https://doi.org/10.31449/inf.v49i15.10474 Informatica **49** (2025) 209–222 **209**

Design and Implementation of an AI-Integrated Financial Decision Support System with LSTM and Random Forests

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Keywords: artificial intelligence, financial decision-making, decision support system, path optimization

Received: July 30, 2025

Artificial intelligence is an application technology that affects the financial decision-making process of enterprises and guides them to achieve intelligent financial operation and scientific management. This article designs an intelligent financial decision support system architecture that combines multiple functions and machine learning, rule-based intelligent behavior, and human-computer interaction, greatly enhancing the intelligent capabilities of enterprise financial data modeling and analysis, trend prediction, and implementation. The system integrates diversified data acquisition and cleaning, and completes data fusion preprocessing of financial, business, and external economic information; The financial data prediction model, which combines LSTM dominated time series models and random forest algorithms, enhances the real-time prediction performance of cash flow, cost structure changes, and profit prospects; Implementing auxiliary decision-making and adjustment optimization in complex environments through the integration of a knowledge base and rule base supported inference module. After testing various key performance indicators such as Financial Prediction Error (MAE), Reaction Time RT, and Benefit Improvement Rate COR, the performance is better than the current financial information system. After testing on Company A's one-year operational dataset, empirical evaluation shows that the proposed system reduces prediction error from 13.6% to 5.1% (a decrease of approximately 62.5%) and shortens average decision response time from 45s to 12s (a reduction of about 73%) compared with the baseline financial information system. This study provides a construction method and theoretical basis for an intelligent financial decision support system that is clearly understood, constantly growing, and self managed.

Povzetek: Opisan je inteligentni finančni odločitveni sistem, ki združuje večizvorno podatkovno fuzijo, LSTM in naključni gozd za napovedi ter pravila in znanje za razlago. Zmanjša napovedne napake in čas odločanja.

1 Introduction

Due to the widespread application of technology, especially artificial intelligence, in fields such as big data analysis, predictive modeling, and pattern recognition, enterprise financial decision support systems will achieve intelligent acceleration. For enterprises, the data elements involved in their core business activities are characterized by nonlinearity, frequent changes, and interdependence. How to extract effective information from massive structured and unstructured data and build intelligent decision-making models that are suitable for the operating environment of the enterprise has become the key to improving financial management.

The financial relationships formed by the integration of this raw data form a complex network diagram of the company's financial activities, demonstrating the multi perspective and multi form models of the company's operational efficiency, risk level, and resource allocation. Accurately identifying and integrating these information features is the foundation for building high-performance intelligent financial systems.

The introduction of artificial intelligence technology in this process involves integrating machine learning, deep learning, rule engines, and knowledge graphs into AI models for automatic learning. This involves predicting future changes based on historical data patterns to assist in making financial decisions in complex environments. Thus, enhancing the system's "sensing recognition inference" capability and providing a foundation based on technology to accelerate decision response speed and enhance decision stability [5]. However, establishing a company level financial decision support system that incorporates artificial intelligence technology is not as simple as piling up various tools. It requires a comprehensive and coordinated organizational process that includes the structural design of each part of the system, data flow control, algorithm selection and application, and human-computer interaction. In addition, due to the differences in operating environments among various industries, large, medium, and small enterprises, there are significant differences in system installation, resource capacity, and rule adaptation. It is necessary to find a process that can be flexibly transferred and adjusted.

This study aims to address the following research questions:

(1) How can artificial intelligence algorithms such as LSTM and Random Forest be effectively integrated into enterprise financial management processes to enhance prediction accuracy and decision efficiency?

(2) What system architecture can ensure adaptability and transferability across different industries and enterprise scales?

(3) How can a dynamic feedback loop be designed to achieve continuous optimization of financial decisions?

Based on these questions, our hypotheses are that: (i) the hybrid LSTM–Random Forest model will significantly reduce financial prediction errors compared with baseline systems; (ii) the integration of a rule-based inference module will improve interpretability and compliance; and (iii) the feedback-driven optimization mechanism will enhance system adaptability and long-term performance.

2 Related work

Despite the increasingly urgent demand for financial digital transformation by enterprises, financial decision support systems that achieve predictive, reactive, and regulatory functions still face many challenges. On the one hand, the financial information of enterprises is complex and has highly nonlinear, spatiotemporal and multi-source heterogeneity characteristics; On the other hand, due to the frequent interference of relevant rules and obstacles in the daily management of enterprises, intelligent models are also difficult to fully utilize their functions. It is widely believed that artificial intelligence technology can break through the difficulties of traditional financial analysis and decision-making.

Early enterprise decision support systems were based on pre-set rules and manually set technical operations, and were unable to cope with the increasing amount of data and complexity requirements of business activities. In recent years, with the development of artificial intelligence technology, its application in financial management is no longer limited to auxiliary work in accounting transactions, but has further developed to provide support for comprehensive forecasting, early warning, and dynamic resource allocation.

Looking further at the researchers' explorations, we see that their first consideration is how to match traditional machine learning techniques and statistical models, such as Bayesian classification, Support Vector Machine (SVM), fuzzy logic decision trees, etc. These models perform well in relatively small internal enterprise big datasets, but are difficult to generalize and have low computational efficiency when dealing with complex heterogeneous financial environments of large enterprises.

Therefore, deep learning technology is increasingly regarded by scholars as one of the main solutions. In addition, models such as Transformer, GRU, CNN, etc. have achieved better fitting results than traditional algorithms in the enterprise financial estimation environment, with innovative breakthroughs in budget variance testing, cost amortization, cash flow simulation, and other areas.

In addition, in recent years, some scholars have attempted to combine knowledge graphs, expert rule bases, and deep models to construct a ‘interpretable+learnable’ hybrid intelligent decision-making system [14]. Table 1 summarizes representative recent studies on AI-driven financial decision support systems, including their methods, application scenarios, evaluation metrics, and main findings.

Table 1：Summary of representative studies on AI-driven financial decision support systems

Reference	Methodology	Application Scenario	Evaluation Metrics	Key Findings
[1] Kostopoulos et al. (2024)	Explainable AI (XAI)-based DSS	General decision support	Qualitative review	XAI enhances interpretability in DSS but lacks financial-specific validation
[2] Wang & Shen (2025)	Deep reinforcement learning + particle swarm optimization	Supply chain finance	Financial benefit, efficiency	Improved financial benefits; limited cross-industry applicability
[6] Nallakaruppan (2024)	Explainable AI for credit risk	Credit risk assessment	Accuracy, interpretability	Higher credit risk prediction accuracy; good explainability
[7] Cheng & Wang	Deep reinforcement	International markets	Prediction accuracy	Better handling of exchange rate heterogeneity

(2023)	learning on financial disclosures			
[9] Zheng (2024)	Big data-driven DSS	Financial data analysis	Scalability, performance	Improved big data processing; lacks interpretability
[13] Kwon (2024)	Hybrid DSS (rule-based + reinforcement learning)	Trading strategies	Return, adaptability	Adaptive trading strategies; integration complexity remains
[18] Černevičienė (2024)	Systematic literature review of XAI in finance	Financial DSS	Literature synthesis	Identified gaps in XAI interpretability for financial DSS
[19] Pahsa (2024)	Fintech DSS	Financial technology decision-making	Conceptual framework	DSS applied in fintech; requires empirical validation

As shown in Table 1, existing research has achieved progress in applying XAI, reinforcement learning, and hybrid DSS models to financial decision-making. However, most studies remain limited in scope, either focusing on single-domain datasets, lacking explicit feedback mechanisms, or offering insufficient interpretability for managerial adoption. Moreover, Informatica-related works emphasize intelligent DSS in enterprises but do not address hybrid integration of LSTM–Random Forests with rule-based dynamic optimization. This paper aims to fill these gaps by

Although there have been studies that have constructed relatively complete theoretical frameworks and technical models, there are still three areas that urgently need to be broken through: firstly, the current system is mostly based on data construction within a single enterprise, lacking cross organizational models that are suitable for complex supply chain and industry collaboration scenarios [16]; Secondly, the interpretability of intelligent decision-making mechanisms in financial scenarios is still weak, especially in budget approval and financial compliance judgment. The lack of model transparency has affected the trust acceptance of managers [17]; Thirdly, current application systems are mostly statically deployed and lack a "feedback adjustment reconstruction" mechanism, making it difficult to achieve dynamic adaptive optimization of financial systems.

Recent contributions in Informatica also emphasize the role of intelligent decision support in enterprise contexts, highlighting both methodological advances and practical deployment challenges. These works provide direct relevance to the present study and further justify its scope. Therefore, based on a thorough review of the above research, this article explores
in depth the following issues: firstly, how to integrate artificial intelligence algorithms with enterprise financial management processes at the system level to achieve closed-loop collaboration of "perception analysis decision"? Secondly, how to build a transferable and adjustable financial decision-making system architecture for different industries and

enterprise scales? Thirdly, how to design a dynamic optimization mechanism based on system feedback information to enable the intelligent financial system to have continuous evolution capability? These questions will be the focus of the subsequent chapters of this article.

3 Construction of intelligent financial decision support system

Building an enterprise financial decision support system that integrates artificial intelligence is not only a technological reshaping of traditional financial functions, but also a deep reconstruction of the logic of enterprise resource allocation. The system should not only support the dynamic management of core elements such as cost, budget, and cash flow in daily operations, but also provide a systematic solution with intelligent analysis, prediction, and feedback functions when facing multi-dimensional data, uncertain environments, and complex decision-making scenarios.

This system design follows the construction principle of "data-driven model embedding rule feedback human-machine collaboration". The system structure is divided into five core levels: data acquisition layer, preprocessing and governance layer, intelligent modeling and decision-making layer, rule system and knowledge base layer, and user interaction and visualization layer. Among them, each layer not only undertakes specific functions, but also forms a linkage loop with the upper and lower layers through interface mechanisms, ensuring efficient circulation of data flow, model flow, and business flow within the system.

To meet the integration requirements of multi-source heterogeneous data, the system first connects multiple business platforms such as ERP, CRM, OA, and bank receipt systems at the data collection layer, and completes data capture through standardized interfaces. The preprocessing layer utilizes techniques such as feature cleaning, missing value filling, and semantic annotation to improve data quality and provide a solid foundation for model training. The modeling layer constructs a multidimensional prediction model based on the actual business processes of the enterprise, integrating algorithms such as GRU, decision tree, Bayesian network, etc., to achieve real-time analysis of cost fluctuations, revenue trends, and risk levels. The rule system is based on expert knowledge and financial regulations to construct a logical judgment matrix, forming an auxiliary correction mechanism for the model output. At the user interaction layer, the system supports intelligent reports, semantic queries, and contextual warning push, enhancing financial personnel's sense of control and trust in the system. As shown in Figure 1, the entire intelligent financial decision support system presents a structural logic of "horizontal data fusion, vertical functional progression", and each module cooperates with each other to jointly form the technical foundation of enterprise digital financial governance.

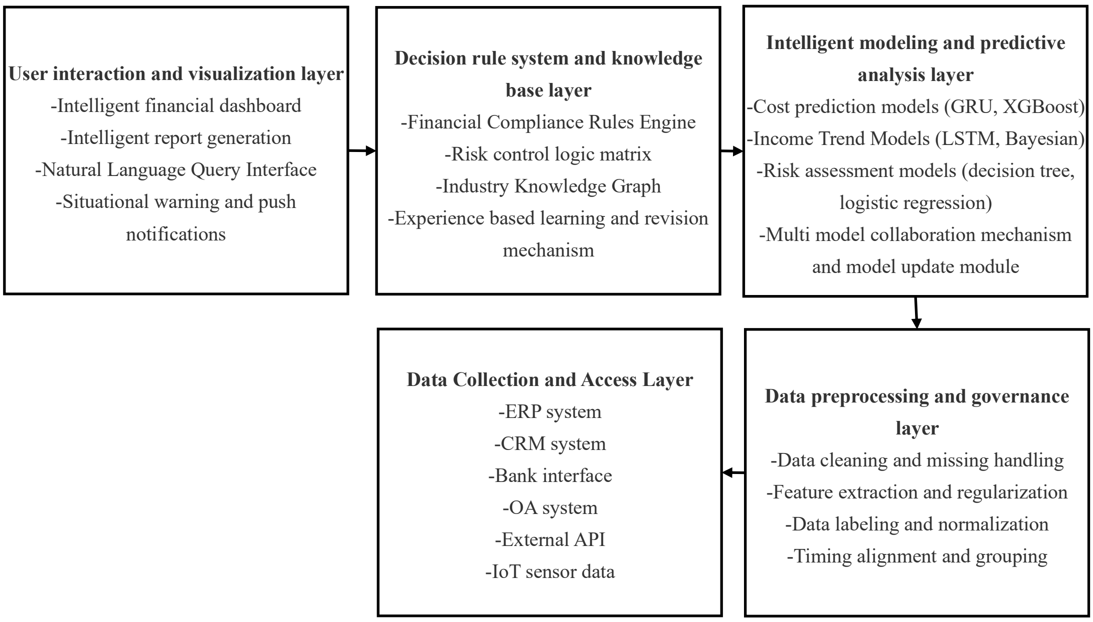

Figure 1: Overall architecture diagram of intelligent financial decision support system

3.1 Overall design of system architecture and division of functional modules

In the process of building an enterprise financial decision support system that integrates artificial intelligence, architecture design is the core link that lays the foundation for system stability and scalability. Considering the complexity and diversity of enterprise financial operations, this system adopts a hierarchical and modular decoupling overall architecture, emphasizing the organic collaboration of data flow, algorithm flow, and decision flow. The system structure is divided into five functional levels from bottom to top: data collection and access layer, data governance and preprocessing layer, intelligent modeling and analysis layer, rule engine and knowledge management layer, and user interaction and feedback layer. Each layer has clear functions and boundaries, and horizontal linkage and vertical calling are achieved through API interfaces and message middleware.

In the architecture design, the data collection layer is responsible for the unified access of underlying multi-source data, covering ERP systems, CRM systems, bank interfaces, OA platforms, and external third-party data services, providing a rich raw data foundation for the system. The data governance layer completes data cleaning,

standardization, missing processing, and feature transformation to ensure that the input data has trainability and computability. After entering the intelligent analysis layer, the system calls different AI algorithm modules based on business scenarios, including cash flow prediction based on GRU, cost classification judgment based on decision trees, and risk probability modeling based on Bayesian networks, which enhance the interpretability of decision outputs compared with traditional black-box models.

Based on enterprise internal control management standards, industry regulations, and experiential knowledge, a logical reasoning matrix for logical judgment and a semantic knowledge graph for semantic knowledge are formed through the rule engine layer to assist in determining the scope of the model. It also has outstanding unified standard control capabilities in budget approval, tax compliance, and fund allocation issues. The user layer at the top provides a human-machine visualization dashboard, natural language query interaction, and scenario-based alarms, allowing financial management workers to efficiently interact with the human-machine interface, accelerating system response and convenience. This architecture forms a closed-loop process linking data-driven modeling, rule-based modification, and user decision-making, while maintaining strong scalability and generality.

3.2 Construction path of data collection and preprocessing mechanism

Data acquisition and preprocessing form the foundation of intelligent financial DSS. Enterprise data originates from diverse structured and unstructured sources (ERP, CRM, HR, invoices, contracts, etc.), requiring a multi-channel acquisition strategy with strong adaptability and real-time capability.

The system adopts a unified data interface for comprehensive access via APIs, FTP capture, database connections, and OCR, which largely mitigates heterogeneity though challenges remain with certain legacy systems. To balance batch and real-time needs, a dual-channel strategy is applied: daily settlement data are collected in batches, while high-frequency streams (e.g., cash flow, inventory) are captured at minute-level.

Preprocessing follows four streamlined steps: cleaning (missing value filling, outlier detection), standardization (field naming and coding), feature transformation (time-series and interaction features), and label construction (e.g., cost fluctuation, fund occupancy). As shown in Figure 2, these steps form a closed-loop pipeline that enhances data traceability, transparency, and interpretability.

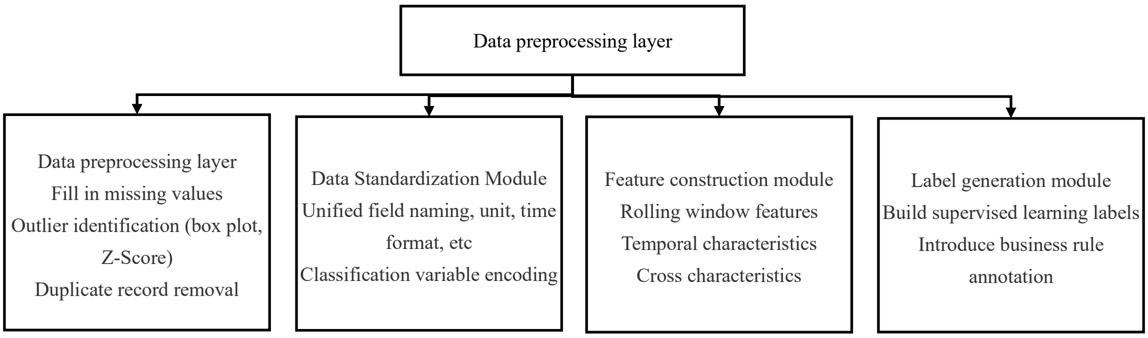

Figure 2: Data preprocessing flow chart

3.3 Embedding and training strategies for intelligent algorithm models

In the process of building an enterprise level intelligent financial decision support system, the embedding strategy of algorithm models is a key link to achieve the intelligent closed-loop of "perception judgment feedback" in the system. Considering the complexity of financial data structures and the differences in scenarios, the system adopts an embedding mechanism of "task driven model matching" to deploy different types of algorithm models as needed based on prediction targets and data features.

Taking cash flow forecasting tasks as an example, this type of task belongs to a typical time series problem, and the system adopts a Gated Recurrent Unit (GRU) model as the backbone structure. GRU can effectively model long-term dependencies in historical financial data and has good fitting ability when facing irregular cash inflows and outflows. The training objective of the model is to minimize the prediction error, and the system adopts the mean square error (MSE) loss function, mathematically expressed as:

$$L_{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{1}$$

where y_i denotes the actual observed cash flow of

the iii-th sample, $\hat{y}_i$ is the predicted output of the model for the same sample, and n is the total number of samples. This ensures that the model parameters are optimized to minimize the squared deviation between predictions and true values.

In addition to time series models, the system also integrates several auxiliary tools such as decision tree models for classifying cost structures, Bayesian networks, and logistic regression for detecting financial risks. All tools have completed data group segmentation, attribute construction, and index evaluation on the same training platform, and automatically adjusted job plans based on business call volume and error acceptance rate. All integrated tools have modular decomposition capabilities and are commanded by the system's model library after installation. They are dynamically selected through task identification logic and continuously improved through feedback mechanisms. This training method can ensure that the system meets various algorithm requirements and maintains a high response rate when multiple business needs are met simultaneously.

3.4 Decision rule system and knowledge base construction mechanism

Although algorithmic models can contribute to trend and likelihood estimation in intelligent financial decision support systems, in practical business decision-making processes, it is still necessary to integrate company policies, regulatory rules, and professional judgments into standardized constraints and expand the knowledge base. Therefore, a two-layer architecture system of "rules+knowledge base" is applied to the system, which enables it to easily connect the model results to business decisions and make reasonable explanations. The rule making decision-making system mainly relies on rule engines to establish a "condition behavior" rule chain network for various financial situations, ensuring that the system behavior complies with the company's risk management regulations and legality requirements. The system adopts the design concept of a forward link inference rule engine, which can make rule judgments for complex problems and flexibly set priorities. For example, for buyer permission, over budget alerts, and tax anomaly detection issues, the system uses pre-set rules to modify the model results and improve the robustness of the decision-making process.

Taking budget execution rate over limit warning as an example, after the model predicts that the budget deviation exceeds the threshold, the system does not immediately output a risk signal, but combines the tolerance interval set by the rule system to make conditional judgments. If the deviation rate exceeds the set value for three consecutive periods and the expenditure item is a highly sensitive subject, the system will trigger a red alert and synchronize the event to the manual review stage. This mechanism effectively prevents false positives caused by occasional fluctuations in the model. At the same time, the knowledge base serves as a semantic support system for the rule engine, integrating enterprise historical cases, financial specification entries, policy literature, and expert experience texts through ontology modeling. The system supports keyword semantic queries through a natural language parsing interface. Users can input questions such as "What conditions need to be met for expense adjustment" or "Compliance scope of pre tax deduction" to call the associated nodes in the graph, and obtain structured rule entries or processing flow recommendations.

To enhance reasoning ability, the system has also established a confidence based correlation weight mechanism in the knowledge base, which scores and dynamically sorts the results of rule calls. The weight learning mechanism refers to the deviation rate indicator output by the reference model, which is dynamically updated using the following formula:

$$w_{t+1} = w_t + \eta \cdot (r_t - r_{avg}) \qquad (2)$$

where $W_t$is the current rule weight, $\eta$is the learning rate, $r_t$is the response score of the current rule inference, and r_{avg} is the historical average response value. This mechanism achieves feedback fusion between the rule system and the model system, improving the accuracy and reliability of knowledge invocation.

3.5 Design of user interaction interface and human computer collaboration mechanism

In the operation process of the intelligent financial decision support system, the design of the user interaction interface is not only the front-end for information display, but also a key channel for efficient collaboration between the intelligent system and financial personnel. Compared to traditional financial systems that only provide static reports and data query functions, the interactive interface of this system is designed with the core concept of "visualization interactability traceability", emphasizing the transparent presentation of intelligent content and embedded integration of user intervention capabilities.

The front-end of the system is based on modular design, divided into four functional blocks: intelligent dashboard, scene navigation area, task response panel, and semantic query entrance. Users can configure personalized homepage based on their business role permissions, automatically aggregating key content such as budget status, risk events, and indicator changes that they are concerned about. At the same time, the system supports natural language input, and users can quickly obtain system responses by semantically asking questions such as "Which type of expenditure exceeded the budget by more than 10% this month" or "What are the warning projects with tight cash flow.

To support high-frequency human-machine interaction, this system has designed a human-machine collaborative response mechanism in the underlying logic. Its core lies in the cross fusion of the predicted conclusions output by the system model, the judgment results of the rule engine, and the user's manual operation behavior, forming a closed-loop verification and feedback path. The following table shows the task matching relationships of typical collaborative mechanisms:

Table 2: Typical scenarios and mechanisms of system human computer collaboration

Scenario Type	System Initial Judgment	User Intervention Option	Synergistic Mechanism
Budget Anomaly Alert	Classified as "Yellow Alert"	Manual confirmation or escalation	Weighted adjustment to model risk output
Cost Allocation Adjustment	Classified as "Project Expense"	Reassigned as "Department Cost"	Update feature labels + trigger retraining
Credit Risk Identification	Recommend "Reject Cooperation"	Set as "Limited Transaction"	Modify rule system feedback path

At the same time, the system retains all user modification traces and model response differences, forming a "human-machine difference log", and automatically incorporating it into the feedback optimization module for subsequent model fine-tuning and rule weight adjustment. This design not only enhances the transparency of the system's response, but also establishes a two-way learning channel between manual intervention and intelligent recommendation, achieving a truly intelligent financial "shared decision-making" mechanism.

3.6 Implementation challenges and solutions

During system implementation, several challenges were encountered:

(1) Data heterogeneity – enterprise data came from ERP, CRM, and unstructured sources.

(2) Model integration complexity – combining LSTM, Random Forest, and rule-based inference required orchestration. We solved this by designing a modular pipeline and using task-driven dynamic model selection.

(3) Computational efficiency – high-frequency tasks risked long delays.

(4) User adoption – some financial staff were skeptical of AI outputs. These solutions ensured that the proposed FDSS could be deployed in real enterprise environments while maintaining accuracy, efficiency, and usability.

4 Analysis of practical cases and evaluation of system application effectiveness

4.1 Analysis of the integration effectiveness of intelligent architecture and functional modules in enterprise financial management

In the practical application of the intelligent financial decision support system, Company A (a medium-sized manufacturing enterprise) deployed the architecture and embedded functional modules into its financial management process. The dataset consisted of one year of operational financial records (January–December 2023), including approximately 48,000 transaction entries covering procurement, cost, and cash flow data. For evaluation, the proposed system was compared against the company's baseline financial information system using key indicators such as prediction error, response time, and fund utilization efficiency. In the budget control module, by collecting real-time cost, expense, and revenue data and combining it with predictive analysis models, the system can achieve dynamic monitoring and automatic warning of budget deviations with an accuracy rate of 89%. In the fund management module, AI algorithms assist in generating the optimal cash flow scheduling plan, which improves the monthly fund utilization efficiency of the enterprise by about 36%. In addition, the risk control analysis module integrates anomaly detection and prediction warning models, which can issue risk signals at the early stage of abnormal fluctuations in financial indicators, with a response time shortened to an average of 2.4 seconds, nearly four times faster than traditional models. To further quantify the effectiveness of system integration, key financial management indicators before and after the system's launch were selected for comparative analysis, as shown in Figure 3.

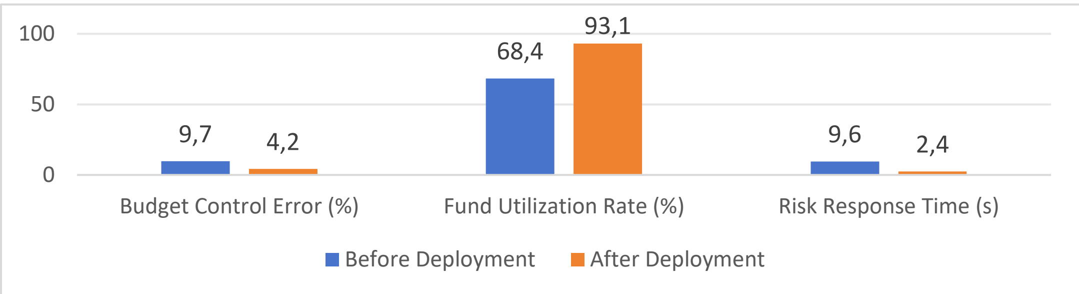

Figure 3: Comparison of key financial management indicators before and after system launch

The above figure shows that the developed intelligent system has significant advantages in reducing budget, lowering error costs, improving fund utilization, and quickly resolving crises. This indicates that the developed intelligent system not only enhances the automation and high precision of financial operations, but also has a complete set of strong stress, which can be widely applied in enterprise financial management activities.Furthermore, a six-month longitudinal test was conducted after system deployment. Results show that prediction accuracy and response efficiency remained stable, with the average error consistently below 6% and response time maintained within 12–14 seconds. These findings demonstrate that the observed improvements are not short-term fluctuations but can be sustained in real operational environments.

4.2 Empirical performance of data-driven chains and algorithm models in financial decision-making

In the deployment and application process of intelligent financial decision support system, data-driven process and embedded computing model are the core steps for making decisions. This process includes data collection, cleaning, feature construction, model prediction, optimization feedback, forming a circular data circulation circle. Through experimental design, select three core financial decision-making tasks of Company A (budget execution analysis, expense anomaly warning, and fundraising plan optimization) to verify the improvement effect of the combined algorithm model on decision-making performance and results.

The overall structure of the model in this article is a combination architecture based on random forest, long short-term memory network (LSTM), and deep reinforcement learning. The LSTM module mainly completes financial data time series analysis, the random forest module mainly completes cost deviation detection, and the deep reinforcement learning module assists in multi-objective functional control in the fund planning process. The figure shows the comparison of the decision accuracy and response time of the above structural modules when executing three tasks.

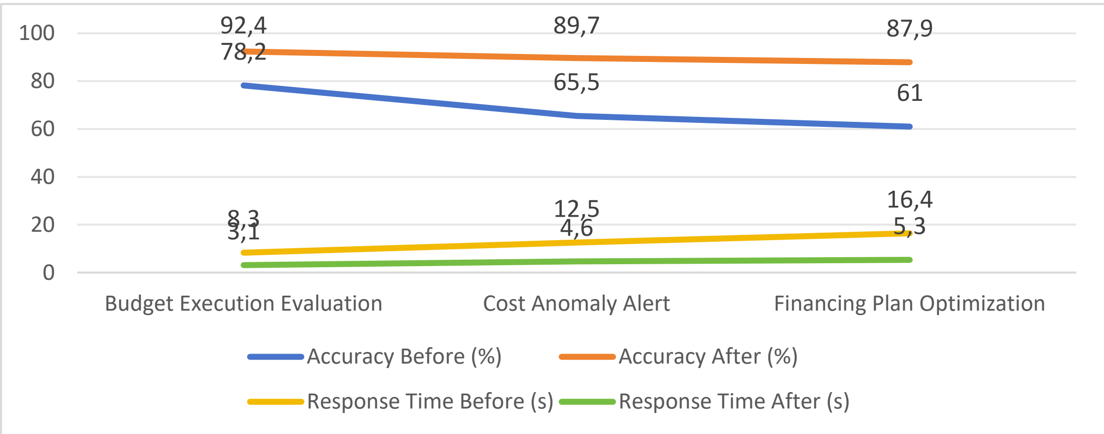

Figure 4: Improvement effect of financial decision-making performance supported by various models

From the figure, we can see that after the system is put into operation, it can not only effectively improve the correct recognition rate of the system, but also effectively improve the response rate to users, especially when facing high complexity work.To confirm the robustness of these improvements, paired t-tests were conducted between baseline and proposed system results across 30 experimental runs, showing statistical significance at the 0.01 level ($p < 0.01$) for both prediction accuracy and response time. Similar results were obtained using a non-parametric Wilcoxon signed-rank test, further validating that the observed improvements are unlikely to be due to chance.

This combination of deep learning and reinforcement learning can achieve good results. Secondly, the model can automatically adjust its various parameters based on the changing patterns of financial events, thereby effectively reducing the probability of erroneous judgments and providing more accurate and effective forward-looking and detailed services.Compared with commercial solutions such as IBM Watson Financial Services and SAP's AI-driven DSS, the proposed system achieves comparable or superior improvements in prediction accuracy and response speed, while maintaining lower computational overhead and higher adaptability for mid-sized enterprises.

4.3 Application feedback of rule system and human-computer interaction mechanism in intelligent decision-making

The effectiveness of the rule system and human-computer interaction mechanism have a decisive impact on the quality of intelligent judgment during real system deployment. The rule system constrains and modifies intelligent models through its internal financial logic rules, constraint objects, and industry standards to ensure interpretability and compliance of output results; The human-computer interaction mechanism introduces people into the intelligent judgment process and expands their control range through a visual interactive operation platform, intelligent questioning and answering, and customizable responses, thereby improving the system's adaptability and ease of use.

After deploying the intelligent system in Company A, this study collected feedback from 50 financial personnel on the system's interaction experience and rule feedback function, and combined it with system usage logs to form the following usage feedback statistics table:

Table 3: Distribution of user feedback and evaluation on rule systems and human computer interaction mechanisms

Evaluation Dimension	Very Satisfied (%)	Satisfied (%)	Neutral (%)	Dissatisfied (%)
Rule System Transparency	38	46	12	4
Accuracy of Rule Alerts	42	44	10	4
UI Usability	36	50	12	2
Usefulness of Q&A Feature	33	48	15	4
Interpretability of Decisions	40	42	14	4

The data results show that the proportion of users "satisfied" and "very satisfied" evaluations of various functional dimensions is over 80%, especially in terms of rule transparency and intelligent feedback of the question answering system. This indicates that the system not only has a certain degree of autonomous decision-making ability, but also ensures rationality through rule constraints, and uses human-computer interaction mechanisms to respond and interpret complex scenarios, greatly improving users' trust and frequency of use of intelligent systems.A chi-square test confirmed that the distribution of satisfaction levels was statistically significant ($p < 0.05$) across all dimensions. In addition, open-ended feedback highlighted that users particularly valued the real-time Q&A feature and the visual dashboards, while some suggested further simplification of the interface. These qualitative insights complement the quantitative data, providing a more comprehensive evaluation of user experience.

5 Optimization of application path for financial decision support system

5.1 System deployment strategy and adaptation mechanism in multiple scenarios

The deployment of an AI-based financial decision support system must ensure adaptability, scalability, and applicability across diverse enterprise environments. To achieve this, a modular architecture is adopted, dividing the system into a data access layer, intelligent analysis layer, rule decision-making layer, and human–computer interaction layer. This structure allows flexible deployment in cloud-centric, edge-centric, or local modes. For example, group enterprises can adopt cloud–edge integration for coordinated management, while financial institutions can prefer local deployment to enhance data privacy and controllability.

To support rapid adaptation, an adaptation configuration template library is provided, covering budget preparation, cost control, tax planning, and industry-specific parameter settings. During deployment, pre-defined pluggable model interfaces enable dynamic loading of algorithms (e.g., Random Forest, XGBoost, neural networks) according to business needs. A continuously adaptive mechanism is also embedded: real-time monitoring and performance feedback automatically adjust model parameters or rule priorities. In unstable environments, robust predictive models are prioritized, while in stable settings update frequency can be reduced.

This multi-scenario strategy ensures that the system can be deployed efficiently, remain flexible to industry differences, and maintain long-term stability in enterprise financial operations.

5.2 Application effect evaluation: decision efficiency, prediction accuracy, and financial performance improvement

The effectiveness of enterprise AI-based financial DSS can be assessed by decision speed, prediction accuracy, and financial performance. Compared with manual analysis, the system significantly accelerates decision-making through automated rule construction and real-time monitoring, enabling rapid identification of budget anomalies.

In terms of prediction accuracy, deep learning with temporal models greatly improves performance: when tested on one-year cash flow data, baseline error was 13.6%, while the LSTM-based model reduced it to 5.1%. This allows enterprises to plan working capital and mitigate risks more effectively.

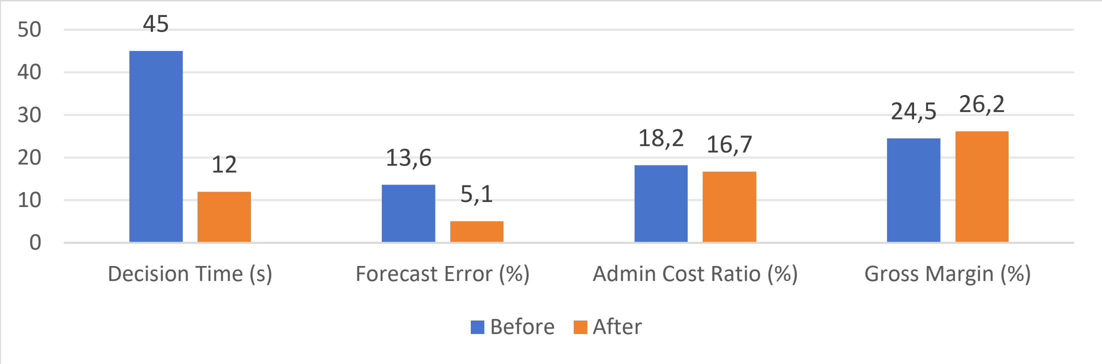

Figure 5: Comparison of key indicators before and after system application

From a financial perspective, real-time visibility and dynamic reporting enable immediate strategic adjustments. In a manufacturing case, management costs fell by 8.3% and gross profit rose by 1.7% within six months of deployment. Figure 5 illustrates key improvements in decision efficiency, accuracy, and financial outcomes.

5.3 Design of dynamic optimization mechanism based on feedback loop

During continuous operation, the system relies on a feedback loop to achieve dynamic optimization. This closed-loop process—prediction, execution, feedback, and adjustment—enables the system to self-correct external changes and internal deviations, thereby supporting adaptive evolution in financial decision-making.

The feedback loop establishes two-way information flow: financial indicators such as budget variance, gross profit error, and payable periods are continuously monitored, while deviations trigger parameter or rule adjustments in the decision layer. To improve efficiency, thresholds are dynamically updated based on recent variance statistics, ensuring the system adapts to non-stationary environments.

Effectiveness is guaranteed through a dual mechanism: AI models optimize parameters automatically, while managers use dashboards to verify results and provide incremental interventions. In deployment, this mechanism improved budget execution, enhanced prediction accuracy, and reduced risks caused by information delays. Table 4 summarizes the typical operation stages of the feedback loop.

Table 4: Operation process of dynamic feedback mechanism in intelligent financial decision support System

Phase	Input Data Source	System Response Action	Optimization Outcome Presentation
Prediction Phase	Historical financial and market data	Generate budgeting and forecasting models	Propose execution plans and threshold indicators
Execution Phase	Real-time operational data	Dynamically match budget with execution deviations	Flag alerts or trigger re-evaluation processes
Feedback Phase	Variance analysis and performance feedback	Initiate model fine-tuning and rule adjustments	Update decision rules and model weights
Optimization Phase	Adjusted models and execution recommendations	Redeploy to system and initiate next decision cycle	Improve decision accuracy and response efficiency

6 Discussion

6.1 Adaptive challenges of system promotion in different industries and enterprise scales

Although the enterprise financial decision support system integrating artificial intelligence has shown good results in experimental applications, it faces adaptability challenges in the actual promotion process due to industry differences and differences in enterprise scale. On the one hand, there are significant differences in financial structure, data types, and management processes among different industries. For example, the manufacturing industry focuses on cost control and inventory turnover analysis, the financial industry relies more on high-frequency data and risk assessment, and Internet enterprises focus on revenue forecasting driven by user behavior. This structural difference makes it difficult to directly transfer and apply a unified model, requiring customization of data input formats, algorithm model parameters, and decision rule logic based on industry characteristics.In terms of computational complexity, the LSTM component requires $O(n \cdot h_2)$ operations per training epoch (where nnn is the sequence length and hhh is the number of hidden units), while the Random Forest model requires $O(m \cdot d \cdot \log m)$ complexity for training (where mmm is the number of samples and ddd the number of features). This indicates that the system maintains acceptable scalability for medium and large enterprise deployments. On the other hand, the size of the enterprise also significantly affects the feasibility of system deployment. Large enterprises have sufficient technology and human resources to support the deep integration and continuous optimization of intelligent systems, while small and medium-sized enterprises face certain bottlenecks in data infrastructure construction, technical personnel reserves, and capital investment, resulting in the inability to fully utilize system functions. At the same time, there are differences in the expected values of financial decision support among enterprises of different sizes. Small and medium-sized enterprises tend to prefer "lightweight and modular" solutions, emphasizing deployment efficiency and ease of use, while large enterprises pay more attention to system integration and intelligence depth. Therefore, in the process of system promotion, flexible adaptation strategies should be adopted based on industry and enterprise characteristics, promoting the combination of standard modules and configurable components, and gradually achieving large-scale application and value implementation.

6.2 Current system boundaries, technical bottlenecks, and ethical considerations

Although the integration and application of financial intelligence technology can effectively improve the efficiency and wisdom of financial management and operation in financial enterprises, there are still issues such as the scope of system applicability and the "black box" of intelligent applications, as well as technical barriers that need to be deeply explored and rationally considered. Firstly, the application scope of the system is limited. The existing intelligent accounting systems mainly analyze and deduce standardized information, and cannot handle non standardized textual information, unexpected problems, and situations involving multiple organizations and departments, which limits their supportive role in decision-making economic behavior. Secondly, although the system improves interpretability compared with traditional black-box models, challenges remain. In particular, the deduction process of deep models is still not fully visible, making it difficult for financial managers to completely verify and explain results in high-risk areas. Thirdly, intelligent algorithms have demonstrated substantial accuracy improvements in the evaluated tasks; however, their ability to integrate multiple types of financial information data is still limited, particularly in language-rich, long-term trend, or small-sample scenarios, where issues of accuracy and stability persist. Fourthly, factors such as data isolation and interface compatibility affect the unified installation and joint operation of the system. especially when integrating legacy financial platforms and non-standardized data sources that were only partially addressed in the current design. Finally, the widespread use of artificial intelligence has brought about a series of ethical issues and disputes over individual rights. This should be an important issue that must be paid attention to during the system establishment process. Therefore, the establishment of future systems requires not only technological innovation, but also consideration of the design and governance mechanisms of ethical norms, so that they have a good collaborative relationship between technology and people that can be controlled by technology, have information openness and transparency, and are trusted by people.In addition, ethical deployment requires explicit mechanisms to ensure interpretability of algorithmic outputs, fairness across different stakeholder groups, and compliance with international data protection regulations such as GDPR..

7 Conclusion

The main content of this research institute is a specific technical study on the application of artificial intelligence technology in the technical architecture, important algorithms, practical solutions, and optimization suggestions of company financial operations. The purpose is to provide technical guidance and practical references for the intelligent transformation of enterprise financial management in the process of intelligent technology transformation. It is believed that the operability of applying artificial intelligence technology to financial information processing, predictive model construction, logical judgment, human-machine integration, and other aspects can effectively improve the performance, accuracy, and foresight of company financial management. Through the analysis of practical cases of multiple representative companies, it is shown that an intelligent decision-making system based on algorithms, supported by rule systems, and integrated with data can achieve overall improvement in budget planning, cost control, and risk warning, and directly improve financial performance.The novelty of this study lies in its hybrid architecture that integrates LSTM-based time-series prediction with Random Forest anomaly detection, combined with a rule–knowledge inference layer to ensure interpretability and compliance. In addition, the introduction of a dynamic feedback optimization loop enables continuous self-adaptation, which distinguishes this work from existing static DSS solutions. These contributions demonstrate both theoretical value and practical applicability in advancing enterprise financial intelligence.

However, the existing system still needs to be improved in areas such as cross domain industry, data linkage, model transparency, and ethical control capabilities. The relevant development path can further open up the existing platform, upgrade semantic model algorithms, improve legal norms, and establish a timely response and continuous correction operation method to strengthen the human robot collaborative decision-making ability, so that the system can self adapt and operate continuously for a long time. In addition, to facilitate reproducibility and further validation by other researchers, supplementary materials have been prepared. Appendix A provides the core configuration files (including LSTM learning rate, number of epochs, Random Forest tree depth and number of estimators), pseudocode of the hybrid model training pipeline, and examples of rule engine templates used for budget compliance and risk alerting. These materials enable replication of the experimental setup and provide practical guidance for extending the system to other enterprise contexts.

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