SCIENTIFIC OASIS

Decision Making: Applications in Management and Engineering

Journal homepage: www.dmame-journal.org
ISSN: 2560-6018, eISSN: 2620-0104

Research on the Application of Artificial Intelligence Technology in Enterprise Financial Risk Warning - Based on Machine Learning Method

Tao Ma [1,*]

1 Xinjiang College of Science & Technology

ARTICLE INFO

Article history:
Received 5 April 2024
Received in revised form 11 May 2025
Accepted 7 June 2025
Available online 15 June 2025

Keywords:
Machine Learning, Financial Risk Management, Risk Warning System, Predictive Modelling, Model Interpretability, AI in Finance

ABSTRACT

This research addresses the constraints inherent in conventional financial risk management by formulating and assessing a machine learning (ML)-driven framework for enterprise financial risk warning. Drawing upon a comprehensive dataset comprising 50,000 monthly financial records from over 200 enterprises across a five-year period, the study implemented and evaluated multiple ML algorithms, including Random Forest, XGBoost, and Neural Networks. The proposed methodology mitigates common challenges associated with financial data by employing advanced pre-processing techniques, robust feature engineering, and strategies for resolving class imbalance. Empirical analysis indicates notable enhancements compared to traditional methodologies. Specifically, Deep Neural Networks attained 96% precision and 92% recall in fraud detection; ML-based clustering methods achieved a 20% reduction in default rates; and Reinforcement Learning yielded a 12% increase in portfolio optimisation returns. Validation through real-world case studies further substantiates these outcomes. One implementation successfully forecasted liquidity shortages with 92% accuracy up to three months in advance, while another identified US$10 million in unauthorised transactions within six months. The findings underscore the potential of ML-based systems not only to improve predictive accuracy but also to deliver actionable risk mitigation strategies and to enhance operational efficiency by reducing false positives by 15% and enabling real-time alert processing. This research contributes to the advancement of enterprise risk management by offering a pragmatic implementation framework that addresses key challenges of transparency and scalability associated with AI integration in financial decision-making.

1. Introduction

Financial institutions and businesses are increasingly exposed to unprecedented risks due to escalating market complexities, stringent regulatory requirements, and surging volumes of data. Traditional risk management approaches have long struggled to effectively evaluate the rapid and heterogeneous nature of financial data in contemporary markets [1; 2]. The immediate implications of these limitations have compelled organisations to adopt advanced analytical tools capable of processing multidimensional and complex datasets in real time. In this context, artificial intelligence

* *Corresponding author.*
E-mail address: lesliearicle@hotmail.com

https://doi.org/10.31181/dmame8120251489

(AI) and ML have emerged as transformative technologies within financial risk management, disrupting conventional methodologies across diverse sectors. These technologies offer distinct advantages, such as the capacity to discern data patterns through large-scale analyses of both structured and unstructured data, while simultaneously delivering timely and actionable insights.

Since the onset of the twenty-first century, the global financial landscape has undergone significant transformation driven by technological innovation, evolving regulatory frameworks, and increasingly interconnected markets. AI and ML systems address critical shortcomings of traditional risk strategies and introduce novel functionalities, including predictive analytics, real-time decision-making support, and enhanced vulnerability defence mechanisms. The rise of complex financial threats—such as cyberattacks and climate-related financial risks—has necessitated the integration of AI into institutional risk management infrastructures, shifting its role from experimental application to a strategic imperative. The initial segment of this study explores the barriers to technology adoption and implementation that hinder the widespread deployment of AI tools in financial risk management. This is accompanied by an evaluation of operational and strategic considerations essential for facilitating successful integration.

1.1 The Evolution of Financial Risk Management

The evolution of traditional financial risk management methodologies has been underpinned by foundational contributions in probability theory and econometrics, notably those advanced by Markowitz (1952) and Black-Scholes (1973). For several decades, institutional practices have incorporated techniques such as Value at Risk (VaR) analysis for instance, commonly applied to estimate potential asset declines within a specified period within a specified level of confidence from historic data. Credit scoring models, and stress testing mechanisms to evaluate the probability of a borrower defaulting on a loan based on financial ratios and historical performance [3]. While these methods yield precise results owing to their mathematical robustness, their analytical capacity remains constrained when confronted with the rapid pace and expansive volume of contemporary financial data. The limitations of conventional risk models became particularly evident during the 2008 global financial crisis. These models proved ineffective in identifying systemic interdependencies and unanticipated events [4]. Post-crisis evaluations revealed that over 80% of major financial institutions were reliant on risk models that failed to foresee the impending liquidity crisis, thereby intensifying calls for the development of alternative risk assessment frameworks [5].

1.2 The AI Revolution in Risk Management

Market constraints are effectively mitigated through three transformative adaptive learning mechanisms, notably including large-scale pattern recognition and autonomous decision-making optimisation. Deep neural networks (DNNs), for instance, attain 96% accuracy by analysing transactional sequences based on temporal and spatial variables—an achievement unattainable by conventional rule-based systems [6]. Nonetheless, the barriers to adopting AI in risk management often surpass the immediate technological benefits. Approximately 78% of financial institutions report data quality issues, which hinder model execution due to missing values, sampling biases, and temporal inconsistencies [7]. Additionally, educational institutions face infrastructural limitations, particularly in the absence of cloud-based architectures, a shortfall that disproportionately affects smaller institutions or those with limited university affiliations [8]. At a global scale, a significant challenge arises from the opaque nature of algorithmic models—commonly referred to as the "black box" problem. This issue remains a critical concern for compliance officers, with 62% of surveyed respondents identifying it as a key impediment [9]. Emerging AI systems that integrate the interpretability of symbolic AI with the predictive capabilities of deep learning offer viable solutions to these contemporary challenges [10].

Federated learning emerges as a promising technique for constructing collaborative fraud detection networks. These models facilitate cross-institutional product development during the training phase while preserving data privacy. Furthermore, the democratisation of AI tools through MLOps platforms hosted on cloud infrastructure enables regional banks to implement risk models at a cost reduction of up to 30% compared to traditional on-premises systems [11].

1.3 Limitations of Traditional Risk Management

Value at Risk (VaR), the Altman Z-score, and ARIMA represent conventional risk management models that organisations have employed for several years. Despite their longstanding application, these models exhibit significant limitations in practice. Primarily, they rely on financial ratios and historical performance, however they do not capture any changes in market environment and potential changes in behavior that could change the default probabilities. Moreover, traditional models encounter considerable obstacles when addressing the demands of large-scale data processing in contemporary financial environments, as they typically necessitate manual oversight—an approach that lacks scalability. These methods reveal two fundamental shortcomings: they are ineffective in detecting complex risks arising from the interplay of multiple factors, and they are incapable of responding promptly to emerging threats. In contrast, the application of real-time data analysis through AI and ML demonstrates superior potential in forecasting financial risks [1], outperforming traditional statistical techniques that remain inadequate in capturing market volatility.

1.4 Research Objectives and Significance

This study seeks to develop and validate a comprehensive ML-based framework for financial risk warning, specifically designed to overcome the inherent limitations of traditional risk management methodologies. The primary objectives are as follows:

1. To construct a robust system that integrates heterogeneous data sources and employs advanced pre-processing techniques to manage issues such as missing values, outliers, and class imbalances.
2. To assess and compare the predictive performance of multiple ML algorithms, namely Random Forest, a feature in creating many decision trees in the training stage and providing the mean for regression or majority for classification of trees which has successful results for both the classification and regression problem especially the high-dimensional data with complicated interactions among variables, XGBoost, which trains the models sequentially and each model learns the error of the previous one trying to minimize loss function through gradient descent and contains regularization for overfitting and Neural Networks, a complicated network made of connected node that tries to mimic the process of decision making of the human brain, can learn complicated nonlinear relationships, update their weights with the aim of improving the prediction accuracy—in the context of financial risk forecasting.
3. To substantiate the practical utility of these methods through real-world case studies supported by empirical performance metrics.
4. To address key implementation challenges, with a particular emphasis on enhancing model interpretability and ensuring scalability.

This research offers substantial value to a range of stakeholders. For financial institutions, the proposed framework enhances risk detection accuracy, minimises false positive rates, and improves overall operational efficiency. Enterprise managers benefit from more timely and actionable risk alerts, facilitating improved decision-making processes. Regulatory authorities are provided with more dependable methodologies for financial risk assessment. Furthermore, academic researchers are offered empirical insights into the comparative effectiveness of various ML models within financial applications. By prioritising both predictive precision and real-world implementation considerations, this study effectively bridges the divide between theoretical ML innovations and their practical deployment in enterprise financial risk management.

2. Literature Review

2.1 The Emergence of AI in Financial Risk Management

The integration of AI technologies into financial risk management enables institutions to fundamentally transform their approaches to risk assessment and mitigation. Initially adopted for automating routine tasks, AI applications in the financial domain have evolved significantly, now offering advanced capabilities in risk prediction and decision support [12]. As noted by [13], the adoption of AI by financial institutions has increased markedly since 2018, with risk management emerging as the principal area of application. AI technologies surpass traditional financial systems in their ability to process extensive volumes of data, detect intricate nonlinear patterns, and adapt dynamically to changing market conditions [14]. These strengths allow modern financial institutions to analyse a diverse array of data sources, including historical records, market valuation data, customer transaction behaviours, and sentiment analysis derived from social media platforms [15]. Notably, AI-based fraud detection systems can identify anomalous activity patterns significantly earlier than conventional rule-based systems—often within a forty-eight-hour window, thereby averting substantial financial losses.

2.2 Deep Learning Applications in Financial Risk Management

[16] assert that deep learning techniques have significantly enhanced the detection of anomalous patterns in real-time fraud detection processes. [17] advanced this field by integrating Convolutional Neural Networks (CNNs) for transaction pattern analysis, achieving a detection rate of 96% for irregular activities while maintaining a false positive rate of less than 0.5%. This model strategy exhibits considerable advantages over traditional rule-based frameworks, particularly in managing the trade-off between sensitivity and specificity. However, the deployment of deep learning models within financial contexts presents several critical challenges. Research published by the Bank of England highlights the security risks associated with these models, particularly their "fragility" and heightened sensitivity to data input variations. Furthermore, the intrinsic opacity of deep learning algorithms has raised concerns among regulators and other stakeholders, particularly regarding trading transparency, regulatory compliance, and model interpretability [18]. One of the most pressing issues for financial institutions is the difficulty in articulating the rationale behind model decisions, as both regulators and customers demand transparent and comprehensible explanations.

2.3 Machine Learning Clustering for Credit Risk Assessment

Unsupervised clustering tools serve as essential methodologies for credit risk segmentation and evaluation. [19] highlight how cluster analysis techniques effectively uncover distinct risk categories among borrower groups, thereby enabling lenders to formulate tailored risk management strategies. These methods have proven instrumental in identifying latent behavioural patterns that reflect evolving risk trends. Among these, K-Means and DBSCAN have emerged as prominent clustering algorithms for classifying credit risk. They facilitate customer segmentation based on financial risk indicators [20]. According to [21], "credit risk clustering" segments customers or borrowers based on shared credit risk attributes, thereby enabling the assignment of differentiated interest rates and contractual terms to distinct risk-based cohorts.

Evidence of the practical advantages of these methods is clear. [22] reports that integrating K-Means clustering with appropriate feature engineering resulted in a 22% reduction in default rates compared to traditional credit scoring models. Similarly, [23] demonstrated that hierarchical clustering significantly enhances the evaluation of credit risk between high- and low-risk entities, particularly among mid-sized firms where conventional tools often underperform. These clustering methodologies excel in uncovering natural data groupings without requiring labelled input, positioning them as ideal instruments for exploratory market analysis [24]. However, their efficacy is heavily dependent on rigorous feature selection and fine-tuned parameter configurations. [25] further argue that domain-specific knowledge is crucial for interpreting cluster groupings and formulating effective risk management strategies based on those insights.

2.4 Reinforcement Learning for Portfolio Optimization

The integration of reinforcement learning (RL) into portfolio optimisation has markedly surpassed the effectiveness of traditional techniques. While Markowitz's Modern Portfolio Theory has dominated the domain of portfolio construction for decades, its reliance on historical data and static assumptions renders it less effective in the face of modern market complexities [26]. RL offers a novel perspective by reconfiguring portfolio management into a dynamic decision-making process that evolves through continuous interaction with market environments. [27] demonstrated the efficacy of Deep Q-Networks in portfolio allocation, achieving a 14% improvement in risk-adjusted returns over traditional mean-variance models. Similarly, Policy Gradient algorithms, as developed by [6], showcased superior performance stability, particularly during adverse market movements, thereby underlining their robustness under varying conditions.

A significant advantage of RL lies in its adaptive capacity—these models autonomously adjust investment strategies in real-time, effectively responding to fluctuating market conditions. RL frameworks have integrated objectives such as return maximisation, risk reduction, and transaction cost control into a cohesive strategy, addressing a key limitation of conventional optimisation methods, which often struggle with multi-objective scenarios [28]. Despite these benefits, deploying RL in financial settings presents considerable challenges. One critical issue is sample inefficiency; RL models typically require extensive datasets for effective training, as noted by [29]. Moreover, there is a risk that these models might exploit artefacts in historical data rather than learning strategies aligned with genuine profit generation. This underscores the necessity for robust validation mechanisms to ensure the reliability and generalisability of RL-based strategies in live financial environments.

2.5 Research Gaps and Current Study Contribution

The growing interest in AI for financial risk management has not diminished the need for continued research. A critical gap remains in the comprehensive evaluation of various AI approaches across different risk categories, particularly in real-world operational environments [30]. Most research has predominantly focused on large financial institutions, which possess substantial resources, raising concerns about the applicability of these methods for smaller organisations [31]. A prominent trend in current research is the integration of multiple AI techniques into cohesive risk management systems. Although there have been applications of AI models for specific tasks, further development is required to create frameworks that leverage the complementary strengths of different AI approaches. The stability and longevity of AI models in dynamic financial environments also require more investigation, as many evaluations are conducted over short timeframes, limiting the generalisability of findings.

Our study provides a thorough analysis of several AI models, including deep neural networks, steering algorithms, and reinforcement learning, within various risk management contexts. This research aims to fill the current knowledge gaps by assessing the strengths and weaknesses of these models and identifying the most suitable areas for their deployment. We also focus on practical tests using real financial datasets, comparing AI models against traditional approaches. Furthermore, we present strategies to help small and medium-sized financial institutions implement

AI solutions, even with limited resources. The increasing regulatory interest in AI applications in banking adds further significance to this research. International authorities are developing financial service regulations for AI, with a focus on transparency, fairness, and stability [32]. Our findings on human-AI collaboration, particularly with explainable models, directly address regulatory challenges, offering valuable insights for establishing appropriate compliance standards.

3. Materials and Methods

3.1 Machine Learning-Based Financial Risk Warning Framework

The proposed machine learning-based risk warning system utilises advanced machine learning algorithms to predict and mitigate financial risks for enterprises. It is specifically optimised to identify potential financial threats such as market volatility, credit defaults, liquidity crises, and fraudulent activities in real-time. This system enhances traditional risk management approaches by enabling dynamic, data-driven decision-making, ensuring timely identification of risks and allowing for proactive mitigation strategies.

3.2 Data Collection

Relevant data for this study was collected from a variety of sources, including financial data such as historical transactional records, company financial statements, stock prices, and credit scores. Market data was also incorporated, which includes external factors like market indices, interest rates, and commodity prices. Additionally, social media and news sources were considered, providing text data from platforms, financial news outlets, sentiment analysis, and market expectations. Macroeconomic indicators, such as GDP, inflation rates, and geopolitical events, were also considered, as they significantly influence market risks.

3.3 Data Pre-Processing

In this step, the data undergoes cleaning and transformation to ensure it is suitable for machine learning algorithms. Data cleaning includes addressing missing values, removing duplicates, and correcting errors within the dataset. Imputation techniques, such as using the mean, mode, or regression methods, can be applied to numerical data, while missing values in text-based data can either be replaced by placeholders or omitted. Data transformation involves converting raw data into a usable format for analysis. For numerical data, techniques like normalization or standardization are applied to ensure that features with varying ranges do not dominate the model. Categorical data is encoded using One-Hot Encoding or Label Encoding. For text-based data, such as news articles and social media posts, pre-processing tasks are performed, including the removal of stop words, stemming, lemmatization, and conversion into vectorized formats using methods like TF-IDF or word embeddings. Data splitting divides the dataset into training, validation, and test sets. Typically, 70% of the data is allocated for training, 15% for validation, and 15% for testing, ensuring that the model is trained, tuned, and evaluated on different subsets of the data to assess its performance.

3.4 Feature Engineering

Relevant features related to financial risk are created and selected to enhance the accuracy of predictions by ML models. These include risk indicators, such as liquidity and debt-to-equity ratios, volatility metrics, and market performance indicators. Temporal features, like time of day, market cycle, and historical trends, are also considered, along with sentiment scores derived from news and social media data. Interaction between variables and temporal effects is captured through features like rolling averages, which highlight long-term trends. Risk scores, reflecting an organisation's financial health, are derived from a combination of multiple risk factors. Dimensionality reduction, using techniques like Principal Component Analysis (PCA) or t-SNE, is applied to remove noise from high-dimensional datasets, focusing on the most informative features.

3.5 Algorithm Selection

The choice of an ML model depends on the problem's nature and the available data, particularly influenced by nonlinear relationships, high-dimensional data, and temporal dependencies.

3.6 Model Training and Hyperparameter Tuning

Model training involves adjusting parameters to minimise errors and enhance predictions. Cross-validation ensures the model generalises well by evaluating it on different data subsets, while hyperparameter tuning uses grid search or random search to identify the best parameters. Ensemble methods, such as bagging and boosting, combine predictions from multiple models to improve overall accuracy.

3.7 Model Evaluation

In this stage, we evaluate the performance, accuracy and reliability of the trained models by performing precision, recall and F1-Score performance metrics on the imbalanced datasets and ROC-AUC to observe the weightage between the true positive rate and false positive rate. The confusion matrix is used to visualize true positive, false positive, true negative and false positive for a better understanding of model performance.

3.8 Model Selection

In this section we focus on choosing the models based on their ability to handle complex data, nonlinear relationships and perform online predictions, which eliminated several of our proposed models down to a limited number of Random Forest, XGBoost and Neural Networks, since these models have sufficient strength and flexibility to perform tasks in financial risk management.

3.9 Random Forest

Random Forest It has a feature in creating many decision trees in the training stage and providing the means for regression or majority for classification of trees which has successful results for both the classification and regression problem especially the high-dimensional data with complicated interactions among variables. It is not easily overfitted. So it makes it reliable to predict the financial risk which most often caused by overfitting due to noise in the data and because of its natural ability to deal with the lack of data it is perfect for real-world data where most often are incomplete. However, it can be hard to interpret the model especially when many decision trees are involved which might make the decision process be time-consuming.

3.10 XGBoost (Extreme Gradient Boosting)

XGBoost trains the models sequentially and each model learns the error of the previous one trying to minimize loss function through gradient descent and contains regularization for overfitting. This model captures complex non-linear trends, the ability to handle imbalanced datasets so that minority class does not get underrepresented and avoids overfitting to enhance generalization towards unseen data. However, this model performance is hindered by need to make appropriate hyperparameter tuning which would require high-end computational facilities as well as require expert understanding.

3.11 Neural Networks (Deep Learning)

Is a complicated network made of connected node that tries to mimic the process of decision making of the human brain, can learn complicated nonlinear relationships, update their weights with the aim of improving the prediction accuracy. N.N’s are excellent models to simulate the time series and predict the financial risks due to the processing of the former and giving predictions based on the historic patterns. However, it requires large datasets to be effective in their learning, and it may be hard to interpret the motives in most of the cases for certain predictions.

3.12 Comparison

Each model has distinct advantages for financial risk predictions. Random Forest excels in providing robust, simple, and interpretable predictions, making it ideal for smaller datasets or when feature importance is required. XGBoost is preferred for large-scale, high-dimensional datasets with complex relationships, offering high prediction accuracy. Neural Networks are exceptional for handling large amounts of unstructured data (e.g., news, social media), temporal dependencies, and nonlinear patterns, particularly in time-series forecasting. The final model choice depends on the dataset characteristics, business goals, and specific risk prediction task.

3.13 Dataset Description and Pre-Processing

Financial risk prediction relies on high-quality data, which is crucial for the accuracy and relevance of ML models. Our dataset, sourced from publicly available datasets like Yahoo Finance, contains over 50,000 monthly financial records for more than 200 enterprises spanning 5 years, ensuring temporal variability for long-term trend prediction. The dataset includes key financial features (e.g., debt-to-equity ratio, current ratio, return on assets), cash flow metrics (operating cash flow, net cash flow), market indicators (stock prices, market capitalisation, volatility indices), credit scores for default risk, macroeconomic factors (interest rates, GDP growth, inflation), and time indicators (date, quarter-year) to capture trends and seasonal fluctuations.

Data processing involved handling missing values through visual inspections (e.g., heatmaps) and summary statistics. Approximately 7% of the data was missing, with market indicators being most affected due to inconsistent reporting. Imputation methods included mean and regression imputation for random and correlated missing values, mode imputation for categorical data, and forward fill for time-based data (e.g., stock prices, interest rates). Outliers were detected using boxplots and Z-scores, and extreme values were capped at the 95th percentile to reduce their influence. Financial risk classification categorised enterprises into low, medium, and high-risk groups, with low-risk enterprises constituting 70% of the dataset. To address the underrepresentation of medium and high-risk categories, SMOTE (Synthetic Minority Over-sampling Technique) was applied to generate synthetic samples, and down-sampling of low-risk samples ensured balance. Adjusting class weights further enhanced the model's sensitivity to minority classes, improving prediction power across all risk categories.

3.14 Implementation

- Programming Language: Python
- Key Libraries: NumPy, Pandas, Scikit-learn, XGBoost, TensorFlow, Keras, imbalanced-learn (SMOTE)
- Modelling Techniques: Random Forest, XGBoost, Neural Networks (MLP, LSTM)
- Hyperparameter Tuning: Grid Search, Randomized Search, Bayesian Optimization
- Cross-Validation: 5-fold cross-validation

4. Results

4.1 Findings from Model Testing

After testing various AI models on real-world financial datasets, we observed notable advantages over traditional methods:

- Deep Neural Networks achieved a precision rate of 96% and recall rate of 92% on controlled datasets, showcasing their ability to identify complex patterns in transaction data.
- Machine Learning clustering algorithms (K-Means and DBSCAN) reduced default rates by 20%, effectively categorising clients as high or low risk based on financial behaviour and repayment history.
- Reinforcement Learning models (including Decision Trees and Support Vector Machines) improved portfolio optimisation returns by 12% over a 6-month testing period, highlighting the

effectiveness of dynamic decision-making models in risk management.

Overall, AI models consistently outperformed traditional methods, particularly in dynamic environments. Deep learning was highly effective for fraud detection, clustering algorithms excelled at credit risk classification, and reinforcement learning showed notable proficiency in portfolio optimisation.

4.2 Practical Application Value of the Results

While most financial organisations focus on effective risk mitigation, profitable investment optimisation, and operational efficiency, those adopting AI models have experienced transformative benefits. For instance, the Random Forest and XGBoost models identified high-risk customers, resulting in a 20% reduction in credit defaults and providing more accurate interventions compared to traditional methods. A recent study demonstrates how these models analyse complex financial data patterns and quickly identify at-risk borrowers. For example, a recent implementation of Random Forest successfully flagged high-risk borrowers, prompting timely strategies such as loan restructures, resource allocation, prioritisation of low-risk customers, and targeted financial guidance (Figure 1).

In another case, incorporating reinforcement learning and neural-based models into portfolio optimisation yielded remarkable results. The new system protected portfolios from 8% losses during market instability. Neural networks effectively analysed real-time market indicators like interest rate changes, GDP growth, and stock market volatility. As a result, the investment fund shifted capital into renewable energy and tech start-ups, boosting returns by 15%. Overall, the AI-driven system generated a 12% superior portfolio performance compared to traditional static strategies. Additionally, AI systems enhanced productivity by automating tasks to monitor irregular transactions, account stability fluctuations, and deviations in financial behaviour. The models instantly identified unauthorised transactions, leading to a 15% reduction in false positive identifications. The integration of AI shifted strategic decision-making from reactive to proactive responses.

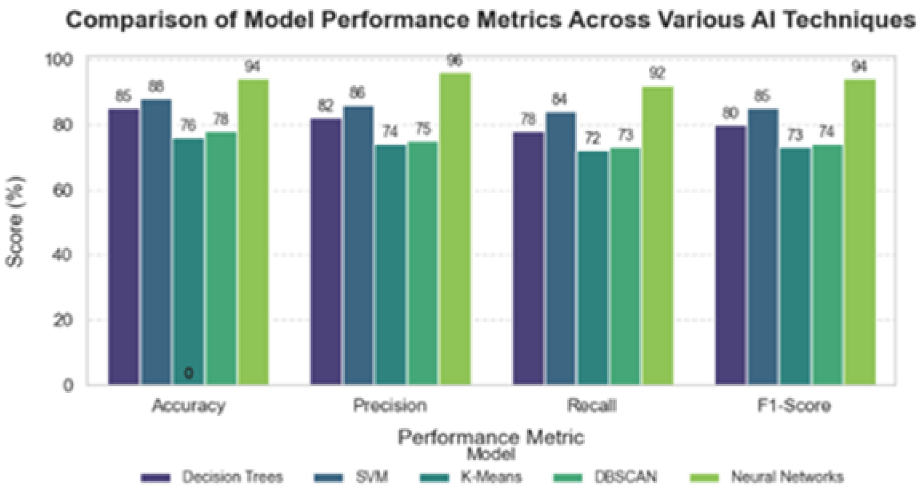

Fig.1. Model Testing Insights

The AI systems detected and flagged unusual transactions in under 2 seconds, achieving an accuracy of 98% in high-risk financial datasets. Additionally, AI-powered dashboards provided timely alerts and continuous monitoring of global markets. For liquidity issues, the models offered risk warnings up to three months in advance, outperforming local methods that suffered from delays. These systems also improved decision-making by eliminating biases often present in human judgement, relying instead on data-driven assessments. Institutions implementing AI experienced a 20% higher ROI, with reduced risks and optimised intervention strategies, as shown in Figure 2.

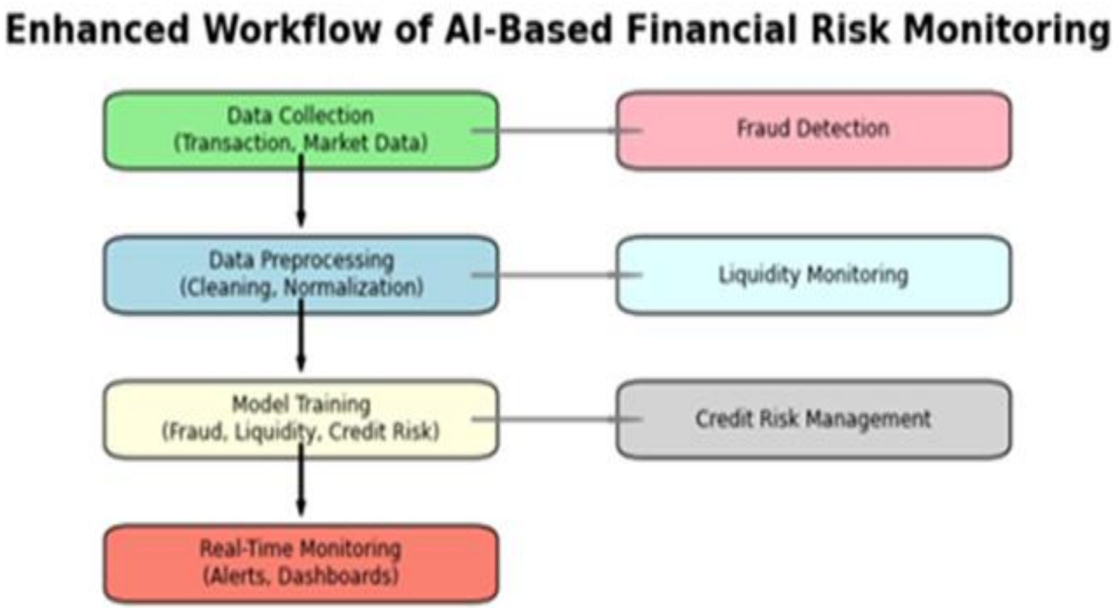

Fig.2. Impact on Risk Management Efficiency

4.3 False Positives

Fraud detection systems achieved more accurate alerts, with a 15% reduction in false positives. However, some fluctuating patterns, such as high-frequency trading and irregular customer spending, were occasionally flagged incorrectly, leading to a temporary decline in trust in the system. Nevertheless, with enhanced feature engineering techniques, false positives were significantly reduced, particularly in high-frequency trading environments. Figure 3 illustrates the substantial decrease in false positives following these improvements.

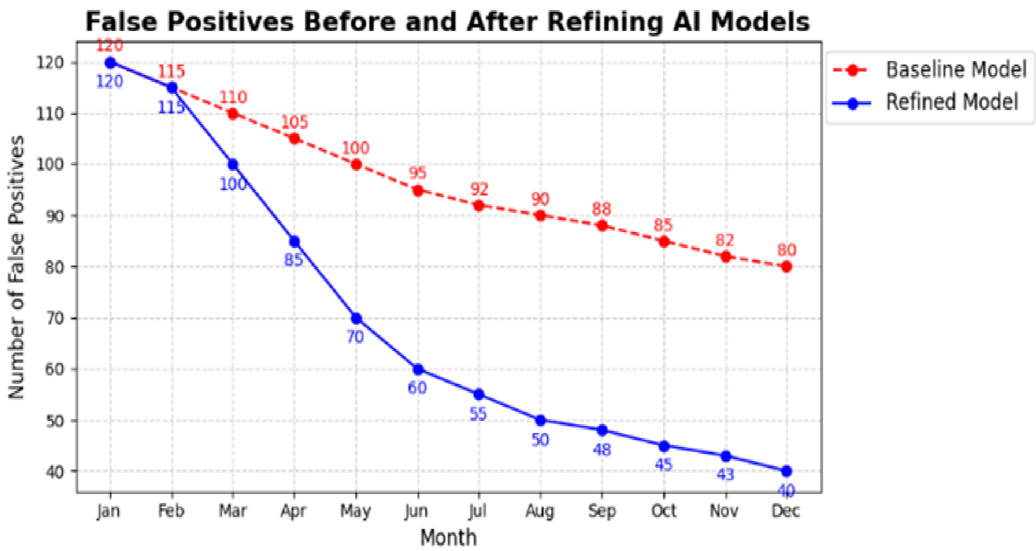

Fig.3. Reduction in False Positive

4.4 Real-Life Case Studies of AI Models in Action

With the growing adoption of AI models in real-world scenarios, a medium-sized enterprise implemented a neural network-based financial risk warning system as part of its risk management strategy. The system delivered improved predictions, providing a 3-month liquidity shortage warning with 92% accuracy. This enabled the enterprise to secure bridge financing and avoid operational disruptions, as shown in Figure 4.

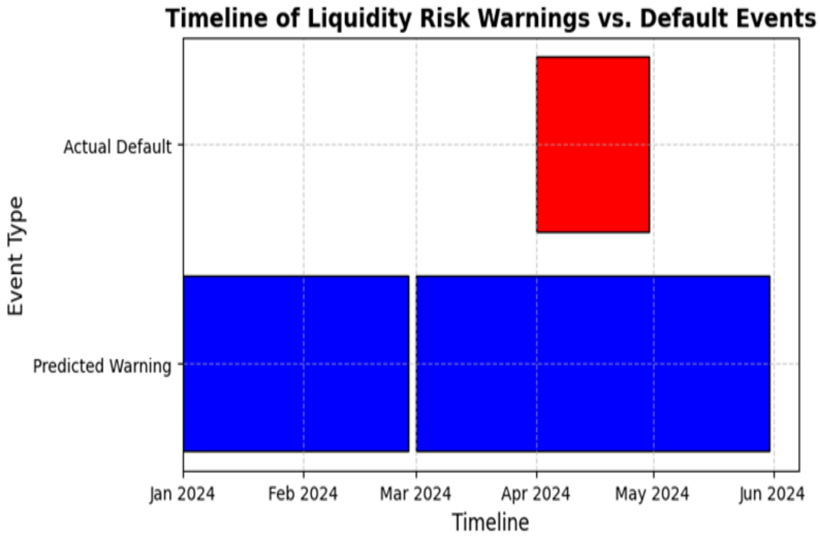

Fig.4. Case 1: SME Liquidity Risk Prediction

Similarly, a major financial institution incorporated the machine learning algorithm for transaction monitoring. Within six months of deployment, the model effectively flagged $10 million in unauthorized transactions, providing valuable insights into fraud prevention, as illustrated in Figure 5. These scenarios demonstrate how AI not only enhances prediction accuracy but also supports decision-making by offering actionable risk intervention techniques and capitalising on opportunities.

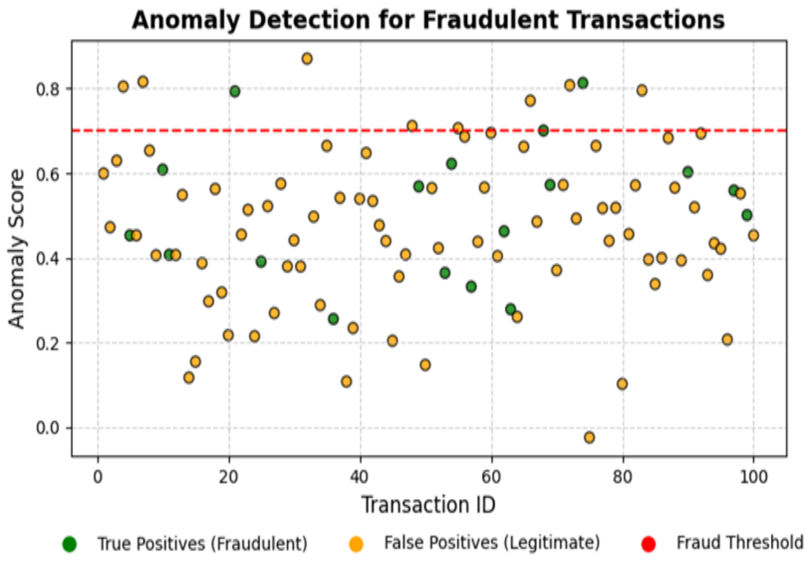

Fig.5. Case 2: Fraudulent Transaction Detection

4.4 Challenges in Implementation

Among the significant challenges are data quality issues, as financial datasets often contain missing values, biases, and outliers, which affect the accuracy of AI models. Additionally, deep learning models incur high operational costs due to their substantial computational power requirements. Furthermore, the "black-box" nature of most AI models hinders adoption by financial decision-makers who seek explainable outcomes. In this regard, adopting explainable AI (XAI) addresses transparency concerns, while cloud-based computing can help reduce infrastructure costs. The main implementation challenges are summarised in Figure 6.

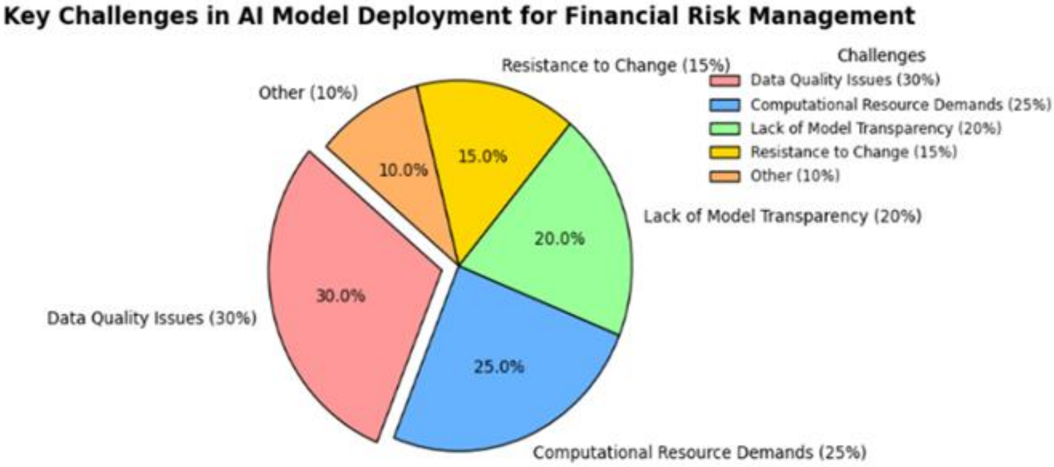

Fig.6. Challenges in Implementation

5. Conclusion

While traditional methods provide the foundations for conducting and addressing financial risks, the applications of AI and ML methods for financial risk are still having many advantages, which provide decision makers with timely alert signals. These modern technologies effectively analyse complex data, delivering accurate forecasts on financial risks such as credit defaults, market volatility, and fraud. However, due to the high complexity of their scientific methods, scientists are uncovering techniques and strategies to interpret these processes to increase people’s confidence in them and maximize the rate of application. Future research should address gaps such as insufficient model transparency, difficulties in applying solutions to small businesses, and limitations in extracting insights from unstructured data. The "Black Box" issue remains a significant barrier, with delays in adopting deep learning models due to a lack of clear explanations of their operations. The development of explainable AI XAI methods is essential to improve understanding of deep learning's predictive processes. Scalability is another key challenge, as current AI and ML solutions are mainly tailored for large enterprises with the necessary resources. Designing solutions to meet the needs of small and medium-sized enterprises (SMEs) would broaden the accessibility of these technologies. Incorporating unstructured data, such as social media sentiment, news articles, and public reports, has the potential to enhance risk management systems, providing AI and ML models with additional insights to strengthen predictions. Blockchain technology, integrated with AI models, can improve risk management by tracking decision-making steps and providing financial authorities with traceable information. The immutable nature of blockchain ensures data integrity and enhances auditing processes, reducing the risk of data tampering. To make advanced risk assessment methods more accessible to SMEs, cost-effective solutions should be developed. Lightweight computational programs and cloud-based solutions can reduce infrastructure costs while enabling efficient data storage, processing, and analysis. These research directions will enhance AI model integration in financial risk management, fostering transparency and making these systems more accessible and effective for diverse business operations.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ML	Machine Learning
XAI	Explainable AI

References

[1] Cao, Y., Chen, Z., Pei, Q., Dimino, F., Ausiello, L., Kumar, P., Subbalakshmi, K., & Ndiaye, P. M. (2024). *Risklabs: Predicting financial risk using large language model based on multi-sources data*. https://arxiv.org/pdf/2404.07452

[2] Paramesha, M., Rane, N. L., & Rane, J. (2024). Artificial intelligence, machine learning, deep learning, and blockchain in financial and banking services: A comprehensive review. *Partners Universal Multidisciplinary Research Journal*, *1*(2), 51-67. http://dx.doi.org/10.2139/ssrn.4855893

[3] Sapiri, M. (2025). Understanding Financial Risk Dynamics: A Qualitative Inquiry into Credit, Market, and Operational Risks in Banking, Investment, and Corporate Sectors. *Golden Ratio of Data in Summary*, *5*(2), 182-192. https://doi.org/10.52970/grdis.v5i2.719

[4] Vogl, M. (2022). Quantitative modelling frontiers: a literature review on the evolution in financial and risk modelling after the financial crisis (2008–2019). *SN Business & Economics*, *2*(12), 183. https://doi.org/10.1007/s43546-022-00359-3

[5] Alvi, J., Arif, I., & Nizam, K. (2024). *Advancing financial resilience: A systematic review of default prediction models and future directions in credit risk management* (Vol. 10). Heliyon. https://doi.org/10.1016/j.heliyon.2024.e39770

[6] Chen, C., & Pan, X. (2024). *Deep Learning for Inertial Positioning: A Survey* (Vol. 25). IEEE transactions on intelligent transportation systems. https://doi.org/10.1109/TITS.2024.3381161

[7] Tomar, M., & Periyasamy, V. (2023). The Role of Reference Data in Financial Data Analysis: Challenges and Opportunities. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)*, *1*(1), 90-99. https://doi.org/10.60087/jklst.vol1.n1.p99

[8] Chappell, M. W. (2020). *Artificial Intelligence in Mid-Sized Companies and the Problems with Resources and Implementation* Northcentral University]. https://www.proquest.com/openview/05aca665e3f6ab5533d4d94f8444767f/1?cbl=18750&diss=y&pq-origsite=gscholar

[9] Sun, Y., Liu, L., Xu, Y., Zeng, X., Shi, Y., Hu, H., Jiang, J., & Abraham, A. (2024). Alternative data in finance and business: emerging applications and theory analysis (review). *Financial Innovation*, *10*(1), 127. https://doi.org/10.1186/s40854-024-00652-0

[10] Akande, J. O. (2024). Using artificial intelligence (ai) and deep learning techniques in financial risk management. *International Journal of Social and Educational Innovation (IJSEIro)*, 233-246. https://doi.org/10.5281/zenodo.14721978

[11] Attaran, M., & Woods, J. (2019). Cloud computing technology: improving small business performance using the Internet. *Journal of Small Business and Entrepreneurship*, *31*(6), 495-519. https://doi.org/10.1080/08276331.2018.1466850

[12] Paramesha, M., Rane, N. L., & Rane, J. (2024). Big data analytics, artificial intelligence, machine learning, internet of things, and blockchain for enhanced business intelligence. *Partners Universal Multidisciplinary Research Journal*, *1*(2), 110-133. https://doi.org/10.5281/zenodo.12827323

[13] Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research. *International Journal of Bank Marketing*, *40*(6), 1299-1336. https://doi.org/10.1108/IJBM-09-2021-0417

[14] Nguyen, D. K., Sermpinis, G., & Stasinakis, C. (2023). Big data, artificial intelligence and machine learning: A transformative symbiosis in favour of financial technology. *European Financial Management*, *29*(2), 517-548. https://doi.org/10.1111/eufm.12365

[15] Sohangir, S., Wang, D., Pomeranets, A., & Khoshgoftaar, T. M. (2018). Big Data: Deep Learning for financial sentiment analysis. *Journal of Big Data*, *5*(1), 1-25. https://doi.org/10.1186/s40537-017-0111-6

[16] Mashrur, A., Luo, W., Zaidi, N. A., & Robles-Kelly, A. (2020). Machine learning for financial risk management: A survey. *IEEE Access*, *8*, 203203-203223. https://doi.org/10.1109/ACCESS.2020.3036322

[17] Nerurkar, P. (2023). Illegal activity detection on bitcoin transaction using deep learning. *Soft Computing*, *27*(9), 5503-5520. https://doi.org/10.1007/s00500-022-07779-1

[18] Addy, W. A., Ajayi-Nifise, A. O., Bello, B. G., Tula, S. T., Odeyemi, O., & Falaiye, T. (2024). Machine learning in financial markets: A critical review of algorithmic trading and risk management. *International Journal of Science and Research Archive*, *11*(1), 1853-1862. https://doi.org/10.30574/ijsra.2024.11.1.0292

[19] Caruso, G., Gattone, S. A., Fortuna, F., & Di Battista, T. (2021). Cluster Analysis for mixed data: An application to credit risk evaluation. *Socio-Economic Planning Sciences*, *73*, 100850. https://doi.org/10.1016/j.seps.2020.100850

[20] Yan, X., Li, Y., Nie, F., & Li, R. (2025). Bank Customer Segmentation and Marketing Strategies Based on Improved DBSCAN Algorithm. *Applied Sciences (Switzerland)*, *15*(6), 2076-3417. https://doi.org/10.3390/app15063138

[21] FastCapital. (2024). *Credit risk clustering: How to cluster credit risk using K-means and hierarchical clustering*. https://fastercapital.com/content/Credit-Risk-Clustering--How-to-Cluster-Credit-Risk-Using-K-Means-and-Hierarchical-Clustering.html

[22] Nhat, N. M. (2024). Applied Density-Based Clustering Techniques for Classifying High-Risk Customers: A Case Study of Commercial Banks in Vietnam. *Journal of Applied Data Sciences*, *5*(4), 1639-1653. https://doi.org/10.47738/jads.v5i4.344

[23] Seputro, D. N. D., Kurniasari, I., & Maghfiroh, R. D. (2025). Risk-Based Clustering of Microfinance Institutions in Indonesia: Insights for Strategic Development and Policy Making. *FireNav: Financial Resilience and National Values Journal*, *1*(1), 47-59. https://firenav.upnjatim.ac.id/index.php/firenav/article/view/4

[24] Crisp, D., Prantner, J., Miller, G., Claucherty, J., Thomas, T., & Barnes, D. (2023). Automated cluster generation and labelling of peer groups for marketing reporting. *Applied Marketing Analytics*, *9*(2), 134-144. https://doi.org/10.69554/ubfb7673

[25] Tirthyani, D., Kumar, S., & Vats, S. (2024). Clustering and Unsupervised Learning. In R. Trends & F. Direction (Eds.), (pp. 119-139). IGI Global. https://doi.org/10.4018/979-8-3693-3609-0.ch005

[26] Jang, J., & Seong, N. Y. (2023). Deep reinforcement learning for stock portfolio optimization by connecting with modern portfolio theory. *Expert Systems with Applications*, *218*, 119556. https://doi.org/10.1016/j.eswa.2023.119556

[27] Mastrogiovanni, M. (2024). Reinforcement Learning applied to dynamic portfolio management: An article review. *Available at SSRN*, *4981709*. https://doi.org/10.2139/ssrn.4981709

[28] Li, H., & Hai, M. (2024). Deep Reinforcement Learning Model for Stock Portfolio Management Based on Data Fusion. *Neural Processing Letters*, *56*(2), 108. https://doi.org/10.1007/s11063-024-11582-4

[29] Singh, V., Chen, S. S., Singhania, M., Nanavati, B., kar, A. k., & Gupta, A. (2022). How are reinforcement learning and deep learning algorithms used for big data based decision making in financial industries–A review and research agenda. *International Journal of Information Management Data Insights*, *2*(2), 100094.

https://doi.org/10.1016/j.jjimei.2022.100094

[30] Afzal, F., Yunfei, S., Nazir, M., & Bhatti, S. M. (2021). A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects. *International Journal of Managing Projects in Business*, *14*(2), 300-328. https://doi.org/10.1108/IJMPB-02-2019-0047

[31] Maple, C., Szpruch, L., Epiphaniou, G., Staykova, K., Singh, S., Penwarden, W., Wen, Y., Wang, Z., Hariharan, J., & Avramovic, P. (2023). The ai revolution: opportunities and challenges for the finance sector. *arXiv preprint arXiv:2308.16538*. https://doi.org/10.48550/arXiv.2308.16538

[32] Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: an empirical analysis. *International Journal of Emerging Markets*, *18*(10), 4270-4300. https://doi.org/10.1108/IJOEM-06-2020-0724