Modern Management Science & Engineering
ISSN ISSN 2052-2576
Vol. 7, No. 1, 2025
www.scholink.org/ojs/index.php/mmse

*Original Paper*

# The Application of Artificial Intelligence and Big Data in Financial Risk Forecasting and Management

Shenglin Yang[1]

[1] City University of Hong Kong, Hong Kong region, China

E-mail: sheyang8-c@my.cityu.edu.hk

Received: October 19, 2025 Accepted: November 28, 2025 Online Published: December 09, 2025

doi:10.22158/mmse.v7n1p34 URL: http://dx.doi.org/10.22158/mmse.v7n1p34

***Abstract***

*In the past, financial risk management has always faced a changing market environment and while there were several traditional predictive models available for use, they have limited capabilities in addressing non-linear or high-dimensional risk factors. Therefore, enhancing the foresight in risk identification as well as the accuracy of decision-making within financial institutions will require further exploration into the application value of artificial intelligence and big data technology. Consequently, the goal of this paper is to conduct a comprehensive evaluation regarding the integration pathways and effectiveness of implementing these two technologies into financial risk predicting and managing practices. Findings from the research indicate that AI algorithms offer a deeper understanding of complex, hidden relationships among large amounts of multiple sources of information, while the availability of big data platforms provides opportunities for continuously monitoring risk in real-time. The combination of the two not only significantly improves the timeliness and accuracy of risk prediction, but also promotes the intelligent transformation of risk management models from passive response to active intervention.*

***Keywords***

*Artificial Intelligence, Big Data, Financial Risk Forecasting, Risk Management*

## 1. Introduction

Traditional risk management methods rely heavily on the statistical patterns and preset rules of historical data, which often appear sluggish and rigid when dealing with rapidly changing information in modern financial markets. The complexity and correlation of financial risks are increasing day by day, and the transmission path of risk factors is difficult to outline with simple models, which makes the demand for more powerful analytical tools urgent. The rise of artificial intelligence and big data technology provides a new perspective and toolbox for solving this dilemma. They endow financial institutions with an unprecedented ability to capture subtle risk signs in real-time from seemingly chaotic massive information flows, and simulate their potential evolutionary trajectories, thereby expanding the boundaries of risk management from known to unknown domains.

## 2. Theoretical Foundations of Artificial Intelligence and Big Data in Financial Risk Prediction and Management

### *2.1 Basic Principles of Artificial Intelligence and Big Data Technologies*

Artificial intelligence and big data concepts have been developed based upon an understanding that processing data effectively allows for the identification of patterns. Big Data Technology has developed the ability to build large databases that consolidate disparate information sources such as transaction histories and consumer opinion surveys to provide a standardized way of analyzing this data. Data Processing creates a base of information upon which risk analysis can occur because it allows for the compilation of all data into a single repository. Machine Learning is, in effect, the basis for the understanding of how algorithms for Artificial Intelligence work through an automatic learning process that allows the algorithm to determine complex relationships between variables from the structured data, discussed above. For instance, there are algorithms that detect attribute combinations that would suggest that an individual will default on loans based upon their earlier history, while there are others that understand how fluctuations in public opinion may impact the prices of financial securities. As these processes enable the continuous extraction of knowledge from data and refinement of decisions based upon such knowledge, they empower machines to aid human beings in greater sensitivity in detecting potential risk signals.

### *2.2 Theoretical Framework of Financial Risk Prediction and Management*

In risk management, a theoretical framework is an essential part of the overall process and establishes the foundational elements of how to manage risk through the identification, assessment, and response phases. In addition, the risk identification phase identifies potential risks through a monitoring system that captures signals of potential risk, which can lead to the exposure of organisations to unknown risks if it is not implemented. In contrast, the risk assessment phase uses quantitative statistics to quantify the level and severity of risk, yet traditional approaches to statistics have difficulty dealing with the complexities of correlation. Finally, in the response phase, management publishes actions based on the assessment, essentially creating and executing a management strategy. The theoretical framework constitutes scientific and systematic deployment of risk management from conception to implementation (Tian, 2025).

## 3. Issues in the Application of Artificial Intelligence and Big Data in Financial Risk Prediction and Management

### *3.1 Insufficient Integration of Technological Innovation with Business Needs*

The lack of integration between technological innovation and business needs is rooted in the systemic gap in cognition and goals between technological research and risk management practices. Technical teams usually pursue the predictive accuracy and technological innovation of models, and their results may manifest as a complex but obscure warning score. However, the core demand of the business team is to translate warnings into clear action instructions. They must be clear on whether a specific rating fluctuation requires initiating customer follow-up, increasing provisions, or suspending trading authorization. The lack of a common design language and collaborative process between the two often results in technical solutions encountering resistance before they are put into production. Business personnel find it difficult to trust the output of the model due to their inability to understand the decision-making basis, while technical teams find it difficult to optimize the practicality of the model due to their unfamiliarity with actual business constraints. This disconnect has resulted in many valuable innovations being shelved and unable to form genuine risk management capabilities.

### *3.2 The Accuracy and Practicality of the Model Need Improvement*

The core dilemma faced by many current risk prediction models lies in the disconnect between their theoretical accuracy and actual utility. A market risk model trained in a laboratory environment may miss important volatility warnings due to its inability to timely incorporate sudden public opinion signals on social media. In credit approval scenarios, overly complex machine learning models sometimes mistake certain non-traditional data features of customers as high-risk indicators, but cannot provide reasonable explanations that conform to business common sense. This "black box" feature often leads frontline business personnel to rely on their own experience and shelve model recommendations when faced with abnormal results generated by the model. If the model can only run in an idealized data environment and cannot adapt to the complex situations of inconsistent data quality and high decision-making timeliness requirements in real business, its actual value will be greatly reduced.

### *3.3 Implementation cCosts and Maintenance Difficulties Are Significant*

The implementation cost and maintenance burden are directly transformed into management decision-making difficulties and operational frictions in practical applications. An intelligent model aimed at improving credit evaluation efficiency often requires banks to restructure their existing approval processes and arrange for a large number of personnel to receive training during the deployment process, which often exceeds the initial financial budget of the project. In daily operations, the model requires the risk team to invest a lot of time in data verification and result calibration, which squeezes the human resources originally used for in-depth risk analysis. When market environment changes require model updates, cross departmental coordination delays and difficulties in adding budgets often lead to iteration plans being put on hold. The lag in maintenance work leads to a gradual deviation between the risk score output by the model and the actual situation of the customer. Credit personnel may begin to question the reliability of the system and rely on subjective experience, which invisibly weakens the unity and scientificity of the risk management system.

*3.4 Prominent Risks in Data Privacy and Security*

The risk of data privacy and security impacts the ability and trustworthiness of the risk prediction process. Financial institutions must continue to add a broader spectrum of individual behavioral and social relationship information to help create more reliable risk profiles for their customers. Collectively grouping and comparing these various types of highly sensitive data increases the overall risk for data breaches if absolute security as defined by the institution does not exist. An added online data supplier also increases the amount of data moving through a financial institution, and any one weak link in the security chain of any supplier can allow for the data to be breached anywhere along the data chain. Therefore, when breaches occur either due to illegal tampering or forgotten backups, it puts financial institutions in a position to deal with severe legal and reputational crises as well as produces "junk data" that will negatively impact the development of effective predictive models. Consequently, any prediction created from such data will misguide financial institutions in their risk analysis and ultimately result in unexpected risk exposure (Renqing & Osama, 2025).

*3.5 Professional Talent Development and Skill Gap*

The existing talent structure is difficult to fully grasp the complex knowledge system required by intelligent risk control. Data science experts are typically able to construct precise predictive models, but they may lack sufficient in-depth understanding of the specific terms of credit policies or the actual management scenarios of market risk limits. At the same time, traditional risk analysts, although familiar with business rules and regulatory frameworks, often have difficulty accurately understanding the logic and limitations of generating model results. This mismatch between knowledge and skills creates a clear communication barrier in daily collaboration. A specific risk monitoring requirement proposed by the business side may lose its core business intent when transformed into a technical development task; However, a complex model delivered by the technical team is often difficult to deploy due to insufficient consideration of the timeliness and compliance constraints in actual decision-making. The speed of talent cultivation and integration has not kept up with the pace of technological application, which directly restricts the depth and efficiency of the intelligent transformation of risk management.

## 4. Innovative Applications of Artificial Intelligence and Big Data in Financial Risk Prediction and Management

*4.1 Intelligent Risk Early Warning and Monitoring System*

The Intelligent Risk Early Warning and Monitoring System constructs a continuously operating, multi-dimensional risk perception network. Its core function lies in the real-time collection, integration, and intelligent analysis of vast amounts of information dispersed across internal and external processes.

The system not only integrates traditional transaction records and financial report data but also continuously crawls news reports, regulatory announcements, and even sentiment indicators from social media related to specific clients or industries, thereby forming a more comprehensive risk assessment context. The embedded analytical engine cross-references these multi-source, heterogeneous information streams based on predefined risk identification rules and dynamically updated pattern libraries. For instance, when the system detects a non-seasonal extension in a manufacturing client's payment cycle, coupled with shifting supply-demand data in its niche market and increasingly negative industry sentiment, it automatically generates a medium-priority credit risk early warning event. This event, along with associated raw data segments and preliminary analysis conclusions, is automatically pushed to the relevant account manager and risk analyst's task list, potentially triggering a pre-set process to automatically send payment reminders to the client. By leveraging the system's comprehensive insights, account managers can engage in more targeted client communications to understand genuine operational changes and provide feedback to update the warning status. This data-driven, closed-loop early warning mechanism transforms risk monitoring from a reactive, manual sampling model into an active, continuous, and traceable routine workflow, significantly enhancing an institution's ability to detect and respond to early warning signals of potential risks (Wang, 2025).

### *4.2 Credit Assessment Models Driven by Big Data*

The model for the credit assessment is based on data from the internet. It also uses information from banks, current companies in the industries that are connected to the customer, and from central banks to help determine if a company should receive a loan. This new method of assessing credits allows banks or lenders to see how companies operate in a day-to-day environment and not just look at the financial numbers. In this example, a software company is looking for a loan to help it grow and has done quite a bit of R&D, which could show that the company is not as financially strong as it may otherwise appear. But the data an alternative model will provide would show positive signs for instance: daily growth of the company when looking at the daily number of active users, customer contract renewal rates, and if there are key team members that have stabilised their position. The overall picture created by the alternative data, and the credit information gathered by the lender will help the lender to evaluate the company’s potential for growth and determine if it meets the bank’s criteria for obtaining a loan. The alternative data provided a detailed look at how the company operates beyond just looking at revenue to evaluate if the company would qualify for a loan. Based on this, approvers can assess the sustainability of the enterprise's future cash flow and make final decisions by combining model recommendations with their own industry insights. This evaluation approach enables banks to serve innovative enterprises lacking sufficient collateral but possessing genuine growth potential more effectively, while the model continuously learns and refines its ability to identify industry-specific characteristics through ongoing tracking of these novel data trends.

*4.3 Application of Adaptive Machine Learning Algorithms*

The application of adaptive machine learning algorithms endows risk models with the self-optimizing capability to respond to dynamic environmental changes, thereby addressing the decline in predictive performance caused by the rigid parameters of traditional static models. The core of this technical system lies in establishing a continuous monitoring and feedback loop for model performance (Chen, 2025). The system compares the risk predictions generated by the model with actual risk events in real time, triggering an automatic calibration process when deviations exceed preset thresholds. For instance, in credit card fraud detection scenarios, where criminals continuously evolve their tactics, adaptive algorithms can dynamically adjust the sensitivity weights of the model to different behavioral indicators (such as abnormal combinations of transaction locations, amounts, and frequencies) based on newly detected fraudulent transaction patterns—eliminating the need for time-consuming quarterly model retraining projects. Similarly, market risk early warning models benefit from this approach. When structural changes occur in the relationships between macroeconomic indicators or asset volatility patterns, the algorithm can fine-tune the predictive equations using the latest market data, ensuring that key metrics like value at risk more closely align with current market conditions. This capability transforms model maintenance from discrete, resource-intensive project-based tasks into an embedded, low-intervention continuous activity. Not only does it reduce long-term operational costs, but more critically, it ensures that risk insights remain synchronized with the evolving financial environment, providing more timely foundations for management decision-making.

*4.4 Interactive Risk Decision Support Tool*

The core of interactive risk decision support tools is to transform complex model analysis into an auxiliary interface that risk managers can directly operate and verify. This tool is typically presented in the form of a visual dashboard, where risk managers can autonomously adjust key assumption parameters on the interface when faced with a specific portfolio risk review task, such as the severity of macroeconomic stress scenarios or correlation coefficients between different asset classes. The system will quickly recalculate and display changes in key indicators such as risk value and stress test losses based on these real-time input adjustments. Risk managers can compare the differences in results under different parameter settings and explore the core risk driving factors and their impact sizes. Through this process of interactive analysis, risk managers are able to see how the risk and stress test losses associated with their portfolios vary across different parameter combinations and are provided with an opportunity to assess the underlying risk drivers and their size or impact. In addition, this process changes what were previously passive and technical measurements of the impact of macroeconomic changes from a reliance on the back office to an active, real-time examination process that business users can engage in and perform without the need to rely on back office personnel, therefore, deepening the user's understanding of the rationale behind the risk assessment model while providing an opportunity to merge the quantitative results with the risk manager's own judgment based on their experience in the market. As a result, the user's ability to make decisions becomes more agile and persuasive in nature (Chen, Lin, & Lu, 2025).

*4.5 Sustainable and Ethical Compliance Technology Integration*

The core of sustainable compliance technology is to embed evolving regulatory requirements and ethical standards into the design and operational logic of intelligent risk management systems. At the beginning of its construction, the system needs to translate specific provisions of relevant regulations into executable data rules and model constraints. For example, in environmental and social risk (ESG) analysis, the data collection scope and evaluation indicators of the model must strictly correspond to the current effective disclosure standards and industry norms. During the continuous operation phase, the system can automatically monitor whether its decision-making patterns may generate biases based on protected characteristics such as geography and gender, and issue warnings for potential deviation trends identified. The compliance teams of financial institutions can regularly review the ethical audit reports generated by these systems and calibrate the model parameters in conjunction with external regulatory dynamics. This fusion mechanism transforms risk management activities from just post compliance checks to a continuous process that dynamically collaborates with regulatory and ethical requirements, thereby systematically reducing the risk of violations and reputational risks while improving operational efficiency (Lin & Qi, 2025).

## 5. Conclusion

The application of AI and big data to the financial risk industry has provided a solid foundation for establishing a framework for the future development of intelligent risk management which has shown the ability to fundamentally alter risk warning systems, credit evaluation processes, and decision support systems. However, to develop to the next stage of maturity, businesses will need to address the problems created by the reliance on technical models; integrate business scenarios into their framework; and overcome issues related to data governance. In addition, future research should focus on producing new intelligent frameworks that allow for broader interpretation, are more robust, and provide a safe and ethical environment for the creation of new innovative technologies that can mitigate the financial risk, while also sustaining responsible and fair technological advancement.

## References

Chen, C., Lin, W., & Lu, C. (2025). Financial Management Risk Prediction Algorithm of New Energy Enterprises Based on Improved Neural Network. *Academic Journal of Computing & Information Science*, *8*(6), 22.

Chen, W. (2025). Enterprise financial risk prediction and intelligent early warning model based on deep learning. *Discover Artificial Intelligence*, *5*(1), 226-227.

Lin, X., & Qi, Z. (2025). Dynamic risk prediction in financial-production systems using temporal self-attention and adaptive autoregressive models. *Frontiers in Physics*, 131627550-1627551.

Renqing, G., & Osama, S. (2025). RiskMamba: A Lightweight and Efficient Model for Enterprise

Financial Risk Prediction With Multi-Scale Temporal Modeling. *Journal of Organizational and End User Computing (JOEUC)*, *37*(1), 19-20.

Tian, T. (2025). Enterprise financial risk prediction model based on modified machine learning classifier algorithms. *Discover Computing*, *28*(1), 246-247.

Wang, Y. T. (2025). Application of Artificial Intelligence and Big Data in Financial Risk Forecasting and Management. *China Collective Economy*, (32), 193-196.