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Reconstruction of the comprehensive risk management system of commercial banks under the empowerment of financial digital transformation

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SUMMARY: *In view of the problems of commercial banks' risk sources interwoven and accelerated transmission, and the recognition lag and decentralized control of traditional risk control system under the background of financial digital transformation, this paper constructs a comprehensive risk management reconstruction framework covering multi-source data governance, intelligent early warning, hierarchical control and feedback update. In this paper, credit information, trading behavior, liquidity indicators, operation logs and external public opinion are integrated into the unified calculation process, and feature engineering, machine learning recognition and rule engine linkage are combined to form a closed-loop mechanism of "identification-early-warning-control-feedback". The experimental results show that the Accuracy of the model on the test set is 0.914, the F1 value is 0.881, the AUC is 0.942, and the Brier Score is reduced to 0.108. The accuracy of risk classification reaches 0.918, and the recall of high risk is 0.872. After dynamic control, 38.4% of high-risk samples fell back to medium risk, 12.7% fell back to low risk, the average response time was shortened to 2.9 hours, and the loss pressure drop was 23.6%. The results show that financial digital transformation can effectively improve the risk identification accuracy, control response efficiency and closed-loop governance ability of commercial banks.*

KEYWORDS: *financial digital transformation; Commercial bank; Total risk management; Intelligent warning*

1 Introduction

Under the background of increasing volatility of financial markets, continuous refinement of regulatory rules and rapid online customer trading behavior, the risk pattern faced by commercial banks has been significantly different from the traditional period. Credit risk, market risk, liquidity risk, operational risk and reputation risk are no longer independent variables separated from each other, but are constantly interconnected through account system, payment link, credit network and external platform data, and risk exposure is more sudden, conduction and conceit [1-6]. Especially after the continuous advancement of financial digital transformation, bank business activities are widely embedded in mobile terminals, cloud platforms, intelligent risk control engines and real-time trading systems, which improves business efficiency, but also brings new problems such as model deviation amplification, data inconsistency, risk identification lag and control chain fracture [7-10]. This means that the traditional risk management model, which relies on manual experience, static reports and line

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management, has been difficult to support the comprehensive risk governance requirements in the high-frequency business environment.

The existing research on risk management of commercial banks mainly focuses on single-type risk measurement, local process optimization or compliance framework, which has a relatively mature theoretical basis, but there are still obvious shortcomings under the condition of digital operation. One kind of methods emphasizes linear statistical analysis and post-hoc verification, which can provide strong interpretability, but it is difficult to deal with the complex association between high-dimensional, multi-source and unstructured data. Although machine learning, data mining and intelligent scoring technology have been introduced into the other kind of methods, many researches remain at the level of "recognition-early warning", and lack of discussion on how the early warning results enter into risk control, strategy implementation and feedback correction [11-18]. For commercial banks, risk management should not only stop at "seeing the risk", but also further solve the problem of "when to intervene, how to deal with, how to correct", and truly form a closed-loop mechanism covering risk identification, classification, strategic response, execution monitoring and continuous feedback.

Based on this, this paper regards financial digital transformation as an important driving condition for the reconstruction of the comprehensive risk management system of commercial banks, and tries to incorporate risk data governance, intelligent early warning model, rule engine, system integration and dynamic control mechanism into a unified analysis framework. The core issues of this paper include: how digital transformation can change the path of risk generation and transmission, how banks can improve the accuracy of risk identification with data aggregation, feature calculation and machine learning methods, and how to realize the transformation of risk management from decentralized response to collaborative governance through closed-loop control architecture. To solve the above problems, this paper intends to complete the following work: construct a risk identification and intelligent early warning model for multi-source risk scenarios of commercial banks; An integrated closed-loop risk control mechanism of "identification-early-warning -control-feedback" was designed. From the two levels of technology implementation and management application, the feasible path of the reconstruction of the comprehensive risk management system under the digital transformation enablement is demonstrated, in order to provide computable and practical analysis ideas for the improvement of the risk governance ability of commercial banks.

2 Related Research

Concerning the research on the comprehensive risk management system of commercial banks, the existing literature can be roughly summarized into three paths: one focuses on the traditional risk management theory and institutional arrangement, emphasizing the standardization of risk preference setting, capital constraint, governance structure and risk reporting mechanism; One category focuses on the reshaping of the bank's business model and risk exposure structure by digital transformation, and discusses the new risk characteristics brought by data-driven business expansion, platform services and technology embedding. Another category introduces machine learning, deep learning and intelligent decision-making methods into risk identification, early warning and control scenarios, trying to improve the risk perception ability in complex environments [1-6].

In traditional research, the core issues of enterprise risk management and bank total risk management are system integration and organizational collaboration. Nocco and Stulz pointed out that the value of comprehensive risk management lies not only in the pressure drop of individual risks, but also in the improvement of risk-return allocation relationship through a unified perspective [11]. Arena et al. revealed the dependence of the implementation of risk management system on the process, responsibility and information transmission mechanism from the level of organizational operation [12]. This kind of research provides a solid foundation for commercial banks' risk governance. However, under the condition of high-frequency digital transactions and real-time risk transmission, traditional frameworks lack support for heterogeneous data integration, dynamic feature extraction and real-time early warning, and are often more suitable for post-hoc analysis than process control.

With the deepening of financial digital transformation, the research perspective has begun to shift from "institutional risk management" to "data-driven risk governance". Starting from the general theory of digital transformation, Vial, Verhoef and other scholars pointed out that there is a co-evolution relationship between organizational boundaries, business processes and technical capabilities [1, 2]. In the banking scenario, Gomber, Alt, Vives and Thakor et al. show that fintech, platform credit, smart advisory and online payment systems improve service efficiency while also changing the formation mechanism of credit risk, liquidity risk and systemic risk [3-6]. Further empirical literature shows that digital transformation is no longer just an upgrade at the tool level, but has changed the underlying logic of bank risk generation, identification and transmission to a considerable extent [7-10]. However, this part of research stays more at the level of influence effect identification, and the discussion on how to complete model deployment, system linkage and control loop closure within the bank is still insufficient.

Another part of the literature approaches the problem of risk management from a computer approach. Leo et al. reviewed the application of machine learning in bank risk management and pointed out that the algorithm model has obvious advantages in credit recognition, default prediction and anomaly detection [13]. Gambacorta et al. further proved that non-traditional data and machine learning methods can improve scoring accuracy [14]. Huang et al. summarized modeling paths and applicable boundaries in financial scenarios from the perspective of deep learning [17]. At the same time, the issues of model risk governance, risk data aggregation and regulatory interpretability have also attracted attention. The relevant documents of Basel Committee and the Federal Reserve have emphasized that data quality, caliber consistency, model verification and result reporting are indispensable basic links for digital risk management [15, 18]. It can be seen that the existing research has provided technical reserves for intelligent risk control, but there are still generally three shortcomings: first, there is no unified modeling framework between multiple risk categories, which is easy to form a "single point of optimization"; Second, the connection between early warning results and control implementation is not tight, and the feedback correction mechanism at the system level is weak. Third, there is still a certain distance between the technical research and the management practice of commercial banks, especially the lack of a landing integrated design of "identification-early-warning -control-feedback". Based on the above shortcomings, this paper attempts to incorporate risk data governance, intelligent early warning model and closed-loop control mechanism into the same analysis framework under the background of digital transformation, and promote the comprehensive risk management system of commercial banks from decentralized management to systematic reconstruction.

Table 1: Summary of related studies and comparison of deficiencies

Research Category	Representative Studies	Main Content	Common Methods/ Techniques	Existing Limitations
Traditional Comprehensive Risk Management Research	[11][12]	Emphasizes risk appetite, governance architecture, organizational coordination, and institutional control	Risk classification management, internal control, and institutional analysis	Insufficient real-time capability and difficulty in handling high-frequency transactions and multi-source heterogeneous data
Financial Digital Transformation and Bank Risk Research	[1]–[10][16]	Examines the impact of digital transformation on business models, risk exposure, and systemic risk	Digital strategy analysis, panel-based empirical analysis, and case studies	Focuses more on impact identification, with insufficient discussion of system integration and closed-loop control
Intelligent Risk Control and Machine Learning Research	[13][14][17][18]	Uses algorithmic models for risk identification, early warning, and score optimization	Machine learning, deep learning, feature engineering, and model validation	Interpretability, model risk governance, and cross-department implementation remain relatively weak
Risk Data Governance and Regulatory Framework Research	[15][18]	Emphasizes risk data aggregation, reporting consistency, and model management standards	Data governance, model validation, and regulatory rules	Places greater emphasis on compliance requirements, while offering limited coverage of internal dynamic execution mechanisms in banks

3 Reconstruction method of comprehensive risk management system of commercial banks

3.1 Analysis on key technologies of enabling mechanism and risk management of financial digital transformation

The impact of financial digital transformation on the risk management of commercial banks is not limited to the online migration of business transaction methods. The deeper change lies in the reorganization of the generation logic, collection path and disposal mechanism of risk information. Traditional risk management is usually based on line segmentation. Credit, liquidity, market and operational risks are recorded and reported by different systems respectively, and the data granularity is not consistent and the update frequency is not uniform, so that risk identification often lags behind business changes. After the digital transformation is promoted, transaction flow, credit lending behavior, customer portrait, channel access log, public opinion text and external credit information can be continuously imported into the unified platform through the data interface, and commercial banks can thus obtain the multi-dimensional risk observation ability covering "customer-product-transaction-account-scenario". Risk management begins to shift from static report analysis to continuous calculation oriented to real-time data stream, which is the technical premise of the reconstruction of comprehensive risk management system.

From the perspective of enabling mechanism, the support of financial digital transformation to the risk management system is mainly reflected in the following aspects.

(1) The ability of data aggregation enhances the integrity of risk identification. In the traditional model, risk judgment relies more on structured financial indicators and post-hoc statistical results, while the digital environment can unify the data of the core system, payment system, credit system, customer service system and external platform, and complete standardized processing in the data warehouse or lake warehouse integrated architecture. In this way, risk identification is no longer dependent on a single financial snapshot, but is built on the sequence of behavior, time characteristics and relationship network, which helps to find potential risk signals.

(2) The feature computing power improves the accuracy of characterizing complex risk relationships. Commercial bank risk is not a simple superposition of several indicators, many abnormal states are often formed in the linkage between high-dimensional variables. For example, there is often a nonlinear coupling relationship between credit expansion speed, customer transaction frequency, debt maturity mismatch and external public opinion fluctuations. With the help of feature engineering, time series modeling, and graph relationship analysis, banks are able to extract more explanatory risk variables from raw data and transform dispersed signals into computable risk representation vectors. Let the set of risk characteristics of a commercial bank at time t be:

$$\mathrm{X_t} = [\mathrm{x_{1t}}, \mathrm{x_{2t}}, \dots, \mathrm{x_{nt}}] \tag{1}$$

Then the comprehensive risk score can be expressed as:

$$\mathrm{R_t} = \sigma\left(\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{w_i}\,\mathrm{x_{it}} + \mathrm{b}\right) \tag{2}$$

where $\mathrm{w_i}$ represents the weight of each risk factor, b is the bias term, and $\sigma(\cdot)$ is the nonlinear mapping function. This expression shows that the risk state is no longer triggered by a single indicator threshold, but forms a continuously changing risk probability under the joint action of multi-source features.

(3) The model-driven mechanism improves the adaptability of the early warning system. Under the condition of digital business, the change speed of customer behavior, transaction scenario and market environment is significantly accelerated, and fixed thresholds and static rules are easy to fail. The machine learning method can continuously update the parameters according to new samples, so that the risk early warning model can maintain the sensitivity to environmental changes. For commercial banks, this ability is particularly important because businesses such as retail finance, small and micro credit, online payment, and supply chain financing are characterized by large sample sizes, high data noise, and rapid risk evolution. Through rolling training, window update and cross-validation, the model can improve the ability to identify novel risks while maintaining stability.

(4) The system linkage ability strengthens the execution closed loop of risk control. Comprehensive risk management does not stop at identifying risks, but also requires that early

warning results can be passed on to subsequent links such as credit approval, quota adjustment, asset pricing, early warning list management and stress testing. Under the digital architecture, the rule engine, model engine and business system can be connected through the interface, so that the risk score can directly drive the control action. For example, when the real-time risk value of a certain type of customer exceeds a preset threshold R^*, measures such as limit contraction, manual review or high-frequency monitoring can be triggered, i.e:

$$\mathrm{Action}_t = \begin{cases} 1, & R_t \geq R^* \\ 0, & R_t < R^* \end{cases} \tag{3}$$

Here, $\mathrm{Action}_t=1$ indicates that the system enters the risk intervention state. This mechanism makes risk management change from "deal with the problem after finding it" to "intervene immediately in the process of problem formation".

Corresponding to the above empowerment mechanism, the reconstruction of the comprehensive risk management system of commercial banks needs to rely on the collaborative operation of several key technologies. One is the risk data governance technology, including master data management, data quality verification, label system construction and metadata management, its role is to ensure that data from different sources can be unified identification, unified calculation, unified call. The other is intelligent identification and early warning technology, including machine learning classification models, anomaly detection models, knowledge graphs and natural language processing methods, which are used to identify risk signals with strong concealment. The other is system integration and feedback optimization technology, which uses microservice architecture, real-time message queue and visual monitoring platform to convert model output into business actions, and modify parameters according to the execution results. If the control result feedback is denoted as F_t, the model parameters can be pressed:

$$w_i^{(t+1)} = w_i^{(t)} + \eta \cdot F_t \cdot x_{it} \tag{4}$$

Dynamic adjustment is performed, where η is the learning rate. In this way, the risk management system is no longer a static tool deployed once, but a continuous evolution system with self-correcting ability. In general, the digital transformation of finance provides the reconstruction of the comprehensive risk management system of commercial banks, not only faster data processing means, but also a set of technical logic composed of data, algorithms, rules and systems. It is under this logic that risk management begins to get rid of the traditional segmentation and lag governance inertia, and gradually shifts to a new system combining real-time perception, intelligent early warning and closed-loop control, which lays a method foundation for the subsequent risk identification model construction and system integration design.

3.2 Construction of comprehensive risk identification and intelligent early warning model for commercial banks

The construction of comprehensive risk identification and intelligent early warning model for commercial banks does not establish isolated discriminators for credit risk, liquidity risk or operational risk respectively, but integrates multi-source business data, behavior data and external environment information into a unified computing framework, and carries out continuous identification, probability estimation and grading suggestions for bank risk status. The digital transformation of finance makes the risk management object no longer limited to the static indicators under the report, but extended to multi-dimensional data such as transaction flow, credit chain, customer behavior trajectory, system access log, abnormal operation record and public opinion text, which provides the basic conditions for the construction of an intelligent early warning model covering "feature extraction-model training -risk score-level early warning". Based on the above data basis and risk scenario characteristics, this paper constructs a weighted integrated early warning model for comprehensive risk management of commercial banks. The model takes multi-source feature fusion as input, focuses on high-risk identification, and realizes the continuous description of risk status through probability output, level division and feedback update, which takes into account both interpretability and dynamic adaptability while improving prediction accuracy.

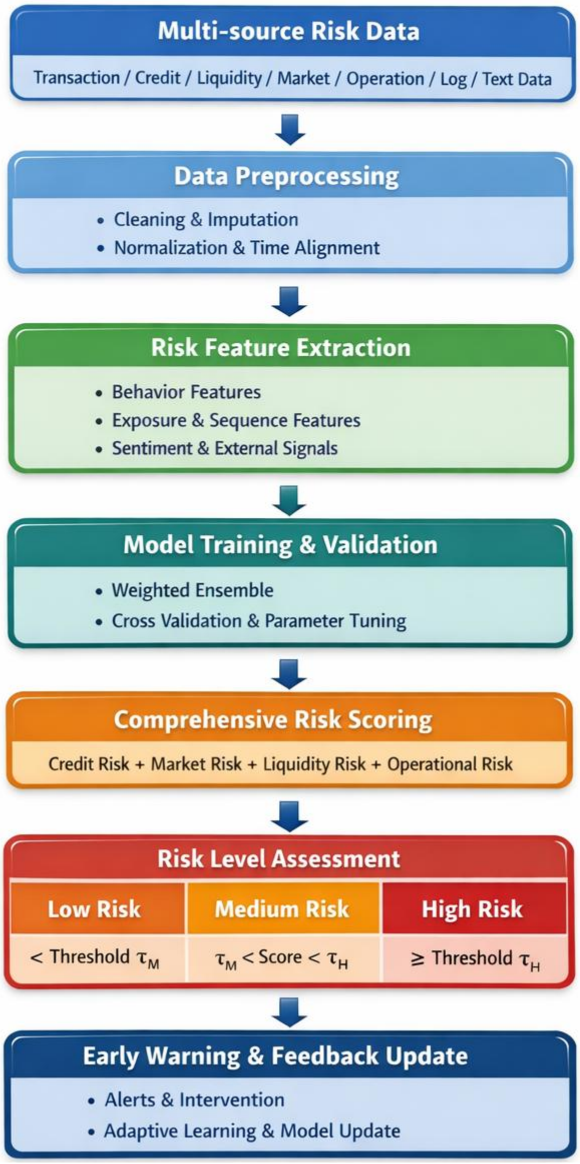

Figure 1: Framework of comprehensive risk identification and intelligent early warning model for commercial banks

As shown in Figure 1, the overall framework of the model is composed of a data preprocessing layer, a risk feature calculation layer, a model training layer, a risk assessment layer, and an early warning trigger layer. After the data enters the system, it first corrects the problems of missing values, outliers and timestamp misalignment, and then completes standardization, windowization and label alignment. Considering the high-dimensional, heterogeneous, and time-varying characteristics of commercial bank risk data, this paper not only maintains traditional financial and regulatory indicators in the feature construction stage, but also introduces derivative variables such as customer transaction frequency, credit limit fluctuation, debt maturity mismatch degree, abnormal login times, and public opinion sentiment scores, so that the model can simultaneously perceive risk changes in business surface, behavior surface, and external shock surface. Let the original feature vector of the ith observation sample be $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]$, and obtain the comprehensive risk representation vector after feature mapping:

$$z_i = \phi(x_i) \tag{5}$$

Here, $\phi(\cdot)$ represents the feature mapping function composed of normalization, coding transformation and time series aggregation.

In the model training stage, this paper adopts the modeling idea of "ensemble classifier + risk-weighted output". Because the high risk samples of commercial banks account for a low proportion of the total samples, if the general classification model is directly used, it is easy to identify the low risk samples well and identify the key high risk states insufficiently. Therefore, this paper introduces a weighted loss function to give higher attention to high-risk categories. Let the sample label $y_i \in \{0,1\}$, where $y_i = 1$ denotes the high-risk state, then the high-risk probability output by the model can be expressed as:

$$P_i = P(y_i = 1|z_i) \tag{6}$$

During training, the model uses a weighted cross-entropy loss function:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[w_1 y_i \log P_i + w_0 (1 - y_i) \log(1 - P_i)] \tag{7}$$

where N is the number of training samples, w_1 and w_0 are the weights of high-risk class and non-high-risk class, respectively. This processing method can improve the sensitivity of the model to the risk samples under the condition of sample imbalance, and avoid the early warning system only pursuing the overall accuracy and ignoring the abnormal state with real management value.

In order to reflect the characteristics of comprehensive risk management, this paper does not simply treat the early warning results as "risk" or "no risk", but further sets up a hierarchical judgment mechanism. Let the comprehensive risk score be S_i, which is obtained by weighting the sub-model outputs of credit risk, liquidity risk, market risk and operational risk as follows:

$$S_i = \sum_{k=1}^{m} \alpha_k P_{ik}, \sum_{k=1}^{m} \alpha_k = 1 \tag{8}$$

Here, P_{ik} represents the risk probability output of the KTH risk submodel for sample i, and α_k is the corresponding weight. According to the optimal identification results on the validation set, two thresholds τ_M and τ_H are set, then the risk level can be divided as:

$$\mathrm{Level}(S_i) = \begin{cases} \mathrm{Low}, & S_i < \tau_M, \\ \mathrm{Medium}, & \tau_M \le S_i < \tau_H \\ \mathrm{High}, & S_i \ge \tau_H. \end{cases} \tag{9}$$

This hierarchical approach is more suitable for bank management practices than single-threshold alarms. It can not only support the warning of general abnormal fluctuations, but also implement key intervention on high-risk accounts, business lines or institutional units, so as to provide a direct basis for quota adjustment, list control, manual review and pressure monitoring.

In order to ensure the continuous adaptation ability of the model, this paper also embeds a feedback update mechanism into the early warning process. After the output of the risk level, the system will synchronously record the manual review results, business disposal results and subsequent default or abnormal events, and re-write these feed-back into the training sample pool for the next round of parameter update. If the feedback signal at time t is denoted as f_t, the update of the model parameter θ can be written as:

$$\theta_{t+1} = \theta_t - \eta \nabla L(\theta_t; f_t) \tag{10}$$

where η is the learning rate. In this way, the early warning model is no longer a static program, but a dynamic system that can be modified continuously with the changes of business structure, customer behavior and market environment.

In general, the comprehensive risk identification and intelligent early warning model of commercial banks constructed in this paper is supported by the data foundation formed by digital transformation, with multi-source feature fusion and hierarchical early warning mechanism as the core, taking into account recognition accuracy, interpretation ability and dynamic adaptability. It can not only identify potential risks early, but also transform risk states into management signals with clear levels and easy to execute, which lays a technical foundation for the subsequent design of closed-loop risk control mechanism.

3.3 Closed-loop risk control mechanism design and system integration

Commercial bank risk has significant characteristics of linkage, time-varying and hierarchical transmission. A static judgment based on only one early warning output can only answer "whether the risk has occurred", but it is difficult to support more valuable management questions such as "how to deal with the risk, whether it is effective after disposal, and when it needs to be corrected again". Based on the comprehensive risk identification and intelligent early warning model constructed in the previous section, this paper further designs a closed-loop risk control mechanism, and integrates risk scoring, level division, strategy matching, execution feedback and model update into a unified system, so that risk management turns from segmented processing to continuous collaborative governance. The core idea is that the quantifiable risk state is given by the model, the differentiated disposal scheme is generated by the rule engine and the control module, and then the model parameters and control rules are corrected by the feedback data, so as to form a loop and iterative operation chain. The overall framework is shown in Table 2.

Table 2: The system framework of the comprehensive risk closed-loop control mechanism of commercial banks

Submodule	Main Inputs	Core Processing Logic	Main Outputs
Risk Identification and Early Warning Submodule	Customer transaction data, credit data, liquidity indicators, market volatility data, operation logs, and historical labels	Generates risk levels through feature extraction, classification prediction, and probability scoring	Risk probabilities, risk classification results, and early warning signals
Control Strategy Matching Submodule	Risk level, customer type, business line, asset structure, and regulatory constraints	Invokes the rule engine and strategy library to match measures such as credit limit adjustment, watchlist control, and manual review	Differentiated risk control schemes
Execution Monitoring and Feedback Iteration Submodule	Control execution results, default performance, rating changes, capital flows, and manual review conclusions	Evaluates control effectiveness and updates the sample set, parameter weights, and rule thresholds	New training samples, updated model parameters, and revised rule base

As shown in Table 2, this closed-loop mechanism does not simply concatenate the model with the business, but embelds "identifie-control-feedback" into the same technical architecture. After receiving the real-time data, the system first outputs the comprehensive risk score S_t and risk level L_t from the early warning model, and then combines the business attribute vector B_t and the control rule base Ω to generate control decisions:

$$u_t = f(S_t, L_t, B_t, \Omega) \tag{11}$$

Here, u_t denotes the set of control actions at time t, which can correspond to different measures such as credit pressure drop, monitoring and encryption, approval and receipt, list warning or manual intervention. This formula shows that risk control is not directly determined by a single score, but is formed by the joint action of risk status, business characteristics and institutional constraints.

In the control execution stage, this paper introduces the comprehensive objective of "risk residue-execution cost-control benefit" to avoid the system pushing up the management cost due to excessive intervention. Let the integrated loss function after the implementation of a certain control scheme be:

$$J(u_t) = \lambda_1 R_t^{res}(u_t) + \lambda_2 C_t(u_t) - \lambda_3 E_t(u_t) \tag{12}$$

Here, $R_t^{res}(u_t)$ represents the residual risk after executing the control, $C_t(u_t)$ represents the control cost, $E_t(u_t)$ represents the risk sustained release effect brought by the control, and λ_1,λ_2,λ_3 are the weight coefficients. The system selects the policy combination that minimizes $J(u_t)$ under the premise of satisfying the regulatory constraints and business boundaries. The significance of such treatment is that risk control is no longer understood as blindly shrinking, but the pursuit of a balance between control intensity, business continuity and governance cost.

In order to make the model output really enter the management process, this paper establishes a differentiated control mechanism according to three levels of low risk, medium risk and high risk. The control objectives and typical measures corresponding to different levels are shown in Table 3.

Table 3: Control objectives and typical measures under different risk levels

Risk Level	Decision Basis	Primary Control Objective	Typical Control Measures
Low Risk	The risk score remains at a low level, with limited indicator fluctuation, and the operating and solvency conditions are generally stable.	Maintain business continuity and avoid ineffective intervention.	Maintain routine credit policies, conduct periodic monitoring, and retain the standard approval process.
Medium Risk	The risk score enters the warning range, and some key indicators show persistent deterioration or amplified volatility.	Contain risk accumulation and slow the expansion of exposure.	Tighten credit limit thresholds, increase monitoring frequency, and strengthen manual review and watchlist observation.
High Risk	The risk score exceeds the high threshold, with clear default signals, abnormal transactions, or liquidity stress.	Rapidly reduce the probability of loss and block risk transmission.	Freeze or reduce credit limits, initiate special reviews, require additional guarantees, and implement centralized disposal or exit plans.
Feedback Update	Behavioral changes, fund performance, rating changes, and default outcomes after the implementation of control measures.	Evaluate control effectiveness and support rule revision and model retraining.	Continuously collect feedback data, write it back into the sample pool, and update thresholds and strategy weights.

As shown in Table 3, the low risk state emphasizes steady state operation, the medium risk state emphasizes early intervention, and the high risk state emphasizes fast stop loss and risk isolation. Such a hierarchical design can avoid the waste of resources brought by the "one-size-fits-all" control, and also make the risk management more in line with the actual needs of the hierarchical governance of banking business. At the system integration level, this paper proposes to adopt a four-layer structure of "data layer-model layer-rule layer-execution layer". The data layer is responsible for unified access to the core system, credit system, payment system and external credit data. The model layer is responsible for risk scoring and level output. The rule layer is responsible for policy orchestration, threshold management and approval logic calls. The executive layer pushes control actions to credit approval, quota management, list system and management cockpit. Through the interface service and message queue connection of each layer module, the warning results can be transformed into business actions in a relatively short time, avoiding the breakpoint problem of "the model has been calculated, but the system can not catch".

Whether the closed-loop mechanism can continue to be effective, the key is also the feedback update. After the control is executed, the system needs to track customer cash flow changes, overdue performance, transaction resumption and manual review conclusions, and write these results back to the training pool as feedback samples. If the feedback sample set is denoted as D_t^{fb}, the model parameter update process can be expressed as:

$$\theta_{t+1} = \theta_t - \eta \nabla L(\theta_t; D_t^{fb}) \tag{13}$$

where θ_t is the current parameter and η is the learning rate. With this mechanism, the model can be continuously modified according to the change of risk structure, and the rule base can also be dynamically adjusted according to the false positive rate, false negative rate and control success rate. Therefore, the comprehensive risk management system of commercial banks no longer stays in the static framework of one-time deployment, but forms a digital closed-loop system that can perceive changes, perform intervention and self-correction, which provides a complete method basis for subsequent experimental design and effect verification.

4 Experimental Design

In order to test the effectiveness of the reconstruction method of the comprehensive risk management system of commercial banks under the financial digital transformation, this paper divides the experimental design into four parts: data construction, environment configuration, comparison model setting and evaluation scheme, and carries out verification around the two goals of risk early warning accuracy and dynamic control effect. Considering that the risk of commercial banks is not driven by a single variable, but is formed by credit changes, liquidity fluctuations, transaction anomalies, customer behavior deviation and external shocks, the experimental sample does not use a single financial statement data, but introduces multi-source heterogeneous data for joint modeling.

The experimental data are from the historical business records and risk event accounts of a commercial bank from January 2021 to December 2025, covering modules such as corporate credit, retail loans, interbank business, account transactions, liquidity monitoring, operation logs and external public opinion information. After field unification, time alignment and abnormal cleaning, 48216 sample records were formed, of which high-risk samples, general risk samples and low risk samples accounted for 12.8%, 31.6% and 55.6%, respectively. In this paper, the samples of overdue, material default, abnormal transaction disposal escalation and internal risk event confirmation are classified as high risk, the samples of slight deterioration of indicators but no major disposal has been triggered are classified as general risk, and the rest are classified as low risk. In terms of variable setting, this paper extracted a total of 36 core features, including bad migration rate, credit concentration, debt maturity mismatch rate, abnormal transaction frequency, customer default history, public opinion sentiment score, system operation deviation degree and early warning disposal response time. In order to avoid the influence of dimensional differences on model training, the continuous variables were standardized, the missing values were stratified imputation, and the categorical variables were one-hot coded. The training set, validation set and test set were divided by 7:2:1, and the corresponding sample numbers were 33751, 9643 and 4822, respectively.

The experimental platform is deployed in Ubuntu 22.04 LTS environment, the processor is Intel Core i7-12700, the memory is 32 GB, and the graphics processor is NVIDIA RTX 3080 10 GB. The development language is Python 3.10, and the main dependency libraries include Pandas, NumPy, Scikit-learn, PyTorch and XGBoost. The model training and result visualization are completed in the same environment. Such a configuration can meet the operational requirements of multi-source risk data preprocessing, feature calculation, model iterative training and dynamic control simulation.

In order to reflect the comparative advantages of the constructed system, this paper selects Logistic regression, random forest, XGBoost and BiLSTM as the comparison objects. Logistic regression is used to describe the baseline level of traditional linear risk recognition methods, random forest and XGBoost are used to compare the recognition performance of ensemble learning models in high-dimensional risk feature scenarios, and BiLSTM is used to test the adaptability of time series modeling methods to continuous risk signals. The model proposed in this paper superposes hierarchical early warning and closed-loop control mechanism on the basis of comprehensive risk score to verify whether the integrated design of "identification-early-warning -control-feedback" is superior to the simple prediction model.

In terms of evaluation indicators, the accuracy, recall, F1 value, AUC and Brier score were used to measure the performance of the model in the risk early warning experiment. The dynamic control experiment further observed the response time delay of warning, the interception rate of risk escalation, the loss pressure drop amplitude after control, and the decline proportion of high-risk samples. Through the above design, the experimental part is not only used to verify the identification ability of the model itself, but also to investigate the stability, executability and continuous correction ability of the digital risk management system in actual operation.

5 Analysis of experimental results

5.1 Analysis of risk warning accuracy and model robustness

In this section, the comprehensive risk identification and intelligent early warning model of commercial banks constructed in this paper is tested from the two dimensions of risk early warning accuracy and model robustness. Considering the characteristics of bank risk samples, such as strong heterogeneity, unbalanced class distribution and obvious time drift, single Accuracy is not enough to describe the performance of the model. Therefore, this paper uses accuracy, Recall, F1, AUC and Brier Score to measure the recognition ability. Log Loss, MCC, Cohen's Kappa and Stability Index were combined to evaluate the stability of the model under repeated training and perturbation conditions.

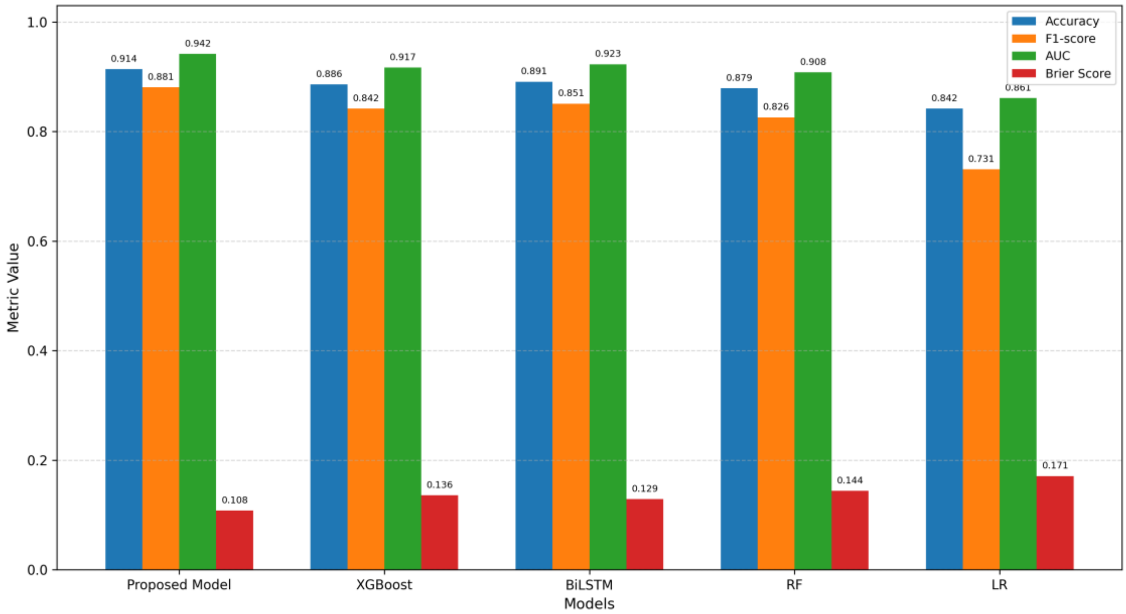

Figure 2: Comparison of core indicators of commercial bank risk early warning model

As shown in Figure 2, the overall performance of the proposed model on the test set is better than that of the comparison model in the binary classification risk early warning task. In terms of Accuracy indicators, the accuracy of the model in this paper is 0.914, which is higher than 0.842 for Logistic regression, 0.879 for standard random forest, 0.886 for XGBoost, and 0.891 for BiLSTM. The F1 value reaches 0.881, which is also significantly higher than 0.731, 0.826, 0.842 and 0.851 of the other models. The AUC index further shows that the proposed model reaches 0.942, indicating that it has a stronger ability to distinguish between high-risk samples and non-high-risk samples. At the same time, the Brier Score is only 0.108, which is lower than all the comparison models, indicating that the deviation between the output risk probability and the true result is smaller, and the probability calibration quality is better. The results show that after the introduction of multi-source risk feature fusion, hierarchical early warning mechanism and feedback update structure, the model no longer stays at single point identification, but can more stably complete the risk state discrimination.

From the robustness results, the proposed model also shows a good level of stability. Ten repeated experiments show that the average Log Loss of the proposed model is 0.276, which is significantly lower than 0.331 of the optimal comparison model XGBoost. MCC reaches 0.801, and Cohen's Kappa is 0.772, which are higher than other models, indicating that the model can still maintain strong consistency and discrimination ability under the condition of class imbalance. The Stability Index is 0.907, and the standard deviation of multiple indicators is controlled within 0.01, which means that the model output is less affected by random initialization and sample fluctuations. The mean value, standard deviation and 95% confidence interval given in Table 4 also show that the proposed model does not accidentally achieve higher results in individual training rounds, but maintains a relatively stable performance boundary under different experimental repetition conditions.

Table 4: Accuracy and robustness results of risk early warning model (10 repeated experiments)

Metric	Proposed Model (mean ± SD)	95% CI	Best Baseline Model (mean ± SD)
Accuracy	0.914 ± 0.006	[0.902, 0.926]	0.891 ± 0.009 (BiLSTM)
Recall	0.873 ± 0.008	[0.857, 0.889]	0.846 ± 0.011(XGBoost)
F1-score	0.881 ± 0.007	[0.867, 0.895]	0.851 ± 0.010(BiLSTM)
AUC	0.942 ± 0.005	[0.932, 0.951]	0.923 ± 0.008(BiLSTM)
Brier Score	0.108 ± 0.004	[0.100, 0.116]	0.129 ± 0.006(BiLSTM)
Log Loss	0.276 ± 0.007	[0.262, 0.290]	0.331 ± 0.010(XGBoost)
MCC	0.801 ± 0.006	[0.789, 0.813]	0.748 ± 0.009(XGBoost)
Cohen’s Kappa	0.772 ± 0.006	[0.760, 0.784]	0.723 ± 0.010(BiLSTM)
Stability Index	0.907 ± 0.005	[0.897, 0.917]	0.861 ± 0.008(XGBoost)

Combining Figure 2 and Table 4, it can be seen that the advantages of the proposed model are not only reflected in a certain index, but also reflected in three levels of recognition accuracy, probability calibration and stability of repeated experiments. This result is consistent with the logic of the method proposed in the previous section: under the background of digital transformation, the risk data of commercial banks has the characteristics of continuous flow, complex structure and dispersed signal. If only relying on a linear model or a single static classifier, it is often difficult to completely capture the risk evolution trajectory. The proposed model shows better adaptability in the test by unifying multi-source features, strengthening the identification of high-risk samples, and introducing a feedback update mechanism. In other words, it is not only easier to "see the risk", but also can still "see the risk" more stably under different sample disturbances and training conditions, which provides a more reliable model basis for the subsequent dynamic control effect analysis.

5.2 Experimental analysis of dynamic control effect and risk classification management

After the accuracy test of risk early warning is completed, this paper further investigates the actual performance of the built system in dynamic control and risk classification management. For commercial banks, if the model output only stays at the risk probability level, its management value is still limited. Only when the early warning results can enter the hierarchical disposal, process intervention and feedback correction links, the reconstruction of comprehensive risk management system has practical significance. Therefore, according to the comprehensive risk score, the samples were divided into three categories: low risk, medium risk and high risk. When Si<0.30, it was judged as low risk. When 0.30≤Si<0.60, it was judged as medium risk; High risk was determined when Si≥0.60. The strategies of routine monitoring, quota tightening and manual review, special review and high-intensity intervention were triggered in different levels, and the classification results and control results were jointly evaluated.

From the perspective of risk classification effect, the proposed model shows good hierarchical discrimination ability in the recognition of three types of samples. Figure 3 shows the comparison results of different models in the three-level risk classification task, and the evaluation metrics include risk classification accuracy, recall of high-risk samples, and risk distribution consistency score. The risk classification accuracy of the model in this paper reaches 0.918, which is higher than 0.889 of XGBoost, 0.896 of BiLSTM and 0.878 of standard random forest. The recall rate of high-risk samples is 0.872, which is 0.041 higher than that of XGBoost and 0.029 higher than that of BiLSTM. The consistency score of risk distribution reaches 0.846, indicating that the proportion of low, medium, and high risk output by the model is closer to the true distribution. This result shows that the proposed method can not only distinguish different risk levels, but also reduce the misplaced situation of medium and high risk samples near the classification boundary, so that the subsequent control strategy has a more reliable trigger basis.

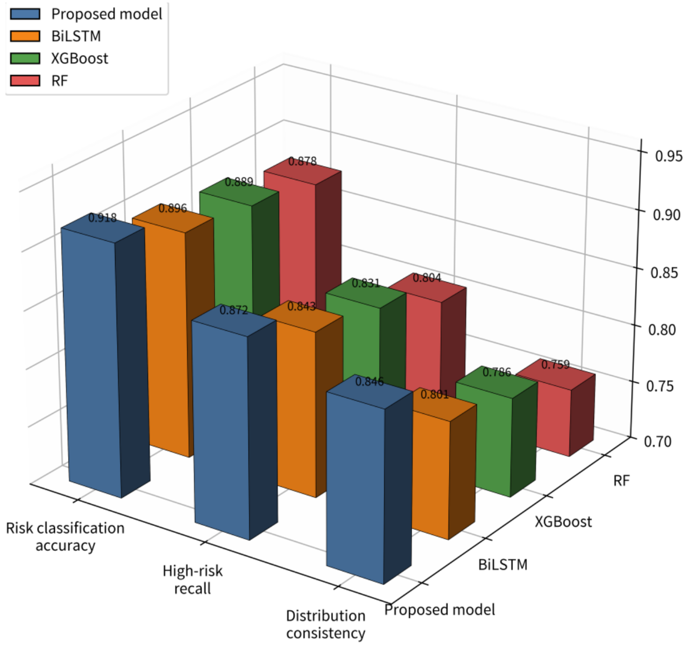

Figure 3: Comparison chart of risk classification management effect

The dynamic control experiment further shows that the closed-loop mechanism has a more obvious slow release effect on the high-risk state. In this paper, the state transition of high-risk samples after control execution is taken as the core observation object, and the average response delay, risk reduction rate and loss pressure drop amplitude after control are synchronously recorded. The results are shown in Figure 4. After the end of a control cycle, 38.4% of the high-risk samples in the proposed system fall back to the medium risk, 12.7% directly fall back to the low risk, and the proportion of high-risk residual drops to 48.9%. In contrast, the proportion of high-risk residues is still 58.6% for the XGBoost linkage rule scheme and 55.9% for the BiLSTM linkage scheme. At the same time, the average response delay of the proposed system is shortened from 6.8 hours before control to 2.9 hours, and the loss voltage drop is 23.6%, which is significantly better than the other comparison schemes. This shows that after the model, the rule engine and the execution system are connected, the risk control is no longer dependent on the lagged manual flow, and can enter the disposal stage quickly after the identification results are generated.

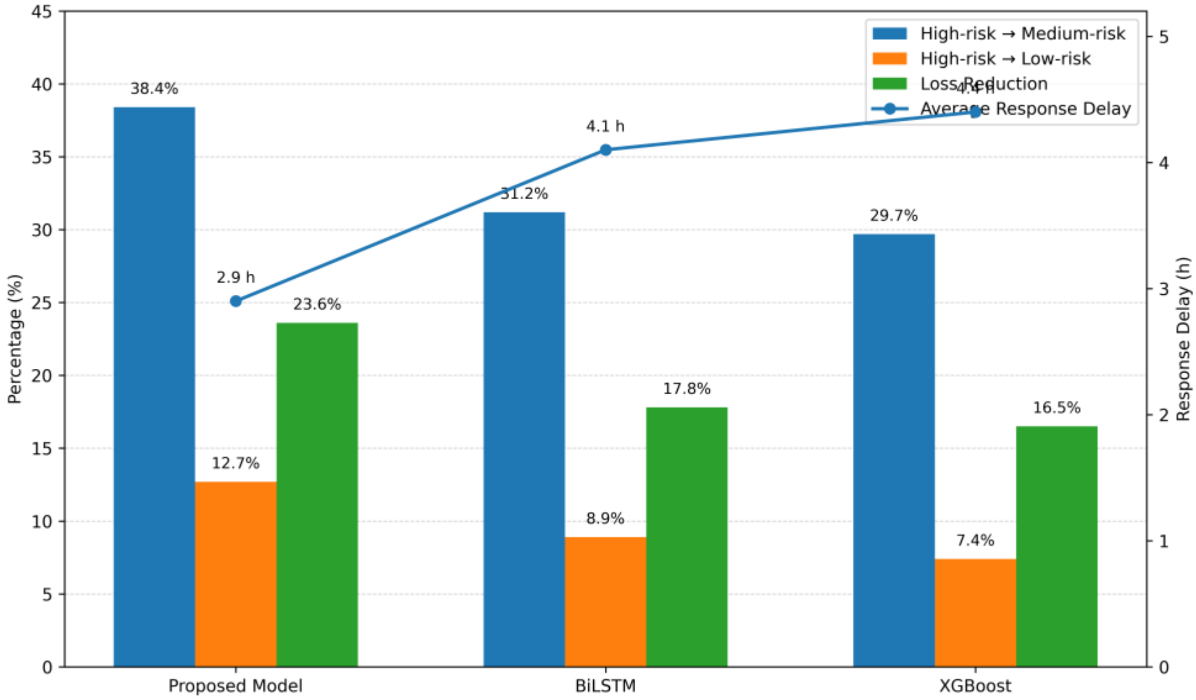

Figure 4: Change diagram of dynamic control effect

Combining Figures 4 and 5, we can see that the advantage of the proposed system is not only reflected in the classification accuracy, but also reflected in the fact that "the classification results can support effective control". More accurate risk stratification means that control resources can be more focused on those who really need intervention. The response time is shorter, indicating that the digital system integration improves the conversion efficiency from early warning to disposal. The higher drop ratio of the high-risk samples and the higher drop amplitude of the loss pressure indicate that the closed-loop feedback mechanism enhances the actual effect of the control action. It can be seen that the comprehensive risk management system enabled by financial digital transformation is not a simple electronic copy of the traditional risk control process, but through the collaborative coupling of data, models, rules and system execution, it improves the overall efficiency of risk classification management and dynamic intervention of commercial banks.

6 Discussion

Combined with the above experimental results, it can be seen that the comprehensive risk management system of commercial banks constructed in this paper shows better comprehensive performance in terms of risk early warning accuracy, hierarchical management effectiveness and dynamic control response. This shows that under the background of financial digital transformation, the improvement of risk governance capability does not simply depend on the local optimization of a certain identification model, but also depends on whether there is a stable connection between data governance, feature calculation, early warning output, rule implementation and feedback correction. An important reason for this method to achieve relatively better results is that it integrates multi-source risk information into a unified computing framework, so that customer behavior, credit fluctuation, transaction anomaly, liquidity pressure and operation deviation are no longer treated separately, but transformed into continuous risk signals through feature engineering and hierarchical judgment mechanism. Thus, the model's ability to perceive complex risk states is improved.

From the perspective of robustness, the standard deviation of the proposed model in repeated experiments is small, which indicates that it is less sensitive to sample perturbations and parameter initialization changes. This is directly related to the idea of ensemble learning, the hierarchical feature selection mechanism and the feedback update design in the digital risk control architecture. By weighting high-risk samples, compressing redundant variables and writing back the control results to the training pool, the system alleviated the influence of class imbalance, noise interference and short-term drift on model judgment to a certain extent. However, it should also be noted that the verification of this paper is mainly based on historical business data and relatively normalized business scenarios. For tail scenarios such as extreme market shocks, sudden liquidity contraction, and sharp adjustment of regulatory rules, it is still necessary to continue to test the model performance. If stress testing, scenario simulation and drift detection mechanisms are introduced in the future, the external adaptability of the system will be further enhanced.

The application value of the proposed method is also reflected in its strong landing possibility. The risk score results can be directly mapped to control actions such as quota adjustment, approval and acceptance, list management, manual review and monitoring encryption through the rule engine, which makes the model output no longer stay at the analysis layer, but can enter the actual business link. From the perspective of system engineering, the framework is suitable for embedding into the data middle office, risk middle office or credit approval platform of commercial banks, and realizes automatic early warning push and policy linkage through interface services, real-time message queue and visual kanban board. In this way, the comprehensive risk management system has a strong continuity of execution and no longer stays in the stage of static reports and post-review. At the same time, the method in this paper also has tradeoffs. Compared with the traditional linear model, the proposed system has stronger predictive ability, but the interpretability is not completely transparent, and part of the decision-making process still needs to rely on feature importance analysis, local path tracking and rule mapping for auxiliary explanation. In scenarios with strict regulatory requirements and strong audit traceability, a balance between model performance and explanatory power still needs to be maintained. At the same time, the deep time series model and graph model still have potential advantages in dealing with relational networks and long sequence dependencies. Although the system in this paper performs well in the current sample size and business scenarios, the fusion path with graph neural network, online learning mechanism and knowledge graph can still be explored in the future to improve the identification ability of cross-institutional transmission risks and complex correlation risks.

7 Conclusions

Focusing on the reconstruction of the comprehensive risk management system of commercial banks under the background of financial digital transformation, this paper completes the overall research of mechanism analysis, model design, system integration and experimental verification, and forms a relatively complete closed-loop risk control scheme. At the theoretical level, this paper revealed that the impact of digital transformation on the risk management of commercial banks was no longer limited to tool substitution, but manifested as the systematic reorganization of risk data aggregation, feature calculation, intelligent recognition, rule linkage and feedback update. At the method level, an integrated framework consisting of multi-source risk feature extraction, comprehensive risk scoring, hierarchical early warning judgment and closed-loop control execution is constructed, which realizes the continuous operation of "identification-early-warning -control-feedback".

Experimental results show that the proposed model has better performance in risk warning performance. In the test set, the Accuracy reaches 0.914, the F1 value is 0.881, the AUC reaches 0.942, the Brier Score is reduced to 0.108, and the Log Loss is 0.276. It shows that the proposed model is better than the comparison models in the identification of high-risk samples, probability calibration and output stability. Repeated experimental results also show that the standard deviation of multiple indicators is controlled at a low level, indicating that the model is less sensitive to sample perturbation and training randomness. The risk classification and dynamic control experiments further show that the accuracy of risk classification is 0.918, the recall rate of high risk is 0.872, and the consistency score of risk distribution is 0.846. After the control, 38.4% of the high-risk samples fell back to the medium risk, 12.7% fell back to the low risk, the average response time was shortened to 2.9 hours, and the loss pressure drop after the control reached 23.6%. These results show that the system proposed in this paper can not only identify risks more accurately, but also effectively transform the early warning results into hierarchical management and dynamic intervention actions.

This paper shows that under the background of the continuous advancement of financial digital transformation, the reconstruction of the comprehensive risk management system of commercial banks should be based on the common foundation of data governance, algorithm modeling and system collaboration, rather than the online replication of traditional risk control processes. The method constructed in this paper provides a computable and implemensible technical path for commercial banks to improve the accuracy of risk identification, enhance the control response ability and improve the efficiency of closed-loop governance. At the same time, this paper is still mainly based on historical business samples and normal scenarios, which lack coverage of complex scenarios such as extreme market shocks, sudden regulatory changes and cross-institutional risk transmission. Subsequent research can further introduce methods such as stress testing, online learning, multi-modal information fusion and knowledge graph to improve the system's adaptability and long-term evolution ability in extreme situations.

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