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Research on the Construction and Application of Intelligent Financial Decision-Making Model Driven by Generative Artificial Intelligence

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Abstract: This study focuses on the construction and application of intelligent financial decision-making models driven by generative artificial intelligence (AI). It analyzes the mechanisms by which generative AI empowers financial decision-making within a dual framework of dynamic knowledge evolution and risk control. The research reveals that generative AI, with its superior data processing, pattern recognition, and autonomous learning capabilities, can transcend the limitations of traditional decision-making models, facilitating a significant shift from causal inference to probabilistic creation in decision-making paradigms. By systematically constructing an intelligent financial decision-making model that includes data governance, core engine, and decision output layers, the study clarifies the functional roles and collaborative mechanisms of each layer. Additionally, it addresses key challenges in technology application, institutional adaptation, and organizational transformation by proposing systematic strategies for technical risk management, institutional innovation, and organizational capability enhancement, aiming to provide robust theoretical support and practical guidance for the intelligent transformation of corporate financial decision-making.

Keywords: Generative artificial intelligence; Intelligent financial decision making; Decision model; Risk control

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1. Introduction

In the era of rapid digital economic development, the environment for corporate financial decision-making is undergoing profound changes. On one hand, as businesses diversify and globalize, and with the widespread use of Internet and IoT technologies, the volume of financial data generated both internally and externally by companies is growing exponentially. The types of data are becoming increasingly complex, including structured financial reports, semi-structured transaction records, and unstructured market sentiments and policy documents. On the other hand, the uncertainty in the global economic landscape has increased, market competition has intensified, and the economic relationships faced by companies have become more intricate. The limitations of traditional financial decision-making models, which rely on fixed rules, historical experience, and static analysis frameworks, have become more apparent. Traditional models lack the ability to efficiently parse and integrate large volumes of unstructured data. In a dynamic economic environment, these models also fall short in risk prediction and adaptive adjustment mechanisms, making it difficult to meet the demands of detailed management and strategic decision-making.

Although research on the application of artificial intelligence (AI) technology in finance has made some progress, most existing studies focus on the localized use of individual technologies or the simple adaptation of general AI techniques. There is a significant gap in developing a systematic model that integrates deep integration and generative AI features with the practical needs of financial decision-making. Additionally, there is no well-established theoretical framework or practical solution for achieving continuous updates of dynamic knowledge and effective risk control during the financial decision-making process. As a cutting-edge technology in AI, generative AI excels in data analysis, pattern generation, and prediction. Its unique technical capabilities offer new possibilities and directions for the innovation of financial decision-making. A deeper exploration of intelligent financial decision-making models driven by generative AI can not only fill the gaps in current theoretical research and further refine the theoretical framework of intelligent financial decision-making, but also promote the transformation and upgrading of corporate financial decision-making towards intelligence and precision from a practical perspective. This can significantly enhance the risk management and decision-making scientificity of enterprises in complex economic environments, which is crucial for enhancing core competitiveness and driving digital transformation in the financial sector.

2. The mechanism of financial decision-making enabled by generative AI

2.1. Technical characteristic adaptability

Generative artificial intelligence, leveraging deep learning algorithms, demonstrates high adaptability in financial decision-making scenarios. Its capability to process multi-source data overcomes the data barriers of traditional financial analysis. It can analyze unstructured texts like policy documents and news articles using natural language processing technology, and handle image data such as invoices and vouchers with image recognition technology. These data are then efficiently integrated with the structured data from the company's internal financial system. In terms of autonomous learning and pattern recognition, generative AI, through extensive training on years of financial data, industry historical fluctuations, and macroeconomic indicators, can uncover hidden nonlinear relationships between financial metrics, such as the potential link between R&D investment and future three-year earnings, and the impact of supply chain fluctuations on cash flow. Particularly, its generative capabilities enable the creation of financial data simulation models for hundreds of market scenarios using techniques like Monte Carlo simulation and reinforcement learning, providing comprehensive data support for investment and financing decisions and cost control scheme evaluations. This technical feature aligns well with the core needs of financial decision-making, including deep data mining, dynamic risk assessment, and forward-looking validation of plans, thereby providing innovative momentum for intelligent financial decision-making at the technical level.

2.2. Comparison with traditional decision models

As shown in **Table 1**, compared with traditional financial decision-making models, the generative AI-driven intelligent financial decision model demonstrates significant advantages in data-handling capacity, decision basis, risk prediction, and decision plan generation.

Table 1. Comparison with traditional decision models

Compare dimensions	Traditional financial decision-making model	Intelligent financial decision model driven by generative AI
data-handling capacity	It mainly relies on manual collection and input of structured data, and a large amount of manual transformation is required for the processing of unstructured data [1]. The efficiency of data cleaning and integration is low, and the processing cycle can last several weeks when facing TB-level data.	Through the API interface, it can automatically connect to ERP, CRM, and other systems to capture structured data in real time; NLP and OCR technology can be used to realize second-level processing of unstructured data, with data cleaning accuracy of more than 98%, and support parallel computing of PB-level data.
Decision basis	Based on historical financial ratio analysis and fixed formula calculation (such as DuPont analysis method), the parameters of the decision-making model are solidified for a long time, which makes it difficult to adapt to external shocks such as sudden changes in economic policies and technological innovation in industries.	The machine learning model with dynamic parameters is built and the training data is updated daily. The decision weight can be adjusted in real time according to the adjustment of the Federal Reserve interest rate and the change of industry standards, so as to ensure the timeliness and accuracy of the decision basis.
Risk prediction ability	Subjective evaluation methods such as Delphi method and scenario analysis method are adopted, and the risk identification dimension is limited to abnormal financial indicators, while the early warning of non-financial risks, such as supply chain fracture and public opinion crisis lags behind.	By integrating multi-source information such as public opinion monitoring, supply chain data, and satellite remote sensing data (such as port freight volume), the algorithm of correlation rule mining can identify systemic risks 6–12 months in advance, and the error rate of risk quantification is reduced by 40% compared with traditional methods.
Decision plan generation	Relying on the experience of financial personnel to formulate 3–5 conventional schemes, the scheme comparison is only based on static data measurement, and lacks dynamic simulation of the implementation process of the scheme.	More than 20 kinds of differentiated decision-making schemes are automatically generated, and the probability distribution chart of the implementation effect of the scheme is output by simulating the market feedback and the chain reaction, such as the adjustment of competitors' strategies after the implementation of the scheme through the generative adversarial network (GAN) [2].

2.3. Core breakthroughs

Generative AI is driving a paradigm shift in financial decision-making from "causal inference" to "probability creation." Traditional financial decisions are based on linear causal logic, such as predicting future revenue through historical sales growth rates, which makes it difficult to handle black swan events and sudden variables. In contrast, generative AI, using architectures like Transformers, can perform unsupervised learning on millions of economic data points. This enables it to break free from the constraints of causal frameworks and generate probability distributions for financial data under various scenarios, such as macroeconomic fluctuations and changes in industry competition over the next 3–5 years, providing decision-makers with more forward-looking decision maps. To balance the explainability of the decision-making process and black box risks, SHAP (Shapley Additive Explanations) value analysis and LIME (Local Interpretable Model-Agnostic Explanations) algorithms are used to break down the logic of model decisions, converting complex neural network computations into metrics that financial personnel can understand. Additionally, a dual verification system is established to validate AI outputs using traditional financial analysis methods and to manually intervene in abnormal decision recommendations by incorporating expert experience. This ensures that while leveraging the powerful decision-making capabilities of generative AI, the decision-making process remains transparent and controllable.

3. Construction of intelligent financial decision-making model

3.1. Data governance layer

The data governance layer, serving as the foundation of the intelligent financial decision-making model, is responsible for managing multi-source data throughout its entire lifecycle. In the data collection phase, this layer establishes a standardized data access platform, using API interfaces to seamlessly integrate with the company's internal ERP and CRM systems, as well as production management systems, to obtain real-time business data such as financial accounting, sales orders, and inventory management [3]. Additionally, it uses web crawling and data interface protocols to gather macroeconomic indicators, industry trends, and market sentiment from external sources like government economic databases, industry research institutions, and social media platforms. Once the collected data enters the cleaning stage, data deduplication algorithms are used to eliminate duplicate records, anomaly detection algorithms are employed to identify and correct erroneous data, and multiple methods, such as imputation and predictive modeling, are applied to fill in missing data, ensuring the accuracy and completeness of the data. In the data annotation and classification phase, natural language processing technology is used to analyze unstructured text data for semantic analysis and keyword extraction, and machine learning algorithms are applied to automatically classify the data into structured formats. Furthermore, the data governance layer has established a robust data security system, using data encryption technology to securely store and transmit sensitive data, implementing access control mechanisms to strictly limit data access permissions for different users, and setting up data audit logs to monitor data operations in real time, thereby ensuring comprehensive data privacy and security, and providing a reliable data foundation for subsequent model training and decision-making analysis [4].

3.2. Core engine layer

The core engine layer, serving as the central hub of the intelligent financial decision-making model, deeply integrates generative artificial intelligence algorithms with professional financial decision analysis models. In data processing and analysis, this layer employs advanced algorithms such as natural language processing, deep learning, and reinforcement learning to deeply mine the standardized data from the data governance layer. A financial risk assessment model is constructed, which uses convolutional neural networks (CNNs) to extract the temporal features of financial data and recurrent neural networks (RNNs) to analyze the dynamic evolution patterns of the data, achieving precise identification and quantitative assessment of various financial risks, including credit risk, market risk, and liquidity risk. Using a Transformer architecture, it learns from historical financial data and related influencing factors to predict the future trends of key financial indicators such as revenue, profit, and cash flow. In decision plan generation, the core engine layer utilizes generative adversarial networks (GANs) and variational autoencoders (VAEs) to simulate changes in financial data under different economic scenarios, market environments, and corporate strategies, generating multiple decision scenarios and corresponding financial data simulation results to provide rich reference for decision-makers. Additionally, the core engine layer has strong dynamic learning capabilities, automatically updating model parameters based on new data, continuously optimizing the model structure, and enhancing the model's ability to analyze financial decision-making issues and improve decision accuracy, ensuring the model remains adaptable and effective in complex and changing financial environments [5].

3.3. Decision output layer

The decision output layer serves as a crucial bridge between the analysis results of the intelligent financial decision-making model and the enterprise's decision-makers. Its primary task is to transform complex data analysis results into intuitive, understandable, and user-friendly decision information. In terms of text report generation, the decision output layer employs natural language generation technology to automatically summarize and refine the conclusions derived from model analysis. This process provides a clear, accurate, and standardized textual description that details the basis for financial decisions, current financial status analysis, potential risk warnings, and specific decision recommendations, enabling decision-makers to quickly grasp the key points of the decision. For visual presentation, this layer utilizes professional data visualization tools to present financial data, risk assessment results, and comparison of decision options through various visual elements such as bar charts, line graphs, pie charts, dashboards, heat maps, and Sankey diagrams. These visual elements intuitively illustrate the relationships, trends, and comparative advantages and disadvantages among different options, helping decision-makers better understand the underlying data. Additionally, the decision output layer supports robust human-computer interaction features, allowing decision-makers to adjust decision parameters, switch analysis dimensions, and view detailed data according to their needs and concerns [6]. This enables them to obtain personalized decision plans and analysis reports, integrating the intelligent decision-making system with human experience, thereby enhancing the scientific and rational nature of financial decisions [7].

4. Implementation challenges and response paths

4.1. Technical risk control

Generative AI technology faces multiple technical risks and challenges in financial decision-making applications. Algorithm bias risks arise from issues such as sample selection biases and data labeling errors in training data, which can lead to systematic biases in model outputs. For instance, in credit risk assessments, these biases can result in discriminatory judgments against specific industries or types of enterprises. Data privacy breaches are also a significant concern, as financial data contains core business secrets and sensitive information. If security measures are inadequate during data collection, transmission, storage, and use, data breaches can occur, causing significant losses to companies [8]. Additionally, the black-box nature of generative AI models makes their decision-making processes difficult to understand and interpret, increasing decision-making risks and regulatory challenges. To address these risks, companies need to establish robust algorithm review mechanisms, regularly assess and optimize model algorithms, and test the fairness and accuracy of models through cross-validation and A/B testing. They should also enhance data security systems by using federated learning technology for collaborative analysis without leaving local data and employing homomorphic encryption to ensure data is processed in an encrypted state, thus securing data privacy from a technical standpoint. Furthermore, companies should actively develop and apply explainable AI technologies, such as causal inference and visual analytics, to increase the transparency of model decision-making logic and reduce the risks associated with technology application.

4.2. Institutional adaptation and innovation

Traditional financial management systems struggle to meet the demands of generative AI-driven intelligent financial decision-making. In terms of data usage, traditional systems lack clear guidelines on new data sources, data sharing scopes, and data usage permissions, leading to inefficient data circulation within companies and failing to fully realize their value. The traditional hierarchical and approval-based decision-making processes are cumbersome and do not meet the time-sensitive requirements of intelligent financial decisions, and they lack effective support for data-driven decision-making. Regarding the division of responsibilities, intelligent financial decisions involve multiple departments, including finance, technology, and business [9]. Under the traditional system, unclear departmental responsibilities can lead to buck-passing, affecting decision-making efficiency and quality. Therefore, companies need to innovate their financial management systems comprehensively, establish specific data usage standards, clarify the standards and permissions for data collection, storage, sharing, and use, and build a data sharing platform to facilitate data circulation. They should also optimize decision-making processes, develop a data-driven agile decision-making mechanism, reduce unnecessary approval steps, and improve decision-making efficiency. Additionally, they should redefine the responsibilities and permissions of each department in intelligent financial decision-making, establish a cross-departmental collaboration mechanism, and enhance inter-departmental communication and cooperation [10]. Furthermore, companies should integrate generative AI technology into their internal control systems, implement corresponding risk prevention measures and supervision mechanisms, and ensure that the intelligent financial decision-making process is compliant and controllable.

4.3. Restructuring of organizational capabilities

Enterprises face significant challenges in implementing intelligent financial decision-making models due to organizational capabilities. From a personnel skills perspective, traditional financial staff primarily focus on financial accounting theories and regulations, often lacking knowledge and skills in data analysis and artificial intelligence technology. This makes it difficult for them to effectively operate and apply these models, thus failing to fully leverage their advantages. In terms of organizational culture, traditional companies tend to have a conservative and experience-focused culture, with low acceptance of new technologies and methods. Employees often resist change, which significantly hinders the promotion and application of intelligent financial decision-making models. Additionally, the current organizational structure is typically divided by function, leading to poor communication and collaboration between departments, making it challenging to meet the cross-departmental and cross-domain needs of intelligent financial decision-making. To address these challenges, enterprises should enhance talent development and recruitment by offering internal training, external professional training, and collaborating with universities to improve financial staff's skills in data processing, analysis, and AI application. They should also actively recruit composite talents who are proficient in both finance and technology. Organizational culture should be transformed through publicity, guidance, setting innovation role models, and establishing incentive mechanisms to foster an open, innovative, and adventurous cultural environment, thereby enhancing employees' acceptance and recognition of new technologies. The organizational structure should be optimized by breaking down departmental barriers and forming project-oriented cross-departmental teams, building agile organizational structures and work models that support intelligent financial decision-making, and achieving a comprehensive restructuring and enhancement of organizational capabilities.

5. Conclusion

This study systematically explores the construction and application of intelligent financial decision-making models driven by generative artificial intelligence. Based on a dual framework of dynamic knowledge evolution and risk control, it delves into the mechanisms by which generative AI empowers financial decision-making. It constructs an intelligent financial decision-making model that includes data governance, core engine, and decision output layers. The study also proposes targeted strategies to address technical, institutional, and organizational challenges encountered during implementation. The research provides a comprehensive theoretical framework and practical guidance for the intelligent transformation of corporate financial decision-making. However, as generative AI technology continues to evolve and innovate, and the corporate financial decision-making environment remains dynamic, further in-depth research is needed to explore the deep integration of technology and financial operations, aiming to develop more efficient, secure, and intelligent financial decision-making models. For example, how to integrate generative AI with blockchain technology to achieve credible sharing and traceability of financial data; and how to use generative AI to better address the impact of global risks such as climate change and geopolitical conflicts on corporate financial decision-making. Through ongoing research and practice, the aim is to continuously drive digital innovation and development in the financial sector, providing robust support for companies to achieve sustainable development in a complex and ever-changing market environment.

Disclosure statement

The author declares no conflict of interest.

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