explain the AI decision-making process and reasons for this.

(4) In the face of new data, AI models may rely too much on training data, resulting in performance decline. To address this issue, it is necessary to introduce more diverse data and balance the degree of optimization and generalization of the model.

5 Conclusion and Outlook

In short, the application of artificial intelligence and big data in financial management is revolutionizing the industry by improving the accuracy, efficiency and decision-making process of financial operations. The integration of these technologies allows financial institutions to quickly process massive amounts of data, revealing patterns and insights previously unattainable. Key areas of impact include risk management, in which AI improves the assessment and mitigation of various risks, and customer relationship management, in which big data analysis helps customize services to individual needs.

However, challenges such as data privacy, security, and the high costs associated with implementing these technologies remain daunting. Ensuring strong data protection measures and overcoming technical complexity are critical to the successful adoption of AI and big data in financial management.

Future studies should focus on further integrating these technologies with existing systems, exploring new applications, and addressing current limitations. With the continuous development of artificial intelligence and big data technology, their impact on financial management will undoubtedly increase, providing new opportunities and challenges for financial institutions.

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