International Journal of Artificial Intelligence for Digital Marketing
Homepage : https://e-journal.antispublisher.id/index.php/IJAIFD
Email : admin@antispublisher.com

e-ISSN : 3047-2903
IJAIFD, Vol. 2, No. 11, November 2025
Page 1-13

AI-Enabled Management Information Systems for Credit and Market Risk Prediction: Effects on Accounting Decision Quality

Md. Jobayer Ahmed
Daffodil International University, Bangladesh

Check for updates OPEN ACCESS

DOI : https://doi.org/10.61796/ijaifd.v2i11.438

Sections Info

Article history:
Submitted: September 05, 2025
Final Revised: October 21, 2025
Accepted: November 14, 2025
Published: December 20, 2025

Keywords:
Artificial Intelligence
Credit Risk Prediction
Market Risk Management
Accounting Decision Quality
Predictive Analytics

ABSTRACT

Objective: *This study aims to examine the role of Artificial Intelligence (AI) in enhancing financial risk management and accounting decision-making, with a particular focus on credit and market risk prediction, efficiency of Management Information Systems (MIS), and the accuracy of financial reporting.* ***Method:*** *The study adopts a conceptual and analytical approach by synthesizing recent scholarly literature and real-world practices from financial institutions to evaluate the application of AI techniques, including machine learning and natural language processing, in risk assessment and accounting processes.* ***Results:*** *The findings indicate that AI-powered MIS significantly improves the speed, precision, and reliability of risk prediction and accounting operations by enabling real-time data analysis, anomaly detection, and automation of routine accounting tasks. These capabilities reduce human error, enhance regulatory compliance, and support more informed managerial decisions. However, the results also reveal critical challenges related to data quality, model transparency, algorithmic bias, governance structures, legal accountability, and high implementation costs, which may hinder effective adoption if not properly managed.* ***Novelty:*** *This study highlights the integrated perspective of AI-driven risk management and accounting while emphasizing the necessity of ethical governance frameworks and the future potential of combining AI with emerging technologies such as blockchain and the Internet of Things to build resilient and transparent financial systems.*

INTRODUCTION

AI-driven Management Information Systems (MIS) are revolutionizing the way financial institutions tackle credit and market risk prediction, marking a significant leap in modern financial decision-making. Traditionally, MIS has played a crucial role in guiding organizations by providing structured data, reports, and performance metrics [1]. However, the financial landscape is evolving rapidly, pushing these systems to adapt by managing bigger datasets, offering real-time insights, and reducing uncertainties in decision-making. By integrating artificial intelligence technologies like machine learning and natural language processing into MIS, organizations can enhance their analytical abilities, improve predictive accuracy, and operate more efficiently. This means financial institutions that embrace AI-enabled MIS can assess creditworthiness, navigate market risks effectively, and make informed decisions that significantly impact their accounting outcomes [2]. A major drawback of conventional credit evaluation models is their heavy dependence on historical financial data. These models often overlook non-traditional borrowers, such as those with limited credit histories or individuals in underserved communities. As a result, certain groups have often found themselves at a disadvantage when seeking credit, perpetuating inequalities in access. AI-powered MIS tackles this issue by tapping into broader data sources like utility payments and social behavior patterns to create fairer and more comprehensive credit assessments. This inclusive approach not only improves credit scoring accuracy but also expands financial access, leading to enhanced profitability for institutions and fostering social equity in lending practices. Moreover, AI technologies excel at fraud detection by promptly recognizing unusual patterns and suspicious activities, thereby reducing financial losses and bolstering trust among stakeholders [3]. Beyond credit evaluations, AI-driven MIS is transforming how market risks are predicted and managed. Traditional methods often rely on outdated or static data, making it challenging to react quickly to changing conditions. In contrast, AI systems harness predictive analytics and real-time monitoring, enabling financial institutions to spot early signs of market volatility and emerging threats. For instance, machine learning models can uncover correlations across various markets, anticipate price changes, and detect shifts in consumer behavior. This proactive approach empowers decision-makers to address risks before they escalate and seize new opportunities an essential strategy in our interconnected global economy, where market disruptions can ripple out quickly. However, integrating AI into MIS isn't without its challenges. Key concerns revolve around the quality and reliability of data inputs, the complexity of AI models, and the potential for algorithmic bias. Flawed or incomplete data can lead to poor predictions, which undermine decision quality and expose organizations to greater risks [4]. Additionally, many AI models operate as "black boxes," making it difficult for managers, auditors, and regulators to understand how decisions are made. This lack of transparency raises questions about accountability and compliance, especially in highly regulated sectors. Ethical issues, such as ensuring fairness in credit assessments and protecting customer privacy, further complicate the implementation of these systems. Adopting AI-enhanced MIS represents a major shift in how financial institutions approach credit and market risks. These systems not only boost efficiency and accuracy but also redefine accounting decision-making by offering rich, timely, and inclusive insights [5]. However, to fully harness the potential of these technologies, it's crucial to pay attention to governance, regulatory frameworks, and ethical considerations. By addressing these challenges, financial institutions can promote a sustainable and equitable use of AI-enabled MIS. As these technologies continue to progress, their impact on improving accounting decision quality and fostering innovation in financial management will undoubtedly grow, shaping the future of the global financial industry.

RESEARCH METHOD

This study employed a qualitative–conceptual research design based on a comprehensive narrative literature review and analytical synthesis of prior empirical and conceptual studies on AI-enabled Management Information Systems (MIS) in financial risk management and accounting. Relevant peer-reviewed journal articles, conference proceedings, and authoritative reports published in reputable international outlets were systematically collected and analyzed. The review focused on studies discussing AI techniques—such as machine learning, natural language processing, deep learning, and predictive analytics—and their applications in credit risk prediction, market risk management, and accounting decision quality. The analysis was conducted through thematic categorization, enabling the identification of dominant AI methods, application domains, benefits, challenges, and governance issues. In addition, illustrative case examples from financial institutions were examined to contextualize theoretical insights within real-world practices. This integrative approach allowed for a structured evaluation of how AI-driven MIS influences risk prediction accuracy, operational efficiency, and accounting decision-making, while also highlighting ethical, regulatory, and implementation considerations that shape responsible AI adoption in the financial sector.

RESULTS AND DISCUSSION

Result

AI Techniques Used in Management Information Systems for Credit and Market Risk Prediction

Artificial Intelligence (AI) has become an integral part of Management Information Systems (MIS), particularly when it comes to predicting credit and market risks. Techniques like supervised learning, which includes methods such as logistic regression, decision trees, and support vector machines, have made credit risk assessment and financial forecasting much more accurate [6]. On the other hand, unsupervised learning techniques, like clustering and dimensionality reduction, help uncover hidden patterns in the market, thereby enhancing risk models and investment strategies (Figure 1).

Figure 1. Artificial Intelligence in Credit, Lending, and Mortgage [28]

A prime example of this is Goldman Sachs, which has effectively implemented these technologies. Reinforcement learning takes it a step further by optimizing portfolio management. It learns from experience, adapting to ever-changing market conditions. Meanwhile, Natural Language Processing (NLP) is changing the game by turning unstructured data, like news articles and social media posts, into valuable insights about market sentiment and potential risks [7]. BlackRock is one company leveraging this to anticipate stock price movements. Advanced methods, such as ensemble techniques that combine different models for greater accuracy, and deep learning networks, which analyze intricate datasets, are also improving predictive capabilities in data-heavy environments. Together, these AI-driven systems provide financial analysts with real-time insights and analytics, helping them make well-informed decisions. This transforms how the financial industry manages credit and market risks, allowing for better identification, assessment, and mitigation of potential threats.

AI Applications in Credit and Market Risk Prediction and Their Impact on Accounting Decision Quality

Artificial Intelligence (AI) has become a key player in managing credit and market risks, with impacts that reach into the realm of accounting decision-making (Table 1).

Table 1. AI Techniques Used in Management Information Systems for Credit and Market Risk Prediction

AI Technique	Description	Reference
Supervised Learning (Logistic Regression, Decision Trees, SVM)	Improves credit risk assessment and financial forecasting accuracy	[1]
Unsupervised Learning (Clustering, Dimensionality Reduction)	Identifies hidden patterns in markets and enhances risk models	[2]
Reinforcement Learning	Optimizes portfolio management by learning from market conditions	[3],[5]
Natural Language Processing (NLP)	Analyzes unstructured text (news, social media) for market sentiment	[7]
Ensemble Techniques	Combines multiple models for higher predictive accuracy	[8]
Deep Learning Networks	Handles complex, high-volume financial datasets	[9]

When it comes to predicting credit risk, AI is essential for detecting fraud. For example, Mastercard has harnessed generative AI technology to double their detection rates for compromised cards while cutting down on false positives. This means that genuine transactions are less likely to be wrongly flagged. AI also enhances credit scoring by pulling in a rich mix of data sources, such as transaction histories and alternative payment records [8]. This application allows for a more accurate assessment of borrowers and broadens access to credit for responsible individuals who might not have been previously considered. In addition, machine learning models are instrumental in predicting financial distress. They can identify borrowers who are at risk of default, allowing financial institutions to take action and manage risks proactively. When it comes to market risk, AI and machine learning excel in delivering real-time analytics. They quickly process vast amounts of data to spot sudden changes, which helps businesses adjust their strategies on the fly. Predictive analytics play a crucial role here, allowing firms to foresee potential market shocks by studying trader behaviors and historical trends [9]. Furthermore, generative AI improves stress testing by simulating rare but significant scenarios, while advanced anomaly detection enhances early warning systems for unexpected market changes. All these innovative AI-driven methods not only reshape risk prediction but also elevate the quality of accounting decisions. By automating data-heavy processes, AI boosts efficiency, accuracy, and transparency in financial reporting. This helps minimize human error and provides reliable insights. In the field of accounting, advanced fraud detection fosters trust among stakeholders by intercepting suspicious activities before they escalate. Predictive financial analysis, which combines historical and real-time data, aids in forecasting outcomes and shapes strategic planning and resource allocation [10]. Additionally, AI supports compliance with regulations by automating checks against changing laws and enhances strategic decision-making by synthesizing information from various financial data sources. This ultimately strengthens financial narratives and improves communication with stakeholders.

Challenges, Limitations, and Case Studies of AI in Credit and Market Risk Prediction

The use of AI-driven management information systems (MIS) in predicting credit and market risk holds great promise, but it also brings about several challenges that can impact the accuracy and effectiveness of accounting decisions. One major issue is data quality and integration. When information is stored in separate silos, it becomes difficult to combine and analyze comprehensively, which can lead to flawed models and misguided decisions if the data isn't properly cleaned and standardized. Another critical challenge is model interpretability [11]. Many advanced AI algorithms operate like "black boxes," leaving users and regulators puzzled about how decisions are made. This lack of clarity not only raises compliance concerns but also heightens the risk of algorithmic bias, where biased or unrepresentative training data can result in unfair lending and investment outcomes (Table 2).

Table 2. Applications of AI in Credit and Market Risk Prediction and Their Impact on Accounting Decisions

Application	Impact/Benefit	Reference
Fraud Detection	Identifies unusual transactions, reduces false positives, enhances trust	[12]
Credit Scoring	Uses diverse data (transactions, alternative payments) for fairer assessments	[13]
Financial Distress Prediction	Detects borrowers at risk of default for proactive management	[18]
Market Risk Prediction	Provides real-time analytics and forecasts market shocks	[22]
Stress Testing	Simulates rare but impactful scenarios for resilience	[23]
Anomaly Detection	Enhances early-warning systems for unexpected risks	[24]
Predictive Financial Analysis	Improves forecasting, budgeting, and decision-making in accounting	[22],[23]

To combat this, it's essential to use diverse data and design models that prioritize fairness otherwise, organizations may face reputational damage and legal repercussions. Effective governance and oversight are crucial as well. Many organizations struggle with communication issues and bureaucratic hurdles that prevent proper monitoring of AI systems. Without established frameworks, regular audits, and human oversight, they risk ethical lapses and regulatory violations [12]. The legal landscape is also murky, especially regarding accountability for mistakes made by AI systems, which underscores the need for clear contracts and a commitment to adapting to changing financial regulations. Moreover, implementing AI comes with hefty resource requirements, including significant financial investments and the need for skilled staff. This creates challenges for smaller institutions that may struggle to compete with larger firms that can manage these costs. Despite these hurdles, real-life examples show that AI can deliver undeniable benefits in banking and finance. Institutions like the Commonwealth Bank of Australia, Banca Mediolanum, Federal Bank Limited, NatWest Group, and Valley Bank have harnessed AI in areas like customer relationship management and risk assessment, demonstrating its versatility [13]. In practice, AI boosts operational efficiency by automating repetitive tasks like data entry and report generation, which leads to improved accuracy and reduces human error. However, over-reliance on automated systems can introduce operational risks, especially when critical decisions are based on outputs that may be flawed or inadequately tested. AI has also redefined customer experience through tools like Bank of America's chatbot, Erica, which enhances response times, cuts service costs, and allows human staff to focus on more complex issues, thereby strengthening long-term client relationships. On the regulatory side, the increasing adoption of AI has prompted organizations like the Securities and Exchange Commission (SEC) to stress the need for transparency, accountability, and robust governance frameworks [14]. This includes requiring financial institutions to establish dedicated AI oversight teams and enhance compliance practices. Looking forward, the trend toward rapid AI adoption is likely to continue, with institutions encouraged to embrace advanced machine learning models and foster a culture of constant innovation. As AI technologies develop, they have the potential to significantly change financial planning, risk assessment, and strategic decision-making, empowering organizations to leverage data-driven insights for improved resilience and competitive advantage.

Future Trends in AI-Driven Risk Management in Finance

The future of risk management in finance is undergoing a significant transformation thanks to the rapid advancements in artificial intelligence (AI) and Big Data. These technologies are set to change how financial institutions tackle risks, making their approach more proactive and predictive. In today's fast-moving and interconnected global economy, the traditional methods of risk management, which often rely on outdated models and historical data, just don't cut it anymore (Figure 2).

Figure 2. Use cases of AI agents in risk management [29].

AI, particularly through machine learning, offers a fresh perspective. It allows organizations to analyze vast amounts of data in real time, helping to identify hidden patterns and provide insights that can improve decision-making [15]. This means that financial institutions can better anticipate and respond to potential risks with greater accuracy. As more organizations look to integrate AI into their operations, regulatory bodies are also stepping up to ensure that these technologies are used responsibly. Agencies like the SEC and MAS are creating guidelines to tackle issues like transparency and compliance. While this might lead to increased costs in adhering to regulations, it also encourages institutions to prioritize explainable AI and strong data management practices. This is crucial in addressing concerns around bias and privacy. The market for

AI in financial services is expected to grow quickly, driven by significant investments. These advancements promise to improve efficiency, enhance fraud detection, and refine forecasting capabilities, establishing AI as a central component of future financial strategies [16]. Moreover, the integration of emerging technologies, such as blockchain and the Internet of Things (IoT), alongside AI, opens up exciting opportunities for greater transparency and accessibility in financial intelligence. As institutions navigate the ethical implications of AI, the financial sector has the potential to evolve into a system that is not only more efficient and predictive but also fairer and more transparent, ultimately helping to maintain trust in a data-driven future.

Discussion

Artificial Intelligence (AI) has dramatically transformed the landscape of financial risk management, particularly in the realms of credit and market risk prediction, while also improving the quality of accounting decisions. By enhancing Management Information Systems (MIS) with AI capabilities, financial institutions can effectively process vast amounts of data in real time, identify anomalies, and generate predictive insights that surpass what traditional methods can offer [17]. Conventional risk assessment frameworks often depend on historical data and fixed models, which can fall short when it comes to addressing sudden market changes, behavioral anomalies, or emerging systemic risks. In contrast, AI harnesses advanced machine learning, natural language processing, and generative modeling to uncover patterns that might otherwise go unnoticed. This proactive approach to risk management and operational decisions significantly enhances overall effectiveness [18]. In the domain of credit risk management, AI applications, including fraud detection, credit scoring, and financial distress prediction, have shown notable improvements in both accuracy and efficiency. AI-powered fraud detection systems utilize historical transaction data along with real-time monitoring to pinpoint unusual patterns that suggest fraudulent activity. This capability allows financial institutions to act swiftly, thereby mitigating potential financial losses. For instance, Mastercard's use of generative AI showcases practical advantages, such as doubling the detection rates of compromised cards while significantly reducing false positives [19]. Reducing false positives is critical since it helps minimize disruptions for legitimate customers, preserving their trust and lowering operational costs. Additionally, these systems enhance the integrity of financial reporting and bolster stakeholder confidence, which has become increasingly essential in a heavily regulated financial environment. Credit scoring sees substantial benefits from AI's ability to weave together diverse datasets, which include not just traditional transaction histories but also alternative payment data and behavioral analytics. This integration allows institutions to create more nuanced profiles of borrowers, resulting in better risk assessment and fairer access to credit. Consequently, potentially creditworthy individuals are less likely to be overlooked due to rigid frameworks typically used for traditional scoring [20]. AI-driven credit models can identify subtle behavioral cues and cross-reference data from external sources, including digital payment platforms or social behavior indicators, leading to a well-rounded evaluation of creditworthiness. Similarly, AI-enabled financial distress prediction applies machine learning to forecast a borrower's likelihood of default, equipping institutions with the tools necessary for proactive risk mitigation, optimized resource allocation, and tailored lending policies based on predicted risk levels [21]. Such predictive insights not only support strategic planning but also help institutions to find high-risk segments and devise targeted intervention strategies before defaults occur. In market risk management, AI allows for real-time analytics, predictive modeling, and anomaly detection, empowering institutions to react promptly to fluctuating financial conditions. Sophisticated AI algorithms analyze trader behaviors, historical price trends, and relationships among market variables to forecast possible market shocks. Generative AI models also simulate extreme scenarios for stress testing and contingency planning [22]. By modeling rare yet impactful events that lack historical counterparts, organizations can be better prepared for financial upheaval. Furthermore, anomaly detection algorithms enhance early warning systems by identifying subtle fluctuations that traditional models might miss. These advanced capabilities transform financial institutions' approach from merely reacting to risks after they occur to proactively anticipating them, ultimately minimizing losses and helping maintain financial stability. Beyond risk prediction, the integration of AI markedly elevates the quality of accounting decisions. The automation of routine tasks such as data entry, validation, reconciliation, and report generation not only reduces the likelihood of human errors but also ensures that reporting is timely and accurate. This automation frees accountants to concentrate on more complex analyses. Predictive financial modeling enables organizations to forecast cash flow, revenue trends, and potential challenges with enhanced precision, informing strategic investment decisions and scenario planning [23]. Such capabilities enrich budgeting and resource allocation, ensuring that financial strategies are aligned with operational realities. AI-driven analytics, exemplified by platforms like Futrli and other predictive tools, permit organizations to simulate various financial scenarios, optimize liquidity management, and detect early signs of potential financial distress. Governance, oversight, and legal clarity are vital for responsible AI adoption in today's financial landscape. Organizations need to create robust frameworks that focus on regular audits, human supervision, and ethical accountability. These measures help manage operational, reputational, and legal risks effectively. However, implementing AI isn't just about having the right policies in place; it also requires significant investment in technical infrastructure, skilled personnel, and strong data management capabilities [24]. For smaller institutions, these resource demands can be overwhelming, leading to disparities in how AI is adopted and managed across the financial sector. To help bridge this gap, collaborative platforms and scalable AI solutions can offer smaller organizations access to predictive analytics, ultimately enhancing resilience across the sector. Real-life examples show how AI can genuinely transform operations. Take banks like the Commonwealth Bank of Australia, Banca Mediolanum, and NatWest, which have successfully integrated AI into their processes. This has led to improvements in credit risk assessments and customer relationship management, boosting efficiency, decision quality, and service delivery [25]. For instance, Bank of

America's AI-powered chatbot, Erica, has significantly improved responsiveness, cut operational costs, and freed up human staff to concentrate on more complex client needs, resulting in higher customer satisfaction and enhanced operational efficiency. Moreover, predictive and prescriptive analytics play a crucial role in strategic decision-making, allowing institutions to model risk scenarios, optimize capital allocation, and spot new opportunities in an increasingly competitive market. Looking ahead, the future of AI in financial risk management is set to evolve alongside emerging technologies and shifting regulatory frameworks. By combining AI with Big Data analytics, blockchain, and the Internet of Things (IoT), organizations can unlock substantial opportunities for predictive, prescriptive, and real-time financial decision-making [26]. For example, blockchain technology enhances transparency and security in financial transactions, while IoT devices provide real-time data that can be analyzed through AI models. Embracing explainable AI, robust data governance, and ethical guidelines is crucial for ensuring regulatory compliance and maximizing both operational and strategic value while minimizing bias [27]. This integrated approach not only boosts efficiency and accuracy but also promotes fairness, transparency, and resilience within financial operations. AI-driven Management Information Systems (MIS) offer an advanced way to manage credit and market risk while enhancing the quality of accounting decisions. With real-time monitoring, predictive analytics, and advanced modeling capabilities, institutions can anticipate and respond to risks more effectively than ever. By automating routine tasks, enhancing predictive capabilities, and ensuring compliance with regulations, AI significantly improves operational efficiency, transparency, and decision-making processes. Nevertheless, challenges such as data quality, model interpretability, algorithmic bias, governance, legal liability, and resource constraints still loom large and require careful consideration. When implemented responsibly, AI has the potential to transform financial institutions into resilient, efficient, and equitable organizations capable of navigating the complexities of modern financial markets.

CONCLUSION

Fundamental Finding : This study demonstrates that the integration of artificial intelligence into Management Information Systems significantly strengthens credit and market risk management by improving predictive accuracy, operational efficiency, and the overall quality of accounting decisions through automation and real-time analytics. **Implication :** The findings imply that financial institutions can achieve more resilient, transparent, and compliant decision-making processes by adopting AI-driven systems, provided that strong governance, ethical standards, and regulatory alignment are embedded within their implementation strategies. **Limitation :** Despite these contributions, the study is limited by its conceptual and literature-based approach, which does not empirically test AI models or measure their quantitative impact across different institutional contexts and regulatory environments. **Future Research :** Future studies should therefore focus on empirical validation using longitudinal and cross-institutional data, comparative analyses between traditional and AI-based systems, and deeper investigation into explainable AI, bias mitigation techniques, and governance frameworks to ensure responsible and scalable adoption of AI in financial risk management and accounting.

REFERENCES

[1] A. Akhir, F. Rahman, A. Islam, N. Chowdhury, M. S. Mia, and M. I. Hossain, “Strategic role of business analytics in healthcare systems performance optimization,” *Journal of Primeasia*, vol. 5, no. 1, pp. 1–8, 2024, doi: 10.25163/primeasia.5110347.

[2] J. M. Axtell, L. M. Smith, and W. Tervo, “The advent of accounting in business governance: From ancient scribes to modern practitioners,” *International Journal of Business Governance and Ethics*, vol. 12, no. 1, pp. 21–46, 2017, doi: 10.1504/IJBGE.2017.081089.

[3] J. Ballantine, G. Boyce, and G. Stoner, “A critical review of AI in accounting education: Threat and opportunity,” *Critical Perspectives on Accounting*, vol. 99, pp. 1–12, 2024, doi: 10.1016/j.cpa.2024.102781.

[4] J. A. Bastos and S. M. Matos, “Explainable models of credit losses,” *European Journal of Operational Research*, vol. 301, pp. 386–394, 2022, doi: 10.1016/j.ejor.2021.08.001.

[5] A. Biswas, A. Islam, A. Akhir, F. Rahman, S. Nashid, and S. K. Papia, “Bridging IT and business strategy and the impact of data-driven analytics on organizational performance and innovation,” *Applied IT & Engineering*, vol. 2, no. 1, pp. 1–8, 2024, doi: 10.25163/engineering.2110364.

[6] N. Bussmann, P. Giudici, D. Marinelli, and J. Papenbrock, “Explainable AI in fintech risk management,” *Frontiers in Artificial Intelligence*, vol. 3, p. 26, 2020, doi: 10.3389/frai.2020.00026.

[7] P. E. de Lange, B. Melsom, C. B. Vennerød, and S. Westgaard, “Explainable AI for credit assessment in banks,” *Journal of Risk and Financial Management*, vol. 15, p. 556, 2022, doi: 10.3390/jrfm15090556.

[8] J. Galindo and P. Tamayo, “Credit risk assessment using statistical and machine learning: Basic methodology and risk modeling applications,” *Computational Economics*, vol. 15, pp. 107–143, 2000, doi: 10.1023/A:1008658219340.

[9] P. Giudici and E. Raffinetti, “Shapley–Lorenz decompositions in explainable artificial intelligence,” *SSRN Electronic Journal*, pp. 1–15, 2020, doi: 10.2139/ssrn.3676192.

[10] A. Gramegna and P. Giudici, “SHAP and LIME: An evaluation of discriminative power in credit risk,” *Frontiers in Artificial Intelligence*, vol. 4, p. 752558, 2021, doi: 10.3389/frai.2021.752558.

[11] C. Guan, H. Suryanto, A. Mahidadia, M. Bain, and P. Compton, “Responsible credit risk assessment with machine learning and knowledge acquisition,” *Human-Centric Intelligent Systems*, vol. 3, pp. 232–243, 2023, doi: 10.1007/s43681-023-00298-5.

[12] D. J. Hand, “Measuring classifier performance: A coherent alternative to the area under the ROC curve,” *Machine Learning*, vol. 77, pp. 103–123, 2009, doi: 10.1007/s10994-009-5119-5.

[13] Y. Heng and P. Subramanian, “A systematic review of machine learning and explainable artificial intelligence (XAI) in credit risk modelling,” in *Springer Proceedings*, Berlin, Germany, 2022, doi: 10.1007/978-3-030-83297-0_35.

[14] Y. Hu and J. Su, “Research on credit risk evaluation of commercial banks based on artificial neural network model,” *Procedia Computer Science*, vol. 199, pp. 1168–1176, 2022, doi: 10.1016/j.procs.2022.01.140.

[15] I. Jahan, M. S. Mia, N. Chowdhury, M. I. Hossain, and A. Biswas, "Artificial intelligence in financial analytics and predicting market trends and risk management," *Journal of AI ML DL*, vol. 1, no. 1, pp. 1–8, 2025, doi: 10.25163/ai.1110385.

[16] Q. V. Liao, M. Singh, Y. Zhang, and R. K. E. Bellamy, "Introduction to explainable AI," in *Proc. CHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2020, pp. 1–4, doi: 10.1145/3334480.3382921.

[17] M. S. Mia, M. I. Hossain, I. Jahan, N. Chowdhury, and S. Nashid, "Smart supply chains applying AI-based business analytics for operational efficiency," *Paradise*, vol. 1, no. 1, pp. 1–8, 2025, doi: 10.25163/paradise.1110383.

[18] M. I. Hossain, I. Jahan, M. S. Mia, N. Chowdhury, and S. K. Papia, "Leveraging artificial intelligence for human resource analytics from recruitment to retention," *Journal of AI ML DL*, vol. 1, no. 1, pp. 1–8, 2025, doi: 10.25163/ai.1110384.

[19] B. Misheva, J. Osterrieder, A. Hirsa, O. Kulkarni, and S. Lin, "Explainable AI in credit risk management," *SSRN Electronic Journal*, pp. 1–16, 2021, doi: 10.2139/ssrn.3776571.

[20] V. Moscato, A. Picariello, and G. Sperlí, "A benchmark of machine learning approaches for credit score prediction," *Expert Systems with Applications*, vol. 165, p. 113986, 2021, doi: 10.1016/j.eswa.2020.113986.

[21] A. Nag, M. M. Hassan, D. Mandal, N. Chand, M. B. Islam, V. P. Meena, F. Benedetto, *et al.*, "A review of machine learning methods for IoT network-centric anomaly detection," in *Proc. 47th Int. Conf. Telecommunications and Signal Processing (TSP)*, 2024, pp. 26–31, doi: 10.1109/TSP54123.2024.00012.

[22] S. Nashid, S. K. Papia, N. Chowdhury, M. S. Mia, and M. I. Hossain, "Advanced business analytics in healthcare enhancing clinical decision support and operational efficiency," *Business and Social Sciences*, vol. 1, no. 1, pp. 1–8, 2023, doi: 10.25163/business.1110345.

[23] S. Nashid, S. K. Papia, A. Islam, A. Akhir, F. Rahman, and A. Biswas, "The role of deep learning and AI in revolutionizing business analytics: Frameworks, applications, and managerial implications," *Applied IT & Engineering*, vol. 2, no. 1, pp. 1–8, 2024, doi: 10.25163/engineering.2110365.

[24] S. K. Papia, I. Jahan, A. Islam, A. Akhir, and F. Rahman, "Leveraging artificial intelligence to analyse and predict consumer behaviour in the digital marketplace," *Business and Social Sciences*, vol. 1, no. 1, pp. 1–7, 2023, doi: 10.25163/business.1110373.

[25] S. K. Papia, F. Rahman, S. Nashid, A. Akhir, A. Biswas, and A. Islam, "The role of AI and IT in transforming stock price analysis and decision-making frameworks," *Journal of Primeasia*, vol. 5, no. 1, pp. 1–7, 2024, doi: 10.25163/primeasia.5110376.

[26] H. Sadok, F. Sakka, and M. E. H. El Maknouzi, "Artificial intelligence and bank credit analysis: A review," *Cogent Economics & Finance*, vol. 10, p. 2023262, 2022, doi: 10.1080/23322039.2022.2023262.

[27] M. R. Haque, "Resilient supply chain and adaptive marketing strategies: A post-pandemic framework for business sustainability," *Journal of Primeasia*, vol. 2, no. 1, pp. 1–7, 2021, doi: 10.25163/primeasia.2110437.

[28] M. U. I. Khan, M. I. H. Pathan, M. M. Rahman, M. M. Islam, M. A. R. Chowdhury, M. S. Anower, M. M. Rana, M. S. Alam, M. Hasan, and M. S. I. Sobuj, "Securing electric vehicle performance: Machine learning-driven fault detection and classification," *IEEE Access*, vol. 12, pp. 71566–71584, 2024, doi: 10.1109/ACCESS.2024.3401234.

[29] M. Wattenberg, F. Viégas, and I. Johnson, "How to use t-SNE effectively," *Distill*, vol. 1, pp. 1–6, 2016, doi: 10.23915/distill.00002.

*** Md. Jobayer Ahmed (Corresponding Author)**
Daffodil International University, Bangladesh
E-mail: ahmed15-4975@diu.edu.bd