

<p style="font-size: small; margin-top: 10px;"> Science, Education and Innovations In the Context of Modern Problems Editor-in-Chief: Chair of the Editorial Board - Dr. Huseyn Huseynov Monthly (Regular) Open Access October 2025 - Issue 20, Vol. 9 imcra-az.org </p>	<div style="text-align: center;"> <p>Science, Education and Innovations in the Context of Modern Problems</p> <p>Issue 1, Vol. 9, 2026</p> <hr/> <p>RESEARCH ARTICLE </p> <hr/> <h2 style="margin: 0;">The impact of financial artificial intelligence models on credit risk management</h2> </div>
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<p>Issue web link</p>	<p>https://imcra-az.org/archive/389-science-education-and-innovations-in-the-context-of-modern-problems-issue-1-vol-9-2026.html</p>
<p>Keywords</p>	<p>Credit Risk, Artificial Intelligence, Machine Learning, Financial Modeling, Risk Management</p>
<p>Abstract</p> <p>With the accelerating digital transformation in the financial sector, artificial intelligence based models have become a critical tool in reshaping credit risk management. Machine learning, deep learning, and natural language processing driven financial models offer higher predictive accuracy compared to traditional statistical approaches, adapt more rapidly to changing economic conditions, and reveal complex relationships within credit risk indicators more effectively. This conceptual study examines the impact of financial artificial intelligence models on credit risk management processes. The role of AI in risk detection, credit scoring, early warning systems and probability of default estimation is evaluated, while the advantages, limitations and implementation challenges of these models are discussed. In addition, the ethical, regulatory and operational dimensions of AI-driven risk analysis are highlighted, and directions for future research are proposed.</p>	
<p>Citation</p> <p>Adıyaman G. (2026). The impact of financial artificial intelligence models on credit risk management. <i>Science, Education and Innovations in the Context of Modern Problems</i>, 9(1), 174–179. https://doi.org/10.56334/sei/9.1.16</p>	
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<p>Received: 24.09.2025</p>	<p>Accepted: 27.11.2025</p>
<p>Published: 23.12.2025 (available online)</p>	

Introduction

Rapid changes in financial markets and the growing environment of uncertainty have made risk management more critical than ever for lending institutions. In particular, credit risk stands out as one of the fundamental factors that directly affect the financial soundness of banks and necessitates more careful and timely decision-making for both individual and corporate customers. Although traditional methods used in credit assessment processes have been functional to a certain extent for many years, the increasing volume of data, the diversification of customer profiles, and the widespread use of digital channels have made the limitations of these approaches more visible. This situation has led to the search for new methods that enable more accurate and effective measurement of credit risk. In this context, artificial intelligence and machine learning-based approaches have emerged as powerful alternative tools in credit risk management. These methods have the potential to analyze a large number of variables simultaneously, uncover complex relationships, and provide more accurate forecasts of future outcomes based on historical data. Although the literature includes numerous studies on AI-supported credit risk models, a significant portion of this research focuses on specific algorithms, limited datasets, or narrowly defined applications. Therefore, the need for studies that address the role of artificial intelligence in credit risk management from a broader perspective and that jointly evaluate theory and practice has been increasing.

The main problem addressed in this study is that traditional credit risk assessment methods do not always demonstrate sufficient performance under today's complex data structures and volatile financial conditions, and that the extent to which AI-based models can overcome these shortcomings has not been clearly established. Accordingly, the aim of the study is to examine the areas of use of artificial intelligence and machine learning techniques in credit risk management, compare these approaches with traditional methods, and evaluate the potential contributions of such models to financial institutions. The scope of the research is limited to the conceptual foundations of credit risk, the operating logic of AI-based models, and examples of their applications in the literature. Due to data confidentiality and access restrictions, proprietary internal bank datasets could not be used; therefore, the study is conducted within the framework of a literature review and conceptual evaluation rather than an applied model test. This constitutes the main limitation of the research.

The contribution of the study to the literature lies in its systematic examination of AI-supported credit risk management studies, identifying gaps in existing research, and evaluating the strengths and weaknesses of different models within a holistic framework. From a practical perspective, the study highlights the key considerations that banks and financial institutions should take into account in AI-based credit assessment processes and provides a guiding perspective for decision-makers.

1. Literature review

Recent academic studies indicate that artificial intelligence technologies offer higher potential in credit risk management compared to traditional approaches. This development is closely related to the transformation of financial decision-making processes within the broader framework of sustainable development goals. Sachs (2015) emphasized that sustainable development has reshaped the global financial structure and that SDG-oriented investments have become inevitable for policymakers. Expanding on this perspective, Sachs et al. (2019) demonstrated that sustainable financing models play a critical role, particularly in the context of international cooperation. More practice-oriented studies in the literature focus on the relationship between sustainability and financial performance. Sullivan and Mackenzie (2020) revealed that ESG principles have systematic effects on investment decisions and performance, while Baker et al. (2021) noted that despite the rapid growth of the green bond market, common international standards remain insufficiently developed. Friede (2021), in a meta-analysis, argued that there is generally a positive relationship between ESG performance and financial returns, thereby strengthening the theoretical foundation of this field. Zerbib (2022) found that the price premium observed in green bonds is persistent in some markets but temporary in others, demonstrating that sustainable finance practices are sensitive to market conditions.

More recent studies concentrate on the relationship between sustainability and credit risk. Khan et al. (2023) suggested that ESG integration contributes to a reduction in banks' credit risk, while Arribas et al. (2024) showed that corporate sustainability performance leads to a significant decrease in the cost of capital. In recent years, studies by Ahmed and Iqbal (2025) and Roy and Vasa (2025) have emphasized that artificial intelligence has become a major accelerating factor in sustainable finance within the SDG framework, clearly revealing the current trend in the literature. When considered collectively, these studies indicate that SDG-oriented financial research has increasingly adopted a data-driven, technology-supported, and multidimensional structure. However, comprehensive studies examining the interaction between SDGs and financial instruments in the context of developing countries remain limited.

Studies focusing specifically on artificial intelligence applications in credit risk management also occupy a significant place in the literature. The systematic literature review conducted by Ahmed and Iqbal (2025) demonstrated that machine learning and deep learning-based models provide higher predictive accuracy than traditional credit scoring approaches. In addition, artificial intelligence has been shown to deliver effective results in areas such as fraud detection and financial inclusion. However, the study also emphasized that issues such as ethical concerns, regulatory uncertainty, and data privacy pose significant challenges to sustainable implementation.

Similarly, the systematic literature review by Fahrezi (2025) revealed that artificial intelligence and machine learning techniques have achieved substantial progress in financial risk management, particularly in credit risk prediction and predictive analytics. While this study noted that these methods accelerate risk assessment processes and offer more flexible forecasts under uncertain economic conditions, it also highlighted limitations related to model transparency and the relatively limited diffusion of real-world applications. Furthermore, a comprehensive review by Roy and Vasa (2025) analyzed the methodological diversity and varying performance outcomes of AI/ML approaches used in both individual and corporate credit risk assessment, thereby identifying key technical trends in the literature.

Overall, existing studies indicate that artificial intelligence-based models provide significant advantages over traditional methods in credit risk management. Nevertheless, comparative studies that comprehensively address the

relationships between model performance, explainability, and implementation strategies remain limited. In particular, there is a clear gap in the literature concerning model transparency, interpretability, and the standardization of implementation processes. This study aims to address this gap by examining artificial intelligence models in the context of credit risk management not only in terms of technical performance but also with respect to application and regulatory dimensions. In doing so, it seeks to contribute to the literature by moving beyond predictive accuracy and offering a sustainable and ethically compliant risk management framework.

2. Methodology

This research is a conceptual review study that examines the effects of financial artificial intelligence models on credit risk management. The primary reason for adopting a review approach is the rapid expansion of the literature on AI-based risk models in recent years and the growing need to evaluate the findings in this field from a holistic perspective. Accordingly, the study aims to systematically examine the theoretical foundations, application examples in the literature, and dominant methodological approaches related to the subject. The research is designed with exploratory and descriptive characteristics. The exploratory dimension focuses on understanding the role of financial artificial intelligence applications in credit risk management processes, while the descriptive dimension aims to identify prominent trends in the literature by comparing the findings of existing studies. In this context, the main research problem is that traditional credit risk assessment models fail to provide sufficient flexibility in the face of economic fluctuations and large-scale data structures. The study discusses to what extent the predictive accuracy, adaptability, and early warning potential offered by artificial intelligence models can overcome these limitations. Within the scope of the study, no empirical model has been constructed and no hypothesis testing has been conducted. Instead, machine learning, deep learning, and natural language processing-based credit risk models commonly used in the literature are examined in terms of their theoretical characteristics. This approach enables a comparative evaluation of the conditions under which different artificial intelligence techniques produce more effective results and the situations in which they exhibit certain limitations.

The population of the research consists of academic publications addressing financial artificial intelligence and credit risk. During the literature review process, the Scopus, Web of Science, Google Scholar, and ScienceDirect databases were utilized, and relevant studies were accessed using the keywords “credit risk,” “artificial intelligence,” “machine learning,” “deep learning,” and “financial risk modeling.” The review primarily covers empirical and conceptual studies published within the last 10–12 years that are directly related to the subject. The main limitation of the research is that it focuses solely on peer-reviewed academic publications. Document analysis was adopted as the data collection method. Within this framework, selected studies were comparatively analyzed in terms of the methods used, artificial intelligence models applied, performance metrics, and obtained results. During the review process, a content analysis approach was employed, with particular emphasis on criteria such as model accuracy, computational cost, operational efficiency, and regulatory compliance. Although no quantitative analysis was conducted in the study, the methodological approaches of empirical studies in the literature were interpreted from a holistic perspective.

3. Findings and Discussion

In recent years, interest in artificial intelligence-based credit risk models has increased markedly in the financial literature. The growing volume of data, the diversification of customer profiles, and the increasing volatility of economic conditions have limited the explanatory and predictive power of traditional statistical methods. This situation has paved the way for researchers and practitioners to turn toward machine learning and deep learning-based approaches. The literature reviewed within the scope of this study reveals that artificial intelligence techniques offer significant advantages, particularly in terms of predictive accuracy, early identification of risks, and rapid adaptation to changing market conditions. A large proportion of studies in the literature indicate that machine learning models generate more successful results in credit risk prediction compared to traditional methods. Yeh and Lien (2019), in their study focusing on credit default prediction, demonstrated that artificial neural networks provide higher classification performance than logistic regression. Similarly, Lessmann et al. (2015), in their comprehensive analysis covering different datasets and model types, showed that random forest, gradient boosting, and support vector machines outperform traditional statistical models in many cases. These results stem from the ability of artificial intelligence models to learn nonlinear relationships and patterns within complex data structures more effectively. On the other hand, the literature also includes studies that present more cautious conclusions regarding artificial intelligence models. Addo et al. (2018) stated that the performance of machine learning methods is largely dependent on the quality of the dataset and that, in some cases, simple logistic regression models provide more stable predictions. Likewise, Bussmann et al. (2021) drew attention to the high computational costs of deep learning-based models and the risk of overfitting in environments with limited data. These findings indicate that artificial intelligence models do not produce superior results under all conditions, and that data structure, sample size, and model selection are critical determinants of performance.

This study evaluates these differing findings in the literature through a systematic approach and addresses the strengths and limitations of artificial intelligence-based credit risk models within a holistic framework. While a significant portion of previous studies focused on the performance of a single model, this research comparatively examines different artificial intelligence approaches in the context of credit risk management. The contribution of the study to the literature lies in providing decision-makers with a guiding perspective on model selection by jointly evaluating empirical findings and methodological trends. In addition, the research complements the existing literature by discussing the implications of artificial intelligence applications for financial regulations, model explainability, and institutional risk management practices.

Conclusion

This study aimed to evaluate the existing academic body of knowledge in a holistic manner by systematically reviewing the literature on the use of artificial intelligence (AI)-based approaches in credit risk management. The review indicates that machine learning and deep learning-based models have become increasingly prominent in recent years in studies focusing on the measurement and management of credit risk. However, significant gaps have been identified in the literature regarding the practical applicability, interpretability, and compatibility of these models with regulatory frameworks. In particular, it is observed that the majority of studies concentrate primarily on technical performance, while aspects such as ethical considerations, governance principles, and regulatory compliance are addressed in only a limited number of studies. In this respect, the present study contributes to the literature by synthesizing research trends related to the use of AI in credit risk management and by offering a more balanced and disciplined perspective.

Main Findings Derived from the Research

The studies reviewed generally indicate that artificial intelligence-based models provide higher accuracy and flexibility in predicting credit risk compared to traditional statistical methods. However, it is noteworthy in the literature that model performance is predominantly evaluated in terms of predictive accuracy, while critical aspects such as model transparency and explainability remain secondary considerations. Machine learning and deep learning models are found to generate more successful results particularly when applied to large, high-dimensional, and complex datasets; nevertheless, this success is largely dependent on data quality and data structure. The literature mainly relies on banking sector data, especially credit card and retail loan portfolios, whereas studies focusing on small and medium-sized enterprises (SMEs) and emerging markets remain limited. In addition, it is observed that the integration of regulations, ethical principles, and fair decision-making mechanisms into AI-based credit risk models has not yet reached a sufficient level of maturity. Although many studies compare different models, systematic comparisons across countries and regulatory frameworks are largely absent.

Recommendations for Practitioners and Researchers

Financial institutions should not focus solely on predictive accuracy when implementing artificial intelligence-based credit risk models; they should also incorporate model explainability, ethical compliance, and regulatory requirements into their decision-making processes. In this context, the integration of explainable artificial intelligence (XAI) approaches into credit risk management will offer significant advantages for both institutional decision-makers and regulatory authorities. Comparative analyses of credit risk models applied across different countries and markets would contribute to reducing generalizability issues identified in the literature. In addition, increasing research efforts focused on the development of AI-based risk models for non-banking financial institutions and small and medium-sized enterprises (SMEs) is of particular importance. Encouraging industry-academia collaborations to reduce the gap between academic research and practical applications will also contribute to the advancement of the literature.

Limitations of the Study

This study does not include empirical test results, as it is a conceptual investigation based on a literature review. Differences in datasets, methodologies, and performance metrics across the reviewed studies limit the possibility of direct comparisons. Furthermore, the fact that a significant portion of the existing literature focuses on specific countries and sectors restricts the generalizability of the findings.

Suggestions for Future Research. Future studies that conduct longitudinal empirical analyses examining the long-term performance of artificial intelligence-based credit risk models would make a valuable contribution to the literature. There is also a need for an increase in interdisciplinary research that addresses ethical concerns, fairness, and discrimination risks by combining quantitative and qualitative methods. Moreover, expanding research focused on the development of regulation-friendly and explainable AI models is of great importance. Finally, studies that

examine the macro-level effects of AI adoption in credit risk management on financial stability are expected to constitute an important area for future research.

Ethical Considerations

This study was conducted in accordance with internationally accepted ethical research standards. As a conceptual and literature-based review, the research did not involve human participants, personal data, confidential financial information, or proprietary institutional datasets. Therefore, formal ethical approval from an institutional review board was not required.

All sources used in the study were publicly available academic publications, and appropriate citations were provided to acknowledge the original authors' contributions. The study adhered to principles of academic integrity, transparency, and responsible scholarship by accurately representing previous research findings and avoiding any form of plagiarism or data manipulation. Ethical issues related to artificial intelligence—such as algorithmic bias, transparency, data privacy, and regulatory compliance—were critically discussed within the analytical framework of the study, reflecting the authors' commitment to ethical awareness in financial AI research.

Acknowledgements

The author would like to express sincere appreciation to the academic community whose scholarly work formed the foundation of this conceptual review. Special thanks are extended to researchers and practitioners in the fields of artificial intelligence, financial risk management, and sustainable finance, whose studies contributed significantly to the development of this research. No institutional or individual assistance requiring formal acknowledgment was received during the preparation of this manuscript.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. The study was conducted independently by the author.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this article. The research was conducted independently, and no financial or personal relationships influenced the study's design, analysis, or interpretation.

Conference Submission Note

This paper has been submitted for presentation and publication within the scope of the 12th International CEO Social Sciences Congress (CEOSSC), to be held on 6-7 December 2025 at Metropolitan University Karachi, Pakistan, with online participation options. The study is prepared in accordance with the academic, ethical, and scientific standards of the CEO Congress and its collaborating international institutions.

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