ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Intelligent Analysis Model and application effect evaluation of Industry and Finance Data Fusion in the Intelligent Transformation of Financial data

Shujing Zhang[1,*]

[1] School of Accounting of HeNan University of Engineering ZhengZhou 451191, HanNan, China

SUMMARY: *In order to solve the problems of poor connection between business data and financial data, lag in risk identification and insufficient collaborative decision-making support in the intelligent transformation of financial data, an intelligent analysis model of industry and finance data fusion was constructed, and the application effect was evaluated with case enterprises. The research established an analysis link around data access, feature fusion, risk identification, decision support and effect feedback, and jointly identified order execution, inventory turnover, payment collection cycle, revenue cost and gross profit change. The results show that after the application of the model, the accuracy of risk identification increases from 83.6% to 92.4%, the average response time of early warning decreases from 26.5 hours to 9.8 hours, the completion rate of collaborative processing of industry and finance increases from 71.2% to 88.7%, and the gross profit rate increases from 22.34% to 23.41%. The research shows that the model can enhance the ability of business risk perception, improve the efficiency of collaborative decision-making, and provide method support and application reference for the intelligent transformation of enterprise financial data.*

KEYWORDS: *Intelligent transformation of financial data; Business and financial data fusion; Intelligent analysis model; Application effect evaluation*

1 Introduction

The continuous evolution of digital technologies, intelligent algorithms and data infrastructure is reshaping the way corporate financial management operates and the logic of value creation. Traditional financial work has long been focused on accounting, reporting and post-hoc analysis. Although it can meet the basic requirements of compliance disclosure and business records, it simply relies on the financial side for information processing under the background of rapid business changes, increasingly diverse data sources and emphasis on real-time response in management decisions. It has been difficult to support the dynamic grasp of the enterprise to the operating state, risk change and resource allocation efficiency. The transformation of financial data intelligence is no longer just a problem of tool replacement or system upgrade, but gradually turns to a deep reconstruction process of data penetration, model-driven and decision-making collaboration and parallel promotion.

From the perspective of enterprise practice, there are some phenomena between financial data and business data for a long time, such as caliber dispersion, inconsistent update rhythm,

*zsj1982202509@163.comn
https://doi.org/10.65102/is2026795 Published: 30 April, 2026

weak indicator correlation and analysis chain breakage. Sales, procurement, production, inventory, supply chain, customer performance and other business information are often deposited in different systems, and the financial system is more responsible for result confirmation and value measurement. Although the two types of data are integrated with each other in the operation of the enterprise, they fail to form a stable, efficient and traceable integration mechanism at the analysis level. The direct consequence of this is that it is difficult to identify budget deviation in time, lack of process explanation of cost fluctuations, unable to realize advance warning of business anomalies, and difficult for management to obtain a clear judgment on the transmission relationship between "business behavior, financial results and risk status". With enterprises moving from informatization to digital intelligence, how to build a computable, interpretable, and applicable intelligent analysis model on the basis of industry and finance integration has become a common concern of financial management research and enterprise transformation practice.

Existing studies have discussed the mechanism of financial digitization, intelligent analysis and decision support from different aspects. Al-Okaily pointed out that the adoption intention of accounting analysis technology under the digital context is closely related to the organization's understanding of the value of data and the degree of management support [1]. Al-Okaily et al. found in the banking industry research that digital accounting transformation can improve financial governance effectiveness through information integration and process reengineering [2]. Artene et al. believe that AI-driven decision-making mechanism is pushing the financial reporting system from "information presentation" to "value identification and management empowerment" [3]. Abhishek et al. proposed that the embedding of digital technology into accounting, auditing, reporting and compliance processes is changing the boundaries of traditional finance functions [4]. Eyadat's research shows that business intelligence tools can significantly enhance the judgment support ability of enterprise management [5]. Abu Rumman et al. verified the positive impact of data architecture capability on risk management and operational decision quality based on structural equation model [6]. Delias and Kitsios emphasized that the combination of operations research analysis and business intelligence is an important fulminant of enterprise digital transformation to realize management value-added [7]. Hezam et al. pointed out in the literature review that big data analysis has gradually become a key method source in audit and financial analysis research [8]. Huang and You believe that the value of artificial intelligence in financial decision-making is not only reflected in the improvement of prediction accuracy, but also in the enhancement of comprehensive recognition ability of complex information [9]. From the perspective of management research, Kraus et al. pointed out that the core of digital transformation does not lie in the isolated deployment of technologies, but in the overall linkage of organizational processes, data resources and decision-making mechanisms [10], as shown in Table 1.

Table 1: Related research context and research entry point of this paper

Research Topic	Representative Studies	Main Focus	Existing Limitations	Entry Point of This Study
Financial Digital Transformation	Al-Okaily [1]; Al-Okaily et al. [2]	Technology adoption, process reengineering, governance optimization	Insufficient exploration of industry–finance data coordination mechanisms	Places industry–finance integration at the core of model design
AI-Driven Financial Decision-Making	Artene et al. [3]; Huang and You [9]	Intelligent analysis, decision support, value identification	Weak explanation of the linkage between business operations and financial outcomes	Strengthens linkage analysis between business behavior and financial results
Business Intelligence and Decision Support	Eyadat [5]; Delias and Kitsios [7]	BI tools for improving managerial judgment	Overemphasis on tool value while underemphasizing integration processes	Builds a complete chain from data governance to decision output
Data Architecture and Risk Management	Abu Rumman et al. [6]	Impact of data architecture on decision-making and risk control	Lack of specific models and application validation	Introduces a case enterprise for risk identification evaluation
Big Data and Financial Analysis	Hezam et al. [8]	Application of big data analytics in financial auditing	Research objects are relatively scattered and scenario integration is insufficient	Designs an intelligent analysis model for industry–finance integration scenarios
Comprehensive Research on Digital Transformation	Kraus et al. [10]	Collaborative transformation of organization, process, and technology	Lack of implementation paths specific to financial analysis applications	Proposes a deployable and evaluable application framework

Although the existing results provide an important basis for this study, there are still several areas worth advancing. One kind of research focuses more on the macro trend, institutional environment and adoption impact of financial digital transformation, and does not involve enough on how to realize unified mapping, collaborative cleaning and linkage analysis of industry and financial data within the enterprise. The other type of research focuses on intelligent decision-making, risk prediction or business intelligence tools, but mostly focuses on single financial indicator system or single scenario data analysis, and does not reveal enough about the dynamic coupling relationship between business behavior and financial results. At the same time, some studies pay more attention to the performance of the algorithm, but relatively ignore the explanatory value and application effect of the model output in business management, resulting in a gap between "model effective" and "management useful". Based on this, it is necessary to further construct an intelligent analysis model that takes into account data governance, risk identification, collaborative decision-making and effect evaluation around the process of financial data fusion, so as to promote the research on the intelligent transformation of financial data from concept discussion to the application level that can be implemented and verified.

This paper focuses on the problem of industry and financial data fusion in the intelligent transformation of financial data. On the premise of sorting out the relevant theoretical basis, this paper constructs an intelligent analysis model for business risk identification and industry and financial collaborative decision support, and evaluates its application effect with an enterprise case. This paper tries to answer three questions: first, how to complete the structural integration and semantic alignment of business data and financial data under a unified analysis framework; Second, how the intelligent analysis model can transform the scattered data clues into decision information that can be used for risk identification and business judgment; Third, whether the model can form an observable improvement in recognition efficiency, response speed, collaborative support and management effectiveness after landing. Around these problems, this paper establishes a continuous analysis chain between model construction, module design, case application and effect evaluation, and tries to make theoretical analysis, technical implementation and management application support each other.

From the perspective of research value, the significance of this paper is mainly reflected in two levels. At the theoretical level, the intelligent transformation of financial data, the fusion of industry and financial data, and the application of intelligent analysis were brought into the same research framework, which was helpful to promote the research of financial management from the discussion of functional digitization to the research of data-driven decision-making mechanism. At the practical level, this paper tries to put forward a set of model design ideas with strong operability, which can provide a reference method basis for enterprises to open up the data link between the business end and the financial end, improve the forward-looking risk identification, and enhance the operation collaborative judgment ability. Compared with the research path that only stays in the system construction description or single indicator analysis, this paper emphasizes the analysis logic after data fusion, the coupling relationship between functional modules, and the evaluability of model application effects, expecting to provide more targeted research reference for the intelligent transformation of enterprise financial data.

2 Theoretical Basis

2.1 The basic connotation of intelligent transformation of financial data

The intelligent transformation of financial data refers to the process of systematic reconstruction of traditional financial management mode by enterprises under the condition of continuous embedding of digital technology, data governance and intelligent algorithms. Its core is not limited to electronic accounting or financial system upgrading, but lies in opening up the data link between business activities, financial records and business analysis, so that financial management turns from result reflection to process perception, from static supervision to dynamic identification, from experience judgment to model support. With the increasingly complex business environment of enterprises, the data faced by the financial department is no longer limited to the information of the report, but continues to extend to multi-source business information such as orders, procurement, production, inventory, customer performance and supply chain collaboration. This change shows that the transformation of financial data intelligence is essentially a collaborative change of data resources, management processes and decision-making mechanisms.

From the perspective of connotation composition, the transformation of financial data intelligence is mainly reflected in three interrelated levels. The first is the reshaping of the data foundation, that is, the business data and financial data originally scattered in different business systems are uniformly collected, cleaned, mapped and integrated to form a sharable and traceable data base. The second is the reorganization of the management process, that is, with the help of automatic processing, real-time calculation and rule embedding mechanism, the financial information transmission lag is compressed, and the response ability of budget control, cost monitoring and risk warning is enhanced. Thirdly, the decision-making function is further improved, that is, the predictive analysis, anomaly recognition and intelligent evaluation methods are introduced on the basis of data fusion, so that the financial department gradually turns from the accounting support center to the operation decision support center. It can be seen that the transformation of financial intelligence not only changes the technical form of financial work, but also reshapes the role mode of financial participation in corporate governance and value creation.

As shown in Figure 1, the transformation of financial data intelligence is carried out along the path of "data through-process optimization-intelligent analysis-value feedback", whose goal is to improve the level of industry and finance collaboration, the efficiency of risk identification and the quality of business decision-making, so as to lay a theoretical foundation for the construction of subsequent industry and finance data fusion intelligent analysis model.

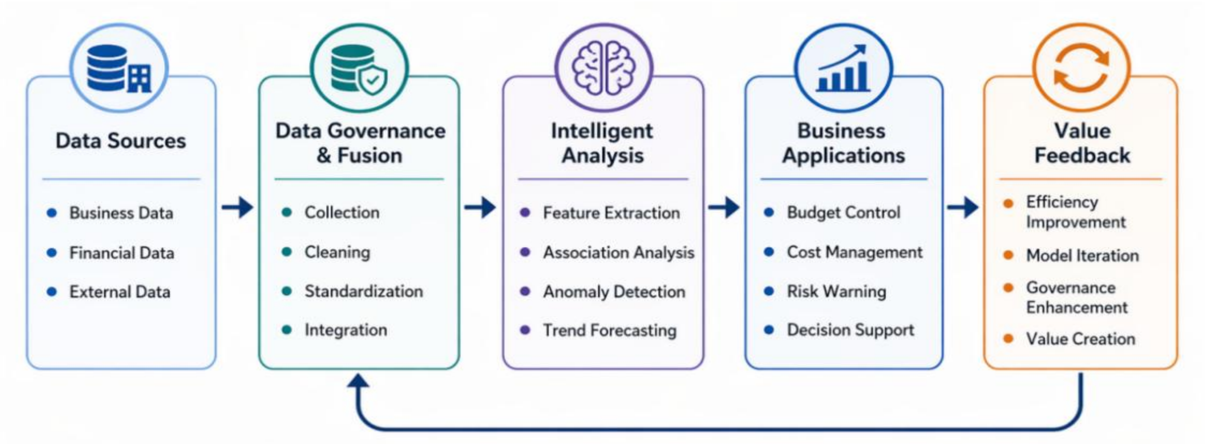

Figure 1: Basic connotation framework of intelligent transformation of financial data

2.2 Theoretical framework of industrial and financial data fusion

Industry and financial data integration refers to the integration of order, procurement, production, inventory, logistics, customer settlement and other data formed in the process of business operation into a unified analysis framework with revenue, cost, expense, profit, assets and cash flow data in the financial system. On the basis of aperture coordination, coding mapping and time sequence alignment, Form a data system that can reflect business process and value results at the same time. The focus is not to simply summarize the two types of data, but to establish the identifiable, traceable and computable correspondence between business behavior and financial results, so that financial analysis is no longer limited to result interpretation, but can be extended to business process identification and management support.

From the theoretical structure, the data fusion of industry and finance includes three levels:

data connection, relationship mapping and analysis output. Data cohesion solves the problem of scattered sources and different standards, that is, establishing unified master data rules around key objects such as customers, products, orders, departments, projects, and transforming heterogeneous information in business systems and financial systems into comparable data units. Relational mapping solves the problem of how to establish a transmission chain between business events and financial results, such as how sales changes affect revenue recognition, how inventory turnover affects capital occupation, and how purchasing price fluctuations are transmitted to the cost structure. On the basis of the above, the analysis output is to further transform the scattered data clues into the information basis required for budget control, risk early warning and collaborative decision-making through feature fusion, anomaly identification and trend judgment. The overall logical relationship is shown in Figure 2.

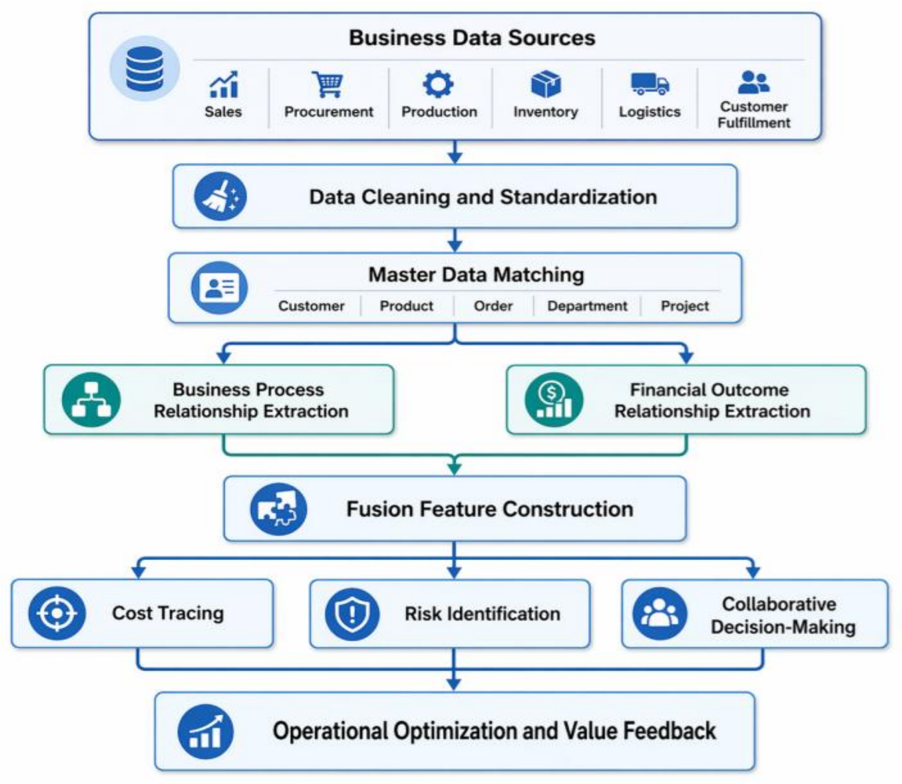

Figure 2: Theoretical framework of industry and finance data fusion

In order to describe the fusion process of business and financial data, let the business feature vector of the ith analysis unit be $\mathrm{B_i}$ and the financial feature vector be $\mathrm{F_i}$, then the fusion representation can be written as follows.

$$\mathrm{Z_i} = \lambda_1 \mathrm{B_i} + \lambda_2 \mathrm{F_i} + \lambda_3 (\mathrm{B_i} \circ \mathrm{F_i}), \qquad \lambda_1 + \lambda_2 + \lambda_3 = 1 \tag{1}$$

where, $\mathrm{Z_i}$ represents the integrated feature after fusion, λ_1、λ_2 and λ_3 represent the business information weight, financial information weight and interaction term weight respectively, and $\mathrm{B_i} \circ \mathrm{F_i}$ represents the coupling relationship between the two types of features. This expression shows that the data fusion of industry and finance is not a linear superposition, but needs to retain the linkage effect between business variables and financial variables, so as to enhance the ability to explain the changes in business status, resource allocation efficiency and financial risk.

2.3 Theories related to intelligent analysis and decision support

Under the background of the intelligent transformation of financial data, intelligent analysis and decision support is not a simple extension of traditional financial analysis methods, but a comprehensive analysis mechanism that integrates data identification, model calculation, rule constraints and management feedback into a unified framework on the premise of business and financial data fusion. Its basic meaning is that, relying on multi-source data processing capabilities, the revenue changes, cost deviations, inventory occupation, capital fluctuations and performance risks in enterprise business activities are continuously identified, and the identification results are transformed into decision-making basis that can serve budget adjustment, resource allocation and business coordination. For enterprises, the value of financial work is no longer limited to result accounting and difference explanation, but gradually turns to business process perception, risk signal capture and decision scheme support.

Table 2: Theoretical composition of intelligent analysis and decision support

Structural Dimension	Main Content	Role in Industry–Finance Integrated Analysis
Data Support	Multi-source data collection, cleaning, integration, and updating	Forms a unified data foundation and ensures that analysis results are comparable and traceable
Model Analysis	Trend forecasting, anomaly detection, risk identification, and correlation mining	Improves the ability to identify the linkage between operational changes and financial outcomes
Rule Constraints	Budget standards, internal control rules, business boundaries, and historical experience	Ensures that model outputs comply with enterprise management requirements and practical contexts
Decision Feedback	Early warning prompts, analytical reports, coordination suggestions, and execution tracking	Promotes the incorporation of analysis results into a closed-loop management process and strengthens decision implementation effectiveness

This theory usually includes four interrelated parts: data support, model analysis, rule constraint and decision feedback. Data support emphasizes the extraction of effective information from sales, procurement, production, inventory, settlement and general ledger, and forms a computable data basis through a unified caliber. Model analysis emphasizes the quantitative expression of the relationship between business events and financial results by means of classification recognition, trend prediction, anomaly detection and association mining. Rule constraints emphasize embedding budget standards, internal control requirements, business boundaries and historical experience into the analysis process to avoid model output deviating from actual enterprise management logic. Decision feedback emphasizes the timely transmission of analysis results to management and executive departments, so that data analysis truly enters the closed loop of business management. As shown in Table 2, each component of intelligent analysis and decision support has its own functional emphasis, but its common goal is to improve the recognition ability and response efficiency of enterprises to complex operating states. When the fused business property data is input into the intelligent analysis module, the business early warning probability at a certain point can be expressed as follows.

$$P_t = \frac{1}{1 + e^{-(w^T x_t + b)}} \tag{2}$$

where, P_t represents the probability of comprehensive risk identification at time t, x_t represents the feature vector of industry and finance fusion at this time, w is the model parameter, and b is the bias term. This formula shows that the intelligent analysis is not based on a single financial index to make an isolated judgment, but combined with the business execution state and the characteristics of financial results to make an overall identification of the operation state of the enterprise. When the P_t exceeds the preset threshold, the system can trigger an early warning and output decision suggestions to the budget management, cost control or operation collaboration module. Therefore, intelligent analysis and decision support theoretically constitute an important intermediary from data to management and from identification to decision in the intelligent transformation of financial data.

3 Research Design

3.1 Principles of model construction

The intelligent analysis model of business financial data fusion in the intelligent transformation of financial data should not only pursue the complexity of the algorithm form, but should establish a stable, usable and interpretable analysis framework around the real needs of enterprise operation and management. In the process of model construction, it is necessary to take into account data consistency, analysis effectiveness, response timeliness, system scalability and security controllability at the same time, so that the model can not only accurately identify the linkage between business activities and financial results, but also adapt to the continuous application of different business scenarios of enterprises.

At the data level, the model should adhere to the principle of uniform caliber. The data sources of the business end and the financial end are different, the update frequency is different, and the field standards are also different. If there is no unified coding, master data matching and exception verification mechanism, the subsequent analysis results are easy to deviate. Therefore, the model input must be based on the consistent mapping of key objects such as orders, products, customers, departments, projects, etc., to ensure that the business process information can be effectively corresponding to revenue recognition, cost collection, profit formation and capital flow. At the analysis level, the model should emphasize both relevance and interpretability. Although relying only on black-box judgment may improve the local prediction accuracy, it is difficult to meet the requirements of financial management for cause tracing and responsibility identification. Therefore, the model design should retain the contribution relationship of key variables, so that the identification results can serve budget control, cost tracking and business collaboration.

At the operational level, the model should also meet the requirements of real-time response and dynamic update. The intelligent transformation of financial data is not a one-time analysis task, but a dynamic process that continues to occur with business activities. The model needs to correct the judgment results in time according to the new data. Let the comprehensive objective function of the model at time t be as follows.

$$J = \eta_1 E + \eta_2 T + \eta_3 S + \eta_4 C, \eta_1 + \eta_2 + \eta_3 + \eta_4 = 1 \tag{3}$$

where, E represents the analysis accuracy, T represents the processing timeliness, S represents the system stability, C represents the result interpretability, and η_1 to η_4 are the corresponding weights. This equation shows that the quality of the model should not be determined by a single accuracy index, but should achieve a comprehensive balance between accuracy, speed, stability and usability. At the same time, model deployment should also follow the principles of hierarchical permission control, sensitive field protection and log retention, so as to ensure the security of industry and financial integration data in the process of circulation and analysis. Table 3 summarizes the main principles followed in the model construction of this study and their specific requirements.

Table 3: Model construction principles and their requirements

Principle Category	Main Requirements	Significance for Model Application
Data Consistency	Unified coding rules, master data matching, abnormal value validation	Ensures that industry–finance data can be connected, compared, and traced
Analytical Effectiveness	Preserve key variable relationships and strengthen identification accuracy	Improves the recognition of operational anomalies and the quality of financial analysis
Result Interpretability	Clarify the contribution direction of indicators and impact pathways	Helps management understand the results and assign responsibility
Real-time Responsiveness	Support dynamic updates and rapid computation	Meets the need for timely analysis in continuous business operations
Scalability and Security	Modular design, access control, and log tracking	Ensures sustainable model deployment and data security

3.2 Overall architecture design of intelligent analysis model

In order to make the business financial data fusion can be stably transformed into executable and evaluable analysis results, this paper designs the intelligent analysis model as a hierarchical and progressive overall architecture. The architecture is not centered on a single algorithm module, but around the logical chain of "data access, preprocessing, intelligent analysis and application output", which integrates the scattered data resources, heterogeneous processing processes and diverse management requirements in business systems and financial systems into the same operating framework. Through the hierarchical design, the coupling degree between different modules can be reduced, and the subsequent model update, function extension and application deployment can be facilitated.

Specifically, the bottom layer is the data access layer, which is mainly responsible for collecting data from sales, procurement, production, inventory, settlement, general ledger and budget, and completing master data matching, timestamp unification and interface standard conversion. The middle layer is the data processing layer, which mainly undertakes the tasks of missing repair, anomaly identification, field mapping, feature normalization, fusion and recombination, so as to improve the consistency and computability of input data. The upper layer is the intelligent analysis layer, which integrates classification recognition, association analysis and trend prediction model methods around the goals of business risk identification, cost deviation diagnosis, financial pressure judgment and collaborative performance measurement. The top layer is the application output layer, which mainly feeds back analysis results to managers in the form of early warning tips, analysis reports, visual kanban boards and decision suggestions. Figure 3 shows the overall architecture of the model.

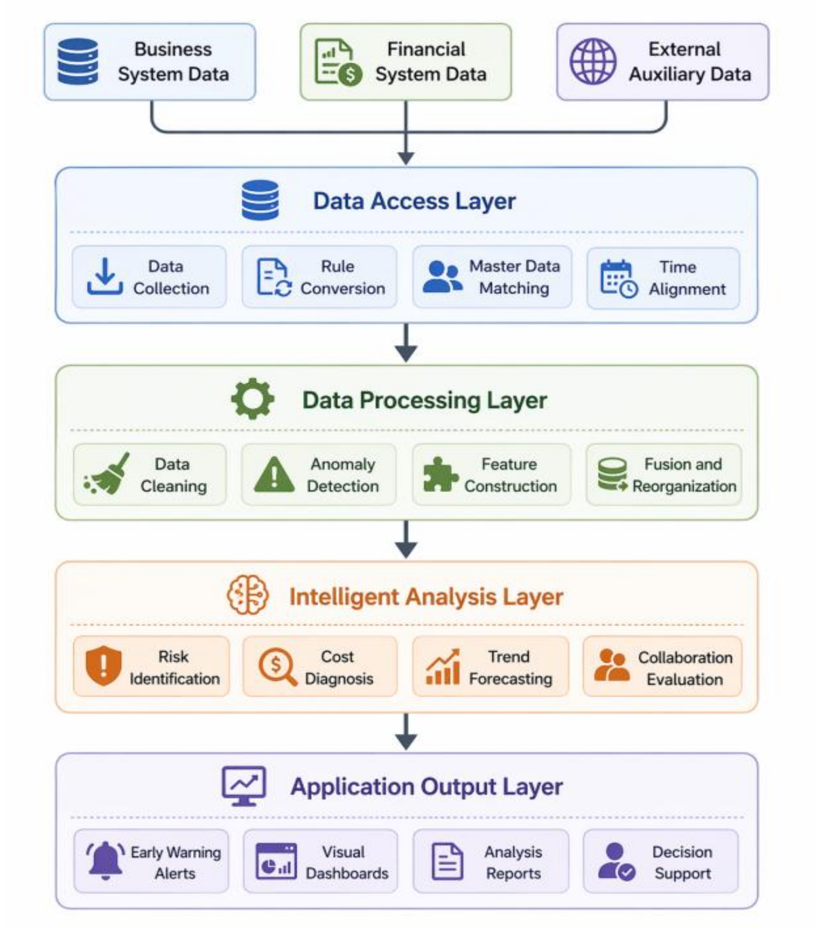

Figure 3: Overall architecture of intelligent analysis model

In order to describe the overall operation process of the hierarchical structure, suppose that the original input data is X_t, and the mapping functions of the data access layer, processing layer, analysis layer and output layer are G_1、G_2、G_3 and G_4 respectively. Then the overall output of the model at time t can be expressed as follows.

$$Y_t = G_4(G_3(G_2(G_1(X_t)))) \tag{4}$$

where, Y_t represents the final comprehensive analysis result. This expression shows that the model output is not generated directly by a single step, but relies on successive passes and refinements after multiple layers of processing. The setting of hierarchical architecture enables the model to maintain good stability, scalability and application adaptability in the face of high-frequency update, multi-source heterogeneous and complex correlation of business and financial data, and also provides a clear implementation basis for the functional module design and case analysis in the following.

3.3 Source and preprocessing of industry financial data

In order to ensure the authenticity and computability of industry-finance fusion analysis, this paper divides the data sources into three categories: business data, financial data and external auxiliary data, and constructs a data preparation process around unified collection, hierarchical storage and standardized preprocessing. Business data mainly comes from the enterprise sales, procurement, production, inventory, logistics and customer performance system, focusing on extracting order quantity, delivery cycle, return rate, raw material consumption, inventory turnover days and customer settlement cycle and other indicators. The financial data mainly comes from the general ledger, receivables and payables, cost accounting, budget management and fund management module, focusing on extracting information such as operating income, operating cost, period expenses, gross profit rate, cash flow and budget implementation deviation. External auxiliary data include industry sentiment index, raw material price fluctuation, tax policy and market demand changes and so on. Data from different sources are entered into the unified data pool through interface extraction, batch synchronization and rule verification, and the mapping and association are completed according to five types of primary keys: customer, product, order, department and period.

Considering the differences in the structure form, update frequency and use scenario of business financial data, this paper adopts a hybrid management method of "relational database + distributed storage". The financial master table and business transaction details with stable structure and strict constraints are stored in the relational database, and the log class, text class and high-frequency flow data are stored in the distributed environment, so as to take into account the consistency requirements and scalability. Table 4 lists the main data categories and their processing emphases in this paper.

Table 4: Sources of industry and property data and key points of preprocessing

Data Category	Main Source	Typical Fields	Preprocessing Focus
Business Data	Sales, procurement, production, inventory, and logistics systems	Order volume, delivery lead time, return rate, inventory level	Code unification, time alignment, duplicate record removal
Financial Data	General ledger, cost, budgeting, accounts receivable and payable, and fund management systems	Revenue, cost, expense, profit, cash flow	Account mapping, caliber unification, abnormal fluctuation identification
External Auxiliary Data	Industry databases, market monitoring, and policy documents	Price index, industry prosperity index, tax and fee changes	Missing value completion, frequency conversion, standardization

In the preprocessing stage, the missing value processing, outlier identification, standardized transformation and interval normalization are performed in turn. For a small number of missing values in continuous variables, the mean of the adjacent periods is used to fill in:

$$x_i = \frac{x_{i-1} + x_{i+1}}{2} \tag{5}$$

For the abnormal samples that deviate greatly from the overall distribution, the standardized residual discriminant method is used:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{6}$$

When $|z_i| > \delta$, the observation is marked as an outlier and censoring or correction is implemented in combination with business rules. In order to weaken the interference of different dimensions on model training, this paper standardizing the amount index with large fluctuation range:

$$x_i^* = \frac{x_i - \bar{x}}{s} \tag{7}$$

For ratio and turnover indicators, interval normalization is applied:

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{8}$$

After the above processing, the business property data originally scattered in different systems, different calibs and different scales are transformed into a unified feature set that can be matched, comparable and input to the model, which provides a stable data basis for subsequent business risk identification, collaborative decision support and application effect evaluation.

3.4 Design of model function modules

3.4.1 Data fusion analysis module

The data fusion analysis module is the basic link of the entire intelligent analysis model. Its task is to match the business data such as sales, procurement, production, inventory and settlement with the financial data such as revenue, cost, expense, profit and cash flow at the object level and feature level. The module takes customer, product, order, department and period as the unified index, and forms the fusion sample that can be used for subsequent recognition and judgment through field mapping, time alignment and semantic calibration. In order to measure the matching strength between business records and financial records, this paper introduces a similarity function:

$$S_{ij} = \frac{b_i^T f_j}{||b_i||\ ||f_j||} \tag{9}$$

where, b_i represents the ith business feature vector, f_j represents the JTH financial feature vector, and the larger S_{ij} is, the stronger the correspondence between the two types of records. What this module accomplishing is not a static concatenation, but a computable foundation for the connection between business behavior and financial results.

3.4.2 Risk identification and early warning module

The risk identification early warning module mainly carries out dynamic identification for problems such as abnormal income, cost deviation, inventory backlog, payment delay and financial pressure. The module takes the historical normal interval as a reference, compares the real-time observation value with the model predicted value, and extracts the abnormal deviation degree. Its deviation degree can be expressed as

$$D_t = \frac{|y_t - \hat{y}_t|}{\hat{y}_t + \varepsilon} \tag{10}$$

where y_t is the actual observed value at time t, $\hat{y}_t$ is the predicted value, and ε is a tiny constant to prevent the denominator from being zero. When D_t exceeds the threshold, the system triggers an early warning and marks the abnormal source, so as to improve the forward identification ability of business risk.

3.4.3 Collaborative decision support module

The role of the collaborative decision support module is to combine the risk identification results with profit contribution, resource consumption and execution feasibility to provide the management with clearly sequenced disposal suggestions. For the KTH item to be decided, its priority index is defined as follows.

$$U_k = \frac{R_k \times M_k}{C_k} \tag{11}$$

Here, R_k represents the risk intensity, M_k represents the management gain or improvement, and C_k represents the disposal cost. The higher the U_k is, the more priority the item should enter the adjustment sequence. With the help of this module, the model output no longer stays at the exception presentation, but is further transformed into decision suggestions with action sequences.

3.4.4 Effect evaluation feedback module

The effect evaluation feedback module is used to test the actual improvement degree of the operation and management after the model is launched, focusing on the indicators such as recognition accuracy, response time, collaboration efficiency and operation improvement range. Let the values of an evaluation index before and after optimization be Vpre and Vpost respectively, then the improvement rate is as follows.

$$G = \frac{Vpost - Vpre}{Vpre} \times 100 \tag{12}$$

The module can feed back the operation effect of the model to the parameter correction and rule optimization, and promote the system to form a closed-loop mechanism of "recognition-decision-execution-evaluation-re-optimization". Figure 4 shows the functional structure of the model.

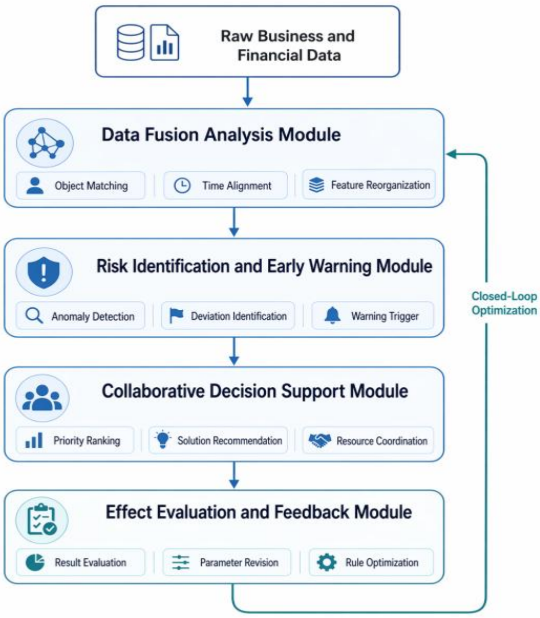

Figure 4: Structure of functional modules of the model

3.5 Model Implementation and application Deployment

In order to ensure that the intelligent analysis model of industry and finance data fusion can run stably in enterprise business scenarios, this paper adopts the deployment idea of module decoupling at the implementation level, and encapsulates data access, feature processing, risk identification, decision support and result feedback into independent services, and completes collaboration through interface call and message passing mechanism. This method can reduce the interdependence between modules, make the model update, fault isolation and function expansion more convenient, and also help to maintain the continuity of system operation under different business scales and concurrent conditions.

In the process of model implementation, this paper combines rule recognition, ensemble learning and time series prediction to build a composite analysis engine. Let the fusion input at time t be x_t and the output of the JTH sub-model be $h_j(x_t)$, then the comprehensive judgment result is expressed as follows.

$$\hat{r}_t = \sum_{j=1}^{p} \omega_j h_j(x_t), \sum_{j=1}^{p} \omega_j = 1 \tag{13}$$

Here, ω_j is the weight of each sub-model. This structure can take into account both stable recognition under rule constraints and nonlinear description ability in complex situations. In order to control the time delay of business property data transmission across systems, this paper uses the synchronization delay index to measure the consistency of data arrival:

$$\Delta_t = t_t^{(f)} - t_t^{(b)} \tag{14}$$

where, $t_t^{(f)}$ and $t_t^{(b)}$ represent the data writing time of financial end and business end at time t, respectively. When Δ_t exceeds the set threshold, the system automatically triggers the process of supplementary acquisition and recalculation.

In terms of running environment, the model is deployed on Ubuntu 22.04 server environment, the development language is Python 3.11, the interface service is FastAPI, the data management is PostgreSQL 14 and Redis 7.0, and the containerization platform is Docker. Unified scheduling is done by Kubernetes. The server is configured with a 32-core CPU, 128 GB memory, and 1 TB SSD storage. In order to realize dynamic resource allocation according to load, let the load weight of the ith service be ρ_i and the total system resource be C, then its allocation amount is as follows.

$$C_i = \frac{\rho_i}{\sum_{k=1}^{n} \rho_k} C \tag{15}$$

The mechanism can dynamically adjust computing resources according to the peak changes of different tasks such as risk identification, report generation and early warning push. After the system is deployed, the stability of the system is evaluated by the availability index:

$$A = \frac{T_u}{T_u + T_d} \tag{16}$$

Here, T_u is the normal operation time and T_d is the fault downtime time. Therefore, the model implementation and application deployment not only complete the implementation of the algorithm, but also constitute a closed-loop support from data update, analysis execution to result feedback. Figure 5 shows the model implementation and deployment structure.

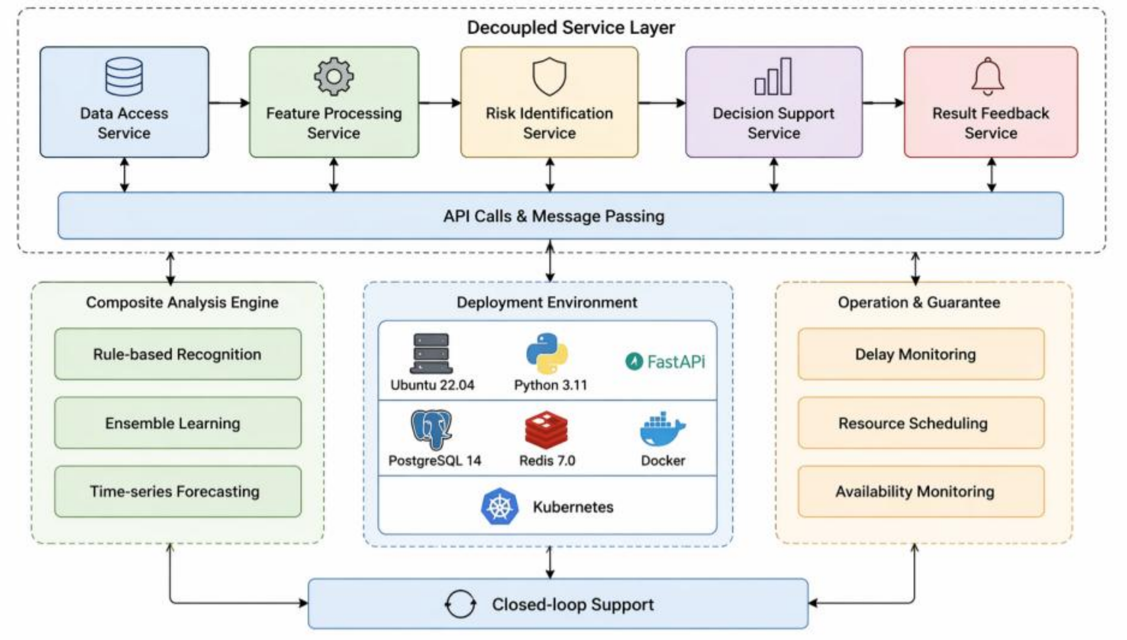

Figure 5: Model implementation and application deployment structure

4 Application case analysis

4.1 Case enterprise background

In this paper, a medium-sized equipment manufacturing enterprise H company in Henan Province is selected as an application case. Founded in 2012, the company is mainly engaged in the research and development, production and sales of intelligent transportation equipment, automated sorting units and supporting control systems. Its products are mainly for manufacturing, warehousing and logistics industries and regional supply chain service enterprises. In 2023, the company achieved an operating revenue of 864 million yuan, an increase of 11.8% year-on-year; Net profit reached 51.2 million yuan, an increase of 6.3% year-on-year; The annual order volume reached 18,700 (including standardized supporting units, spare parts and after-sales service orders), the inventory turnover days were 68 days, and the accounts receivable turnover days were 57 days. With the continuous expansion of the business scale, H Company gradually exposed the problems of inconsistent data between the business end and the financial end, the disconnection between the order execution schedule and the cost collection, and the lag of budget deviation feedback. Especially under the double influence of the fluctuation of raw material price and the compression of customer delivery cycle, the fluctuation range of monthly gross profit rate once reached 4.6 percentage points. Although the company has established ERP, financial sharing and budget management systems, the data linkage between different systems is still insufficient, and it is difficult to identify business anomalies in time. Based on this, Company H has strong demand for industry and financial integration analysis, and is suitable as a case object for the application effect evaluation of intelligent analysis model in the intelligent transformation of financial data.

4.2 Business property data selection and processing

In order to ensure that the case analysis can reflect the linkage relationship between the business process and the financial results of the enterprise more completely, this paper selects representative business indicators and financial indicators in the business data of H company from 2021 to 2023 for joint analysis. At the business end, the order quantity, on-time delivery rate, inventory turnover days and accounts receivable turnover days are selected to describe the sales execution, supply coordination and capital occupation status. The financial end focuses on operating income, operating cost and gross profit margin to reflect value formation and profit changes. The above indicators can not only cover the main operation chain of "order acceptance, production, delivery and payment collection", but also form a clear corresponding relationship with the financial results. As shown in Table 5, the operating income of Company H has maintained an overall growth in the past three years, but the operating cost has increased rapidly, and the inventory and receivable turnover pressure have increased in 2023, indicating that it is difficult to fully explain the source of profit fluctuations based on financial statements alone, and linkage analysis must be carried out with business execution data.

Table 5: Selection results of business property data of H Company

Year	Order Volume (10,000 orders)	On-time Delivery Rate (%)	Inventory Turnover Days (days)	Accounts Receivable Turnover Days (days)	Operating Revenue (CNY 100 million)	Operating Cost (CNY 100 million)	Gross Profit Margin (%)
2021	1.42	95.8	61	49	6.88	5.21	24.27
2022	1.63	94.7	64	53	7.73	5.95	23.03
2023	1.87	93.6	68	57	8.64	6.71	22.34

In the data processing link, this paper carries out preprocessing according to the path of "caliber unification-anomaly correction-scale conversion", and takes the raw material price index and industry boom as background calibration variables into the risk identification process. Aiming at the problem of inconsistent field coding between business system and financial system, the order number, product code, customer number and accounting period were used as the main keys to complete the mapping matching. The mean value of adjacent periods was used to fill the fields with low missing values, and the duplicate records were removed according to the order time and amount information. For the data that significantly deviates from the normal business, the box plot identification results and the original certificates of the enterprise are combined for secondary verification to avoid misjudging temporary promotion or centralized payment collection as abnormal values. After the processing is completed, the standardization transformation of different dimensional indicators is implemented to enhance the comparability between order execution indicators and financial results indicators, so as to provide a consistent and stable data basis for subsequent business risk identification and collaborative decision analysis.

4.3 Intelligent identification and analysis of business risks

In this paper, the order delay rate, inventory pressure index, payment pressure index and comprehensive risk score are used as the core indicators of business risk intelligent identification in the case analysis. Among them, the order delay rate is used to measure the performance stability, the inventory pressure index is used to reflect the inventory occupation degree, the collection pressure index is used to depict the capital recovery risk, and the comprehensive risk score is output by the model after weighted identification of the linkage characteristics of business execution state and financial results. Compared with the way of static judgment based only on financial statements, this group of indicators can more directly reveal abnormal changes in business processes and their transmission effects on business results. As shown in Figure 6, the business risk of Company H in 2021-2023 is generally on the rise, but the rise of different risk items is not completely consistent.

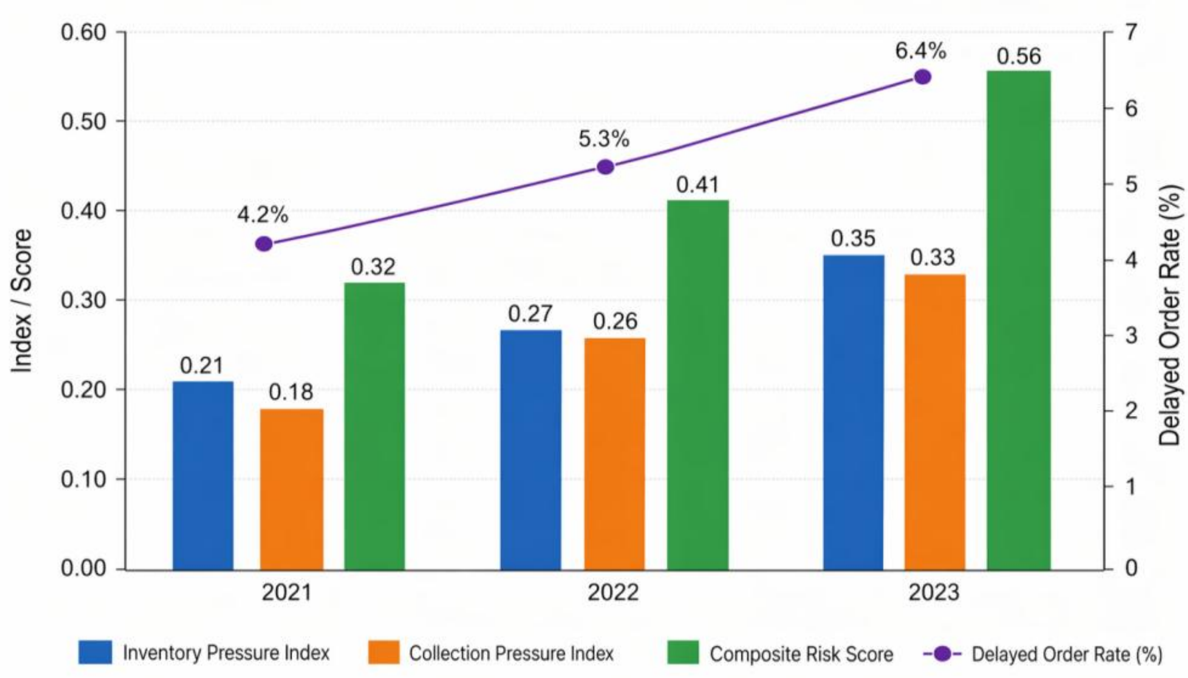

Figure 6: Intelligent business risk identification results of Company H from 2021 to 2023

From the perspective of order performance, the backorder rate increased from 4.2% in 2021 to 6.4% in 2023, indicating that the coordination pressure on the delivery link continues to increase while the order scale expands, which is consistent with the change trend of the on-time delivery rate decreasing from 95.8% to 93.6%. In terms of inventory risk, the inventory pressure index increased from 0.21 to 0.35, and the corresponding inventory turnover days increased from 61 to 68 days, indicating that the increase in raw material preparation and the slow turnover of finished products jointly pushed up the inventory occupation level. In terms of collection, the collection pressure index increased from 0.18 to 0.33, and the turnover days of accounts receivable increased from 49 days to 57 days, indicating that the sales growth did not synchronously translate into faster cash return, and the capital precipitation increased.

Taken together, the composite risk score of the model output increased from 0.32 to 0.56, with the most significant increase in 2023. This result shows that there is no sudden business instability in Company H at present, but strong linkage has been formed among order performance, inventory occupation, payment collection cycle and gross profit rate decline, and the business risk is turning from local fluctuation to cumulative increase. In particular, when the operating income increased from 688 million yuan to 864 million yuan, the gross profit rate decreased from 24.27% to 22.34%, indicating that the scale expansion did not translate into simultaneous efficiency improvement. It can be seen that the intelligent identification model can capture the risk signals that are not easy to appear in time in traditional financial analysis at an early stage, and provide more targeted judgment basis for enterprises to carry out subsequent cost correction, inventory pressure reduction and payment collection coordination.

4.4 Effect analysis of collaborative decision support between industry and finance

In order to test the supporting ability of the intelligent analysis model in the collaborative decision-making of industry and finance, this paper combines the business characteristics of H Company in 2023, and sets up three executable schemes for scenario calculation comparison: Scheme A is the "inventory pressure reduction - procurement rhythm optimization" scheme, scheme B is the "credit policy adjustment - payment collection enhancement" scheme, scheme C is the "procurement, production, sales and financial linkage and coordination" scheme. The evaluation indexes are selected to measure the comprehensive effects of different schemes in terms of profit improvement, capital turnover and operation coordination, including the improvement of gross profit margin, the shortening of cash collection cycle days, the pressure reduction of inventory turnover days and the comprehensive synergy score. As shown in Figure 7, all the three schemes can improve the operating state of the enterprise to a certain extent, but the effects are obviously different.

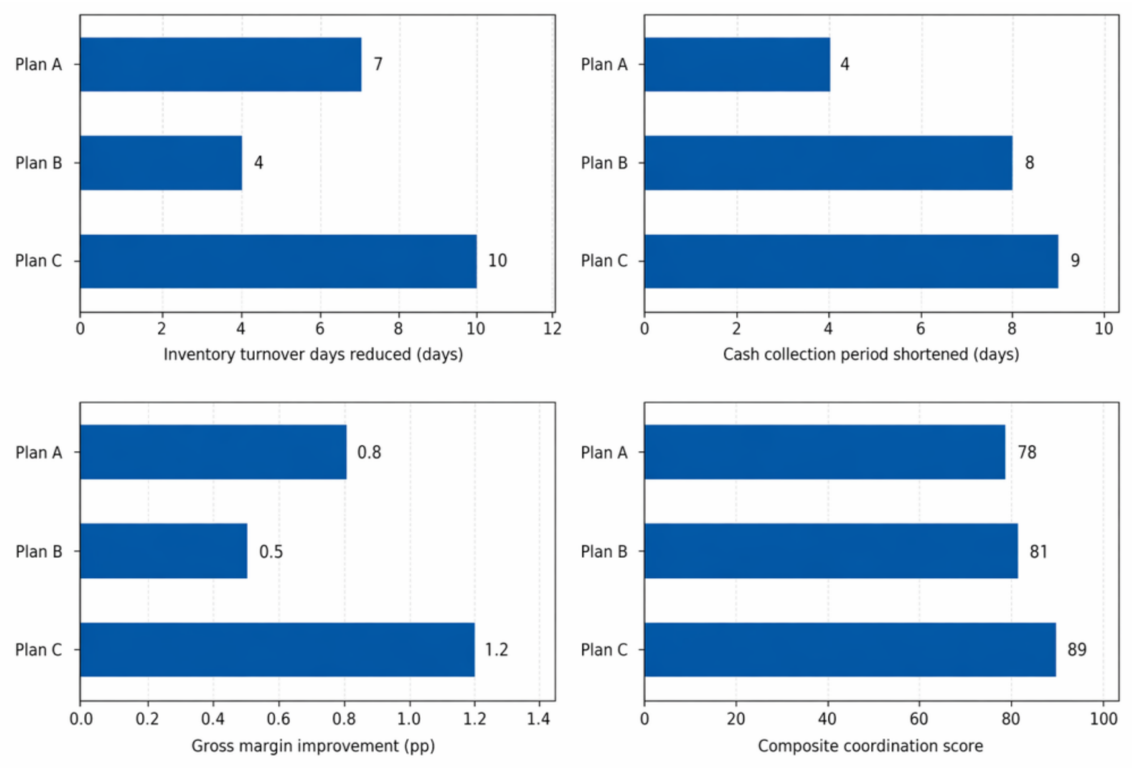

Figure 7: Decision support results of different business finance synergy schemes in Company H

After the implementation of plan A, the inventory turnover days are expected to be reduced from 68 days to 61 days, and the pressure reduction effect is relatively obvious. The operating cost rate is reduced by 0.6 percentage points simultaneously, and the gross profit rate is increased from 22.34% to 23.14%. However, as the program mainly focuses on procurement and inventory links, it has limited drive to accounts receivable management, and the cash collection cycle is only shortened by 4 days. The comprehensive synergy score is 78 points, which is suitable as a partial improvement program. Plan B focuses on strengthening customer credit stratification, account period control and payment collection tracking, accounts receivable turnover days are reduced from 57 days to 49 days, and cash collection is more prominent. However, due to the lack of coordination between inventory and production end, inventory turnover days are only reduced for 4 days, gross profit rate is increased by only 0.5 percentage points, and the comprehensive synergy score is 81 points.

In contrast, scheme C synchronously adjusted the purchase quantity, production scheduling, delivery rhythm and payment collection node under the support of the model. In the scenario calculation, the inventory turnover days were reduced by 10 days, the accounts receivable turnover days were shortened by 9 days, the gross profit rate was increased to 23.54%, which was 1.2 percentage points higher than the base period, and the comprehensive synergy score reached 89 points. It shows that the scheme can not only alleviate the problems of inventory overstocking and payment collection delay, but also improve the quality of profit through the linkage optimization of business process and financial control. It can be seen that the intelligent analysis model of industry and finance fusion has a strong support role for multi-scheme comparison and collaborative decision-making ranking, and scheme C is more suitable as the optimal path for company H to promote the subsequent intelligent transformation of financial data.

4.5 Evaluation of model application effect

In order to test the practical application value of the intelligent analysis model of industry and finance data fusion, this paper compares and evaluates the operation of H company's model in six months before and after its launch from five dimensions: risk identification accuracy, average early warning response time, completion rate of industry and finance collaborative processing, management satisfaction and improvement range of gross profit. Among them, the satisfaction was obtained by issuing a questionnaire to 48 financial, supply chain, sales and production management personnel, and the full score was 10. The other indicators are formed according to the system log, business closed-loop records and monthly operation analysis results. The evaluation results are shown in Table 6.

Table 6: Evaluation results of application effect of H Company's intelligent analysis model

Evaluation Metric	Before Application	After Application	Change
Risk Identification Accuracy (%)	83.6	92.4	+8.8
Average Early Warning Response Time (hours)	26.5	9.8	-16.7
Completion Rate of Industry–Finance Collaborative Processing (%)	71.2	88.7	+17.5
Management Satisfaction Score	7.4	8.8	+1.4
Gross Profit Margin (%)	22.34	23.41	+1.07

From the evaluation results, the application effect of H company is significantly improved after the model is launched. The accuracy of risk recognition increased from 83.6% to 92.4%, indicating that the feature expression after the integration of industry and finance can more effectively identify the business risks such as order delay, inventory backlog and payment anomaly, and reduce the lag caused by relying solely on financial statement analysis. The average warning response time was shortened from 26.5 hours to 9.8 hours, indicating that the model has high efficiency in abnormal triggering, information push and analysis feedback, and can quickly support the management to carry out disposal. At the same time, the completion rate of collaborative processing of industry and finance increased from 71.2% to 88.7%, reflecting the obvious improvement of information transmission and collaborative execution between procurement, production, sales and finance.

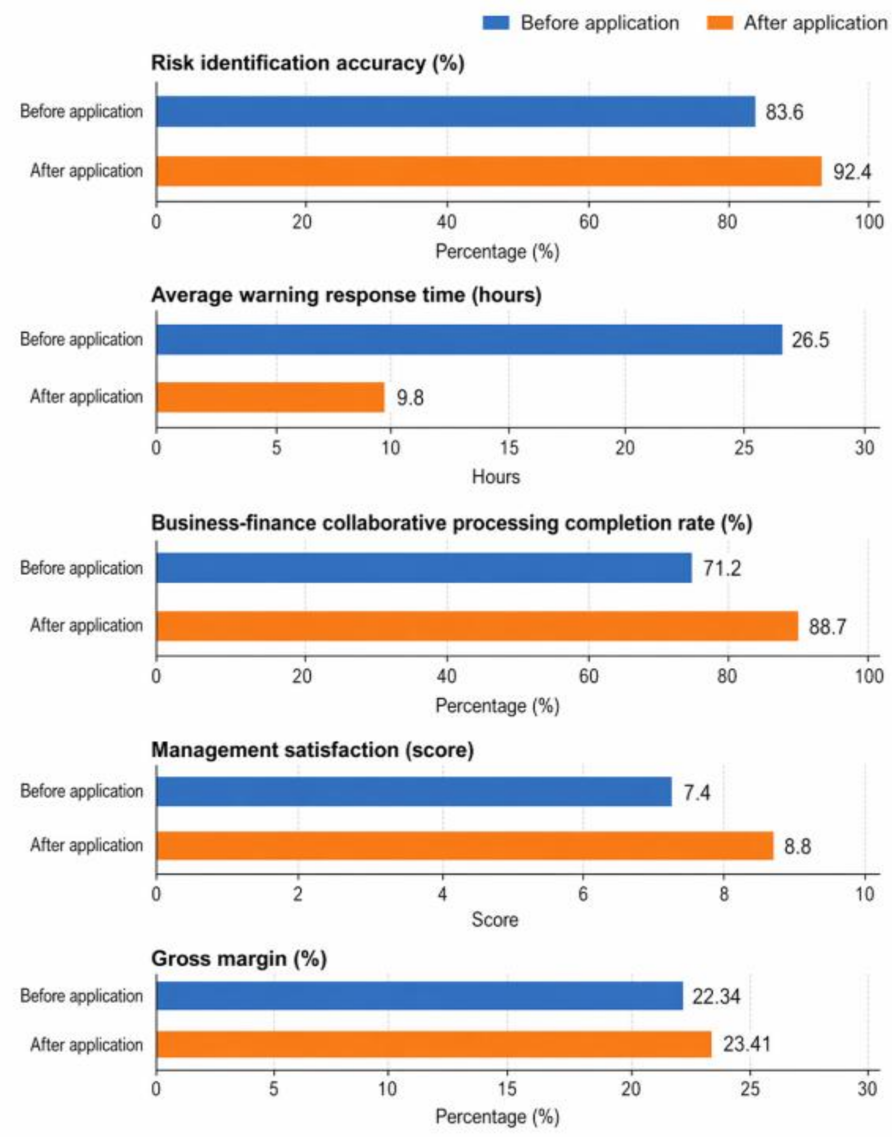

Figure 8: Comparison of effects before and after the application of H company model

From the operating results, the gross profit rate increased from 22.34% to 23.41% after the application of the model, with an increase of 1.07 percentage points, indicating that the collaborative analysis of industry and finance not only improved the efficiency of information processing, but also formed a substantial support for the optimization of procurement rhythm, inventory pressure reduction and payment collection management. Combined with Figure 8, it can be seen that the response speed is improved most significantly, and the recognition accuracy and collaborative execution level are improved synchronously, indicating that the model plays a strong role in the "recognition-early-warning -cooperation-feedback" chain. In general, this model better meets the management needs of H company in the intelligent transformation of financial data, and has a relatively stable application effect in enhancing the visibility of business risks, compressing the decision-making reaction time and improving the efficiency of industry and finance collaboration.

5 Discussion

5.1 Discussion of Results

From the application results of the case enterprise, the intelligent analysis model of industry and finance data fusion shows a relatively stable positive effect in risk identification, response efficiency, collaborative execution and business improvement, which has been verified by the quantitative results above. More noteworthy is that the model connects the data chain between the business end and the financial end, so that order execution, inventory changes, payment collection rhythm and cost fluctuations can be linked and identified under the same framework. These changes show that the value of intelligent transformation of financial data is not only reflected in the improvement of report generation speed or data visualization ability, but more importantly, by opening up the data chain between the business end and the financial end, the original scattered order execution, inventory changes, payment collection rhythm and cost fluctuations can be incorporated into the same analysis framework, so as to enhance the ability of enterprises to perceive business abnormalities. The case results also show that business risk is not generated in isolation, but often manifests as the linkage accumulation between performance deviation, inventory overstocking, capital recovery and profit decline. The model can identify such linkage relationships at an early stage, indicating that the industry-finance fusion analysis is more suitable for dealing with dynamic problems in complex business scenarios than the traditional single financial analysis. At the same time, although the gross profit rate increase is 1.07 percentage points, under the background of the operating income scale has reached 864 million yuan, this improvement has more obvious management significance, indicating that the model output can not only support the identification and judgment, but also can effectively promote the collaborative optimization of procurement, production, sales and finance.

5.2 Enlightenment and Suggestions for the intelligent transformation of enterprise financial data

The case analysis shows that when enterprises promote the intelligent transformation of financial data, the key is not to simply introduce more systems or stack more report modules, but to establish a unified data logic around business activities. If business data and financial data still belong to different caliber, different cycle and different responsibility chain, even if the technology platform is constantly upgraded, it is difficult to really improve the quality of management. Therefore, enterprises need to take objects such as orders, products, customers, projects, departments and accounting periods as the basic indexes of industry and financial integration, and gradually form a traceable, comparable and computable data base. On this basis, the role of the financial department should also change from the result accountant to the operational analysis participant, and improve the forward-looking and explanatory power of management accounting information through the continuous monitoring of the relationship between inventory turnover, cost deviation, credit policy, cash recovery and profit formation. In the case, the early warning response time was shortened by 16.7 hours, and the collaborative processing completion rate was increased by 17.5 percentage points, indicating that once the data-driven collaborative mechanism was formed, the improvement of management efficiency would be more direct. It can be seen that when promoting the transformation of data intelligence, enterprises should strengthen the rule base construction, exception disposal process and cross-departmental feedback mechanism synchronously, so as to avoid the model identification results staying at the technical level and not entering the business closed loop. At the same time, system ease of use cannot be ignored. The satisfaction score increases from 7.4 to 8.8, indicating that only when the model output and management scenarios form a good fit relationship, digital intelligence tools can be truly embedded in daily business decisions.

5.3 Research Limitations and Future Prospects

Although this paper has achieved relatively clear application results in the case verification, there are still some limitations. First, the research object only selected a single equipment manufacturing enterprise, and the industry characteristics, business mode and data structure were relatively concentrated. The applicability of the model in retail, platform service or high project industry still needs further testing. Second, although this paper has included indicators such as order, inventory, payment collection, revenue, cost and gross profit, the use of unstructured information is still limited, and supplier evaluation, customer complaints, contract text and public opinion information have not yet entered a unified analysis framework, which limits the depth of the model to describe the complex business environment. Third, the effect evaluation is mainly based on the stage operation data before and after the launch, and there is still a lack of continuous observation on the robustness, migration and boundary adaptation ability of the model under a longer period. On the basis of expanding the sample scope, future research can introduce multi-industry, multi-enterprise and multi-period data to further compare the differences in the degree of industry-finance integration, management complexity and transformation maturity of different enterprises. At the same time, methods such as text mining, graph structure analysis and reinforcement learning can be integrated into the iteration process of the model to improve its ability to identify nonlinear association, chain conduction and dynamic decision-making. With the continuous improvement of enterprise data governance level, the intelligent analysis model of industry and finance fusion is expected to further develop from a risk identification tool to a business optimization and value creation tool, and play a deeper role in budget preparation, resource allocation, performance evaluation and strategic collaboration.

Funding

This work was supported by Research on the Strategies for Enhancing the Resilience of the Manufacturing Industry's Industrial Chain and Supply Chain in Henan Province Based on ESG.

References

[1] Al-Okaily M. Attitudes toward the adoption of accounting analytics technology in the digital transformation landscape[J]. Journal of Accounting & Organizational Change, 2025, 21(3): 593-613.

[2] Al-Okaily M, Alsmadi A A, Alrawashdeh N, et al. The role of digital accounting transformation in the banking industry sector: an integrated model[J]. Journal of Financial Reporting and Accounting, 2024, 22(2): 308-326.

[3] Artene A E, Domil A E, Ivascu L. Unlocking business value: Integrating AI-driven decision-making in financial reporting systems[J]. Electronics, 2024, 13(15): 3069.

[4] Abhishek N, Suraj N, Rahiman H U, et al. Digital transformation in accounting:

elevating effectiveness across accounting, auditing, reporting and regulatory compliance[J]. Journal of Accounting & Organizational Change, 2024 (ahead-of-print).

[5] Eyadat A A. The impact of business intelligence on promoting decision-making in Jordanian business companies[J]. Business Information Review, 2024, 41(4): 174-180.

[6] Abu Rumman A, Al-Abbadi L. Structural equation modeling for impact of Data Fabric Framework on business decision-making and risk management[J]. Cogent Business & Management, 2023, 10(2): 2215060.

[7] Delias P, Kitsios F. Operational research and business intelligence as drivers for digital transformation[J]. Operational Research, 2023.

[8] Hezam Y A A, Anthonysamy L, Suppiah S D K. Big data analytics and auditing: A review and synthesis of literature[J]. Emerging Science Journal, 2023, 7(2): 629-642.

[9] Huang A H, You H. Artificial intelligence in financial decision-making[M]//Handbook of financial decision making. Edward Elgar Publishing, 2023: 315-335.

[10] Kraus S, Durst S, Ferreira J J, et al. Digital transformation in business and management research: An overview of the current status quo[J]. International journal of information management, 2022, 63: 102466.

[11] Alshenaifi Z, El Sayad S. Adoption of cloud-based accounting solutions in micro, small and medium-sized enterprises: insights from the Kingdom of Saudi Arabia[J]. Journal of Science and Technology Policy Management, 2024.

[12] Faccia A, Petratos P. Big data applications in accounting information systems[C]//Proceedings of the 2024 9th International Conference on Big Data and Computing. 2024: 1-7.

[13] Khan F, Ullah Jan S, Zia-ul-haq H M. Artificial intelligence adoption, audit quality and integrated financial reporting in GCC markets[J]. Asian Review of Accounting, 2025, 33(3): 464-495.

[14] Leitner-Hanetseder S, Lehner O M. AI-powered information and big data: current regulations and ways forward in IFRS reporting[J]. Journal of Applied Accounting Research, 2023, 24(2): 282-298.

[15] Nani A. Valuing big data: An analysis of current regulations and proposal of frameworks[J]. International Journal of Accounting Information Systems, 2023, 51: 100637.

[16] Gao X. Digital transformation in finance and its role in promoting financial transparency[J]. Global Finance Journal, 2023, 58: 100903.

[17] Hasan A R. Artificial Intelligence (AI) in accounting & auditing: A Literature review[J]. Open Journal of Business and Management, 2022, 10(01): 440-465.

[18] Alex Avelar E, Jordão R V D. The role of artificial intelligence in the decision-making process: a study on the financial analysis and movement forecasting of the world's

largest stock exchanges[J]. Management decision, 2025, 63(10): 3533-3556.

[19] Herath S K, Herath L M. Emerging trends and challenges in the digital transformation of accounting: A review of the literature[J]. Global Journal of Accounting and Economy Research, 2024, 5(2): 121-144.

[20] Yusuf R, Muyiwa E D. The future of accounting: Efficacy of big data on accountant's functions in the accounting information systems[J]. Asian Journal of Economics, Business and Accounting, 2024, 24(11): 162-177.