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Artificial intelligence in credit risk assessment

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ABSTRACT

This study presents a structured literature review on the application of AI in credit risk assessment, synthesizing empirical and conceptual research published between 2016 and 2022. It critically examines a range of AI models, including artificial neural networks (ANN), support vector machines (SVM), fuzzy logic systems, and hybrid architectures, with an emphasis on their predictive accuracy, robustness, and operational applicability. The review highlights that AI-based models consistently outperform traditional statistical techniques in handling nonlinear patterns, imbalanced datasets, and complex borrower profiles. Furthermore, AI enhances the inclusivity of credit evaluation by integrating alternative data sources and adapting to dynamic financial environments. However, the study also identifies ongoing challenges related to model interpretability, fairness, and regulatory compliance. By evaluating model performance metrics and methodological innovations across multiple contexts—including emerging markets, peer-to-peer platforms, and digital banking—the study offers a nuanced understanding of AI's strengths and limitations. The paper concludes with a call for balanced integration of explainable AI tools and ethical governance to ensure responsible deployment in financial institutions.

INTRODUCTION

In the aftermath of the global financial crisis, credit risk assessment has emerged as a focal point of academic and institutional scrutiny, with increasing interest in adopting advanced analytical techniques to improve prediction accuracy and decision-making reliability (Chen et al., 2016; Swankie & Broby, 2019). Traditional credit scoring models, primarily reliant on statistical methods such as logistic regression and discriminant analysis, often suffer from inherent limitations, including linearity assumptions, rigid data requirements, and low adaptability to non-linear or high-dimensional financial data (Říha, 2016). These shortcomings have encouraged the integration of AI and machine learning (ML) algorithms into credit risk modeling frameworks. AI-driven models—particularly artificial neural networks (ANN), support vector machines (SVM), and ensemble approaches—offer the ability to process complex datasets, uncover hidden patterns, and learn dynamically from evolving

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borrower behavior (Bhatore et al., 2020; Faheem, 2021). As such, AI is increasingly viewed not merely as a complementary tool but as a transformative force existing possibilities (Rahmatian & Sharajsharifi, 2022).

Despite substantial progress in AI-based risk modeling, several persistent challenges temper its real-world implementation, especially in regulatory and operational environments. First, the issue of interpretability—commonly referred to as the "black-box" problem—remains a significant barrier to the adoption of complex AI models in finance, where transparency is essential for regulatory compliance and stakeholder trust (Hadji Misheva et al., 2021). Additionally, the quality and balance of financial datasets present technical obstacles, particularly where defaulters constitute a small minority, leading to biased or ineffective classification (Khemakhem et al., 2018). Furthermore, while AI models may offer high classification accuracy under experimental conditions, their generalizability and stability across diverse financial systems remain uncertain, especially in underbanked or volatile economic contexts (Mhlanga, 2021). These concerns underscore the need for research that not only improves the technical performance of AI models but also addresses their interpretability, robustness, and ethical implications within practical banking frameworks.

Responding to these gaps, the present study provides a structured literature-based investigation into the application of AI techniques for credit risk assessment, emphasizing the comparative effectiveness of various models across empirical studies. By systematically synthesizing findings from academic and applied research, the manuscript offers a critical appraisal of techniques such as neural networks, fuzzy support vector machines, and hybrid decision systems. Notably, the review highlights the superior predictive performance of AI-based classifiers—particularly in handling complex, nonlinear, or imbalanced datasets—while also acknowledging their limitations regarding transparency and data requirements.

METHODOLOGY

The methodology of this study is based on a structured literature review approach designed to critically examine the application of AI techniques in credit risk assessment. A comprehensive selection of peer-reviewed journal articles, conference proceedings, and academic theses published between 2016 and 2022 was analyzed to identify prevailing AI models, methodological advancements, and empirical outcomes in the domain of financial risk evaluation. Sources were chosen based on relevance, citation frequency, and methodological rigor, with a focus on studies employing machine learning algorithms such as artificial neural networks (ANN), support vector machines (SVM), fuzzy logic systems, and ensemble methods. Particular attention was given to research addressing real-world challenges such as imbalanced datasets, model interpretability, and performance benchmarking. Each selected study was systematically reviewed to extract information on model architecture, data characteristics, evaluation metrics (e.g., accuracy, precision, recall, AUC), and application context. The extracted data were then synthesized to compare model performance and to identify trends, gaps, and best practices in AI-based credit risk modeling.

FINDINGS

Chen, Ribeiro, and Chen (2016) provided a comprehensive review of financial credit risk assessment methods, focusing on the evolution from traditional statistical approaches to modern AI-based techniques. Motivated by the heightened global interest in credit risk modeling—particularly following the financial crisis—the authors underscored the importance of accurately forecasting financial distress and business failure, both for economic stability and societal welfare. The review categorized existing models into two broad classes: conventional statistical techniques such as logistic regression and discriminant analysis, and emerging intelligent systems including neural networks, support vector machines (SVM), decision trees, and hybrid models. The authors highlighted the limitations of traditional models, especially their reliance on strict assumptions and linearity, which often result in suboptimal performance in complex financial environments. In contrast, AI-based models demonstrated superior adaptability, pattern recognition, and predictive capabilities, particularly in handling high-dimensional and non-linear datasets. The paper emphasized recent methodological advances, such as ensemble learning

and feature selection techniques, which have significantly improved classification accuracy in financial distress prediction. Additionally, the authors acknowledged challenges around interpretability, data quality, and overfitting, calling for more research into transparent and robust model development. Ultimately, the review positioned AI as a promising and necessary direction for enhancing credit risk assessment and financial forecasting in modern finance.

Punniyamoorthy and Sridevi (2016) developed and evaluated AI models for credit risk classification, aiming to identify the most effective technique for distinguishing between creditworthy and high-risk borrowers. Motivated by the increased attention to credit risk in the aftermath of the global financial crisis, the study compared the performance of two prominent AI classifiers: the artificial neural network (ANN) and the fuzzy support vector machine (FSVM). While ANN is widely used for financial classification tasks, the FSVM model incorporates fuzzy logic to better handle uncertainty and data overlap—key challenges in real-world credit datasets. In this approach, fuzzy c-means clustering was used to assign membership values to data instances, which then informed the FSVM classifier. Multiple kernel functions were tested to determine the best-performing FSVM configuration. The experimental results, based on credit risk datasets, showed that the FSVM model outperformed the backpropagation neural network in terms of classification accuracy, indicating its superior ability to discriminate between good and bad creditors. The findings suggest that integrating fuzzy logic with SVM enhances robustness in complex classification problems involving ambiguous or noisy data. The authors concluded that FSVM offers a reliable and interpretable model that financial institutions can adopt to improve credit risk assessment and decision-making accuracy.

Říha (2016) conducted a diploma thesis on the application of AI techniques to credit risk assessment, with a focus on comparing traditional statistical models with modern machine learning approaches. The study was grounded in the context of financial institutions' need to more accurately evaluate borrower creditworthiness and reduce loan default risk. Using a structured dataset of credit applicants, the research compared the predictive performance of several classification models: logistic regression (as a conventional benchmark), support vector machines (SVM), random forests, and artificial neural networks (ANNs). Each model was evaluated on its ability to accurately classify clients into creditworthy and non-creditworthy categories. The thesis found that AI-based models—particularly random forests and neural networks—outperformed logistic regression in terms of classification accuracy, robustness, and adaptability to complex patterns in the data. These models were especially effective in capturing non-linear relationships and interactions among variables, which are often missed by traditional methods. The study emphasized the growing importance of AI in credit risk modeling and recommended that banks integrate such tools to enhance their risk assessment frameworks. Furthermore, it highlighted the need for careful model validation and ethical consideration, especially in terms of transparency and fairness in credit decision-making processes.

Khemakhem and Boujelbene (2017) examined the effectiveness of AI models in credit risk assessment within the context of a Tunisian commercial bank. The study aimed to estimate the probability of default as a core measure of credit risk by comparing traditional and AI-based classification techniques. Specifically, the authors constructed three credit scoring models: a logistic regression model (serving as a baseline), an artificial neural network (ANN), and a support vector machine (SVM) model with a radial basis function (RBF) kernel. Model performance was evaluated using standard classification metrics, including confusion matrices and the area under the receiver operating characteristic (ROC) curve (AUC). Empirical results revealed that the SVM with RBF kernel outperformed both the logistic regression and ANN models in terms of accuracy, sensitivity, and specificity, demonstrating the lowest error rates across metrics. These findings suggest that SVM provides a robust and reliable approach for classifying borrowers and predicting default risk in emerging market settings. The authors concluded that integrating advanced AI models, particularly SVM, into the credit assessment processes of banking institutions could significantly enhance their ability to monitor and control credit risk, especially in environments characterized by complex or nonlinear data patterns.

Nazemi and Heidenreich (2017) investigated the application of AI techniques for enhancing credit risk management, with a particular focus on

modeling loss given default (LGD)—a critical but underexplored component of expected loss calculations in financial risk assessment. Prompted by the increased regulatory emphasis under the Basel II framework, the authors aimed to improve predictive accuracy for recovery rates on defaulted corporate bonds. The study utilized a dataset comprising defaults that occurred between 2002 and 2012 and incorporated a range of covariates, including macroeconomic indicators, bond-specific features, and industry-level factors. As a methodological foundation, the research applied Least Squares Support Vector Machines (LS-SVM), comparing its performance against traditional linear regression techniques. Two advanced modifications of LS-SVM were also proposed to assess robustness and model optimization. Empirical results demonstrated that LS-SVM significantly outperformed linear regression in modeling recovery rates, indicating that support vector regression offers a promising and effective tool for LGD prediction. The findings hold practical relevance for both financial institutions managing credit portfolios and investors dealing with distressed debt, as improved LGD modeling directly contributes to more accurate capital requirement calculations and enhanced risk pricing. This study underscored the growing importance of AI methods in addressing complex, nonlinear problems in credit risk management and provided empirical support for their integration into banking risk systems.

Giudici, Hadji-Misheva, and Spelta (2019) explored the integration of network-based topological features into credit scoring models to enhance credit risk management in peer-to-peer (P2P) lending platforms, a sector within FinTech known for its speed, accessibility, and cost efficiency but also for elevated credit and systemic risk. The authors argued that the interconnectedness of borrowers within such platforms introduces a layer of systemic vulnerability that traditional credit risk models do not capture. To address this, they proposed the use of borrower similarity networks, derived from financial data, as an additional dimension in credit scoring. Within these networks, topological metrics—such as centrality, clustering coefficients, and community structures—were computed to reflect each borrower's position and influence in the network. These network features were then incorporated as explanatory variables into machine learning-based credit scoring models. The inclusion of this relational data significantly improved the predictive accuracy of credit risk assessments, offering a more nuanced and systemic perspective on borrower behavior and default likelihood. The paper demonstrated that network science can provide valuable insights beyond individual-level credit attributes, helping P2P platforms better detect hidden risk patterns and enhance consumer protection while promoting financial stability in the growing digital lending ecosystem.

Khemakhem, Ben Said, and Boujelbene (2018) investigated the challenge of credit risk assessment using unbalanced datasets, a common issue in financial modeling where the number of non-defaulting (good) borrowers far exceeds that of defaulters. Such imbalance can bias traditional classification models toward the majority class, undermining the accuracy of predictions for the minority class—i.e., high-risk borrowers. To address this, the authors applied data mining techniques, artificial neural networks (ANN), and support vector machines (SVM), combined with sampling strategies to improve classification performance. Using a real dataset from a Tunisian commercial bank, they experimented with Random Over-Sampling (ROS) and the Synthetic Minority Over-Sampling Technique (SMOTE)to rebalance the data. These sampling methods were evaluated in conjunction with both statistical and AI-based classifiers. The performance of the models was assessed using confusion matrices and ROC curve analysis, which demonstrated that re-sampling significantly improved the models' ability to accurately classify defaulting borrowers. The findings suggest that integrating sampling techniques with AI and statistical models enhances predictive power in default probability estimation and supports more reliable credit risk assessment. The study provided practical implications for banks operating in environments with similar data challenges, reinforcing the utility of hybrid modeling approaches in managing credit portfolios.

Xu, Zhang, Hua, and Wang (2019) developed a dynamic credit risk evaluation framework tailored to e-commerce sellers, using hybrid AI models to address the specific challenges of transaction uncertainty and information asymmetry inherent in

digital marketplaces. The study aimed to support the sustainability and trustworthiness of e-commerce ecosystems by offering a robust and adaptive method for assessing seller creditworthiness. Utilizing a dataset of 609 seller credit cases from Taobao, each containing 23 categorical and numerical attributes, the authors evaluated three hybrid model configurations: (1) decision tree–artificial neural network (ANN), (2) decision tree–logistic regression, and (3) decision tree–dynamic Bayesian network. Among these, the decision tree–ANN model achieved the highest classification accuracy, indicating strong predictive performance for distinguishing high- and low-risk sellers. This combination capitalized on the interpretability of decision trees and the nonlinear learning capabilities of ANNs, offering a model that is both accurate and adaptable to changing e-commerce environments. The authors emphasized the importance of such AI-powered systems in supporting real-time, data-driven credit evaluations that evolve with transaction behaviors and platform dynamics. The proposed model serves not only to promote safer online transactions but also to inform risk-sensitive decisions by investors and platform operators, thereby contributing to the long-term sustainability of digital financial ecosystems.

Leo, Sharma, and Maddulety (2019) conducted a literature review to evaluate the state of research on the application of machine learning (ML) in banking risk management, particularly in the aftermath of the global financial crisis. The review aimed to identify how ML techniques have been utilized across various risk domains—credit risk, market risk, operational risk, and liquidity risk—and to assess gaps between academic exploration and real-world implementation. The authors found that while ML has made inroads into credit risk assessment and fraud detection, the overall application of these methods in the broader risk management landscape remains underdeveloped relative to their potential and growing industry relevance. ML techniques such as decision trees, neural networks, and ensemble models were noted for their capacity to process complex, high-dimensional data, offering banks the ability to enhance prediction accuracy and automate risk monitoring. Despite these capabilities, the paper highlighted that many risk categories remain inadequately studied through the lens of ML, suggesting a disconnect between the rapid evolution of AI tools and their academic exploration in banking contexts. The authors called for further interdisciplinary research to explore ML's potential in underrepresented areas of banking risk, such as real-time liquidity stress testing and operational risk forecasting. They concluded that closing this gap is essential for building more resilient, data-driven banking systems that align with the industry's post-crisis risk management expectations.

Alzeaideen and Abdul Wahab (2019) investigated the potential of artificial neural networks (ANN) as a decision-support tool for credit risk assessment in Jordanian commercial banks, where traditional credit evaluation remains heavily reliant on credit officers' intuition or basic scoring models. Recognizing the limitations of such subjective and static methods, the study proposed an ANN-based model trained on real-world credit application data—comprising both approved and rejected cases—from various Jordanian banks. The research aimed to harness the latent value stored in client data warehouses, treating them as knowledge assets that could be systematically analyzed using advanced data mining techniques. By utilizing applicant-specific characteristics as input variables, the ANN model was designed to support more objective, data-driven lending decisions. The experimental findings demonstrated that ANN offered superior classification capabilities compared to traditional approaches, effectively improving the accuracy and consistency of credit approval evaluations. The authors concluded that integrating business intelligence tools such as ANN into banking decision-making processes could enhance the overall effectiveness of credit risk management. Furthermore, this advancement represents a significant step toward modernizing Jordan's banking sector by introducing AI-driven methodologies that reduce subjectivity, mitigate credit risk, and contribute to the sector's sustainable growth.

Swankie and Broby (2019) explored the transformative role of AI in the evaluation and management of banking risk, positioning AI as a critical enabler of innovation in financial services. Prompted by post-global financial crisis regulatory reforms—particularly those focusing on capital adequacy—the authors assessed how AI techniques can be integrated across various categories of banking risk, including credit, operational, liquidity, and reputational risk. The paper provided a comprehensive overview of AI capabilities, including machine learning, deep learning, natural language processing, speech recognition, and visual

recognition, highlighting their ability to process and interpret large volumes of structured and unstructured data rapidly. In the context of credit risk, AI was shown to enhance the precision and speed of risk assessment models by automating data analysis and supporting predictive modeling, thereby contributing to better lending decisions and risk monitoring. Similarly, in operational and reputational risk domains, AI-enabled systems offered potential for real-time surveillance, fraud detection, and sentiment analysis. The authors emphasized that beyond technical efficiency, the deployment of AI in risk management can yield substantial economic value by reducing exposure to unforeseen losses and improving regulatory compliance. The paper concluded that while challenges remain in implementation and oversight, the strategic adoption of AI presents banks with a significant opportunity to strengthen risk evaluation frameworks and enhance resilience in a data-intensive financial environment.

The study by van Thiel and van Raaij (2019) investigated the application of AI techniques to enhance credit risk prediction in the context of growing digital lending markets. Motivated by the sharp rise in global consumer credit and the parallel transformation toward digital financial services—particularly driven by millennial expectations—the authors explored how AI could support more accurate and scalable credit risk assessments. Focusing on data from three European lenders operating in the UK and the Netherlands—two markets known for their advanced digital lending practices—the study analyzed a dataset comprising 133,152 mortgage and credit card customers across prime, near-prime, and sub-prime segments, collected between January 2016 and July 2017. The research employed supervised learning techniques, specifically neural networks and random forests, due to their ability to process both structured and unstructured data. These AI models were benchmarked against traditional logistic regression models commonly used for estimating probability of default (PD). Through three experimental comparisons, the AI-based models consistently outperformed traditional methods, demonstrating higher predictive accuracy and model quality. The findings suggest that scalable, automated credit risk scoring systems can benefit significantly from AI integration, offering financial institutions improved precision in individual risk assessments. These results support the argument that AI can serve as a foundational technology in modern credit risk management, particularly in the era of rapidly expanding digital lending.

Bhatore, Mohan, and Reddy (2020) conducted a systematic literature review to evaluate the application of machine learning (ML) techniques in credit risk assessment, highlighting the increasing relevance of AI in mitigating non-performing assets (NPAs) and financial fraud. Reviewing 136 scholarly articles published between 1993 and March 2019, the study synthesized research trends, methodological developments, and technical constraints associated with ML-based credit evaluation models. The review underscored that traditional credit scoring mechanisms, often dependent on credit rating agencies, are being progressively supplemented—or replaced—by advanced ML models capable of analyzing borrower behavior, payment history, and other complex variables. Key findings pointed to the rising popularity of ensemble and hybrid methods, particularly those integrating neural networks and support vector machines (SVM), for enhancing predictive accuracy in credit scoring, NPA forecasting, and fraud detection. The authors further examined the influence of hyperparameter tuning on model performance, emphasizing its importance in optimizing predictive outcomes. Despite these advancements, the paper identified several persistent challenges, notably the limited availability of comprehensive and standardized public datasets, which hinders replicability and benchmarking in academic research. The authors concluded that while ML offers significant promise for improving credit risk evaluation, progress will depend on greater data accessibility, more robust evaluation frameworks, and continued refinement of hybrid modeling approaches.

Uzowuru, Odutola, Adeyanju, Odunuga, and Rajani (2020) investigated the optimization of machine learning (ML) models for enhanced credit risk assessment, focusing on the development of AI-driven analytical tools tailored for application in real-world banking environments. The research responded to the limitations of traditional credit scoring models—such as logistic regression and decision trees—which often struggle to capture the complex, non-linear relationships prevalent in

financial data. By leveraging big data and advanced ML optimization strategies, the study aimed to improve the predictive power, accuracy, and operational relevance of credit risk models. The authors evaluated various ML algorithms, including ensemble techniques and deep learning frameworks, emphasizing performance enhancement through model fine-tuning and feature engineering. The resulting optimized models demonstrated superior predictive capabilities compared to conventional methods, offering more accurate identification of default risk and enabling more informed lending decisions. Additionally, the research addressed practical integration, proposing implementation pathways for banks to adopt these models within existing credit assessment frameworks. The study also considered the impact of such AI-driven tools on financial decision-making processes, highlighting their potential to reduce credit losses and improve capital allocation. The findings underscored the importance of model interpretability and scalability, especially in regulatory contexts, and advocated for the continued evolution of AI applications in financial risk management.

Ehtesham Rasi, Karamipour, and Arad (2020) developed a hybrid model combining Multiple Criteria Decision Making (MCDM) and AI-based hyperbolic regression to rate actual bank customers according to credit risk. Focusing on 100 credit customers of the Agriculture Bank in western Mazandaran province, Iran, from 2012 to 2016, the study aimed to identify key determinants of creditworthiness and construct a predictive model to classify borrowers as creditworthy or non-creditworthy. The Analytical Hierarchy Process (AHP) was applied to prioritize seven key risk factors based on expert judgment. These included customer revenue, credit reputation in the market, occupation, duration of customer-bank relationship, type and value of collateral, and average account balance. Following this, the authors employed AI hyperbolic regression, a non-linear modeling technique suited for complex financial classification tasks, to refine the prioritization based on empirical data. The regression model identified credit reputation, revenue, and collateral value as the top predictive features, followed by the relationship duration, collateral type, and occupation. The dual-method approach allowed for both expert-driven and data-driven factor weighting, enhancing the robustness of the risk rating model. The study demonstrated that integrating MCDM techniques with AI regression tools could significantly improve the precision of customer credit risk evaluation, offering banks a structured yet adaptive mechanism for rating and managing loan applicants.

Hadji Misheva, Osterrieder, Hirsa, Kulkarni, and Lin (2021) addressed a critical gap in the deployment of machine learning (ML) for credit risk management by focusing on the integration of explainable AI (XAI) techniques. While ML models offer enhanced predictive power, their lack of interpretability often impedes real-world adoption in the financial sector, particularly in high-stakes applications like credit scoring. The authors implemented two leading post-hoc model-agnostic XAI methods—Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP)—to provide transparency in ML-driven credit scoring models. Using a real-world dataset from the Lending Club, a U.S.-based peer-to-peer lending platform, they applied these techniques to explain model decisions at both local (individual borrower) and global (model-wide) levels. LIME was employed for instance-level interpretability, while SHAP offered both detailed visualizations and consistency in feature importance across the dataset. The study not only compared different kernel implementations for SHAP but also highlighted practical challenges in integrating XAI into financial risk systems, such as computational complexity, usability for end-users, and the trade-off between explanation accuracy and comprehensibility. The authors concluded that while XAI tools like LIME and SHAP are essential for regulatory compliance, fairness, and stakeholder trust, their implementation requires careful consideration of operational and technical constraints. The research provides a valuable framework for financial institutions seeking to adopt interpretable and responsible AI in credit risk modeling.

Bogojevic Arsic Vesna (2021) provided a comprehensive literature-based review examining the evolving role of AI in financial risk management, with particular attention to credit risk, market risk, and operational risk. The paper was motivated by the ongoing transformation of the financial sector due to advances in financial technology, which have rendered many traditional risk management practices less effective. The author identified AI—especially machine learning—as a critical enabler of

faster, more cost-effective, and more accurate risk evaluation and control. Within credit risk management, AI was shown to significantly enhance processes such as data preprocessing, model development, and stress testing. Techniques like natural language processing (NLP) and text mining were highlighted for their role in data augmentation and fraud detection, improving the quality and scope of data used in risk assessment. The study also emphasized AI's contribution to model validation and scenario analysis, which are central to regulatory compliance and capital adequacy evaluation. Importantly, the paper positioned AI not only as a technological upgrade but as a fundamental component of the future financial risk management framework. It concluded that continued AI integration will be essential as the financial industry adapts to digitalization, new business models, and increasingly data-intensive environments. The review offered clear insight into the capabilities and future potential of AI tools in restructuring risk assessment and decision-making across financial institutions.

Sharifi, Jain, Poshtkohi, Seyyedi, and Aghapour (2021) proposed a novel AI-based approach to credit risk prediction using a hybrid model combining artificial neural networks (ANN) with an Improved Owl Search Algorithm (IOSA)and a C5 decision tree. Recognizing the central role of credit ratings in managing and mitigating credit risk in banking institutions, the study aimed to enhance the predictive performance of credit risk models through advanced machine learning optimization techniques. The model was tested using real-world data from Bank Melli in Iran, focusing on accurately classifying borrowers based on quantitative financial attributes. The IOSA was employed to optimize the weighting of the ANN, effectively enhancing its classification capability by exploring the solution space more efficiently than standard optimization methods. The C5 decision tree was used in conjunction with the neural network to improve model interpretability and guide the structure of classification. The hybrid model achieved a 96% accuracy rate, outperforming comparative algorithms in the evaluation. Additionally, the model reported a precision of 0.885 and recall of 0.83, correctly identifying 618 true positive cases, indicating a robust ability to detect potential credit defaulters. The study concluded that the integration of decision trees with metaheuristically optimized neural networks offers a highly reliable and accurate solution for credit risk prediction, supporting better-informed lending decisions in the banking sector.

Celestin and Vanitha (2021) explored the broad impact of AI on the future of banking, with a particular focus on key functional areas such as credit scoring, fraud detection, operational efficiency, and customer service. Drawing on qualitative analysis supported by case studies and comparative assessments of AI adoption in leading banking institutions, the study highlighted significant performance gains associated with AI integration. Notably, AI-driven credit scoring models demonstrated a 40% improvement in predictive accuracy, enabling banks to better manage risk while expanding access to credit among underserved demographics. In the domain of fraud detection, AI systems increased detection accuracy from 55% to 98%, resulting in a substantial reduction in financial losses. Additionally, the implementation of AI tools such as chatbots and intelligent process automation led to a 45% reduction in operational costs, a 60% decrease in processing times, and a 13% increase in customer satisfaction. These outcomes were statistically validated, with strong significance levels for efficiency and satisfaction metrics. The study emphasized that AI not only modernizes banking infrastructure but also facilitates strategic decision-making through faster, data-driven insights. However, it also stressed the need for ethical oversight in AI applications—particularly in credit scoring—to ensure fairness, transparency, and regulatory compliance. The authors concluded that as AI continues to evolve, banks must invest in both technology and governance frameworks to responsibly harness its full potential.

Yanenkova, Nehoda, Drobyazko, Zavhorodnii, and Berezovska (2021) proposed an advanced modeling framework for bank credit risk management utilizing a cost risk model enhanced by neural-cell technologies and fuzzy logic systems. Recognizing the limitations of traditional risk assessment approaches, the authors developed a hybrid methodology grounded in the Value-at-Risk (VaR) framework and extended through fuzzy programming and neuro-fuzzy integration to forecast the likelihood of loan defaults and the

overall health of a bank's credit portfolio. The model was designed to support real-time monitoring and decision-making processes for managing non-performing loans (NPLs). It incorporates both quantitative and qualitative indicators, allowing for early-stage detection of deteriorating loan performance and trends in credit risk exposure. The approach leverages simulation modeling to forecast changes in the degree of credit problematicity in response to variations in borrower and macroeconomic indicators. By applying these AI-enhanced methodologies, the model improves the reliability of credit risk assessments and provides banks with actionable insights for developing risk mitigation strategies. The authors recommended integrating this modeling approach into bank decision-support systems as a software solution, particularly for dynamic environments where credit portfolios are subject to rapid changes. The study demonstrated the potential of combining machine learning with fuzzy logic to provide more granular, adaptive, and forward-looking risk evaluations in banking.

Faheem (2021) explored the transformative impact of AI on credit scoring and default prediction, highlighting how AI-driven risk assessment models are reshaping financial decision-making processes. The study critiqued the limitations of traditional credit scoring systems—such as FICO—which rely heavily on structured, historical data and fixed rules, resulting in static and often exclusionary models that fail to adapt to behavioral and economic shifts. In contrast, AI technologies—particularly those incorporating machine learning and real-time data processing—enable financial institutions to evaluate creditworthiness with greater granularity and adaptability. The paper examined the use of alternative data sources, including online behavior, social media activity, and transaction history, which allow for more inclusive and accurate assessments, especially for underbanked populations. Faheem also addressed the critical ethical and regulatory considerations tied to AI adoption, including concerns over algorithmic opacity, fairness, bias, and compliance with data privacy laws such as the GDPR. Emphasis was placed on the importance of integrating Explainable AI (XAI) to ensure transparency and accountability in model decisions. Emerging technologies like natural language processing and blockchain were identified as future enablers of further innovation in credit risk modeling. Ultimately, the paper advocated for a balanced approach that promotes innovation while maintaining ethical rigor and regulatory alignment in deploying AI for credit risk assessment.

Milojević and Redzepagic (2021) examined the evolving role of AI and machine learning (ML) in banking risk management, with a primary focus on credit risk. Motivated by the increased adoption of advanced data-driven technologies following the global financial crisis and more recently the COVID-19 pandemic, the paper analyzed both the opportunities and challenges associated with integrating AI and ML into banking operations. The authors argued that these technologies offer substantial potential for improving the precision, speed, and scalability of credit risk assessment by enabling more granular analysis of borrower behavior and risk profiles. Additionally, the paper extended its scope beyond credit risk to consider the relevance of AI and ML in other key risk domains, including market, liquidity, and operational risk. Emphasis was placed on the value of deep learning and big data analytics as complementary tools that enhance model performance, particularly in processing unstructured or high-dimensional data. However, the authors also acknowledged the risks of over-reliance on algorithmic systems, highlighting concerns around model transparency, regulatory compliance, and implementation costs. Ultimately, the study concluded that the thoughtful and measured deployment of AI technologies—supported by regulatory guidance and robust governance—could significantly enhance banks' capacity to manage diverse risk exposures in an increasingly complex financial environment.

Mhlanga (2021) conducted a conceptual and documentary analysis to explore how AI and machine learning (ML) can enhance credit risk assessment in the context of financial inclusion in emerging economies. The study addressed the challenges faced by underbanked populations, who often lack access to traditional forms of collateral or verifiable identification—factors that typically preclude them from obtaining credit from formal financial institutions. Through a comprehensive literature review, the paper found that AI and ML algorithms enable lenders to overcome issues of information asymmetry, adverse selection, and moral hazard by leveraging alternative data sources, such as publicly available behavioral and transactional data. These technologies allow for

more robust and individualized assessments of creditworthiness, enabling financial institutions to evaluate customer behavior and repayment capacity beyond conventional indicators. Mhlanga emphasized the potential of AI and ML to expand credit access to marginalized or financially excluded groups, advocating for strategic investment by banks and credit institutions in these technologies. The study concluded that deploying AI-driven credit risk tools can significantly contribute to improving financial inclusion in emerging markets by enabling responsible lending to previously excluded individuals, thereby supporting broader economic development goals.

Locatelli, Pepe, and Salis (2022) detailed four key applications of AI within credit risk modeling, emphasizing how machine learning (ML) techniques and alternative data sources enhance the predictive capabilities and flexibility of traditional models. Focusing primarily on the estimation of the Probability of Default (PD), the authors illustrated how AI tools can uncover complex borrower behaviors and patterns—such as seasonality in business income or early warning signals—often missed by conventional statistical approaches. For instance, AI-enabled models proved effective in identifying counterparty risk during the COVID-19 crisis and provided improved discrimination in cases with irregular income flows. The chapter also presented a "two-step approach," where traditional credit risk models generate initial outputs, followed by a second phase in which AI techniques refine or adjust the results, thereby enhancing model robustness. In addition to applications in PD estimation, the authors explored the integration of AI into asset management, where AI models assist investment decision-making by evaluating borrower creditworthiness in portfolios. Finally, the chapter discussed the role of AI in benchmarking and validating internal credit risk models, particularly in regulatory capital estimation contexts. The authors emphasized that while AI holds substantial promise in elevating the precision, adaptability, and automation of credit risk assessments, its deployment must be carefully aligned with regulatory requirements and validation practices.

Locatelli, Pepe, and Salis (2022) provided a comprehensive examination of the integration of AI and alternative data in internal credit rating systems, with a particular emphasis on the methodological, regulatory, and ethical implications of this transformation. The book critically analyzed how the banking industry—traditionally reliant on structured financial and behavioral data and statistical models such as linear or logistic regression—is increasingly adopting AI techniques like decision trees, neural networks, and ensemble methods to enhance predictive accuracy in credit risk modeling. Central to this shift is the utilization of alternative data sources, including sociological, geographic, and digital behavioral data, which allow for a more nuanced understanding of borrower profiles. The authors explored both the opportunities and challenges associated with this evolution. On the one hand, AI enhances the granularity and responsiveness of credit risk assessment, enabling more dynamic and individualized evaluations. On the other hand, the opacity of AI models, particularly in high-stakes financial decisions, introduces concerns around interpretability, explainability, and fairness. The book underscored the tension between model performance and regulatory requirements, especially under frameworks that demand transparency in decision-making processes. Drawing on contributions from academics, practitioners, and consultants, the work illustrated case studies that demonstrate practical applications and the complexities faced in real-world implementations. It concluded by asserting the need for balanced innovation—leveraging AI and big data without undermining the ethical and supervisory foundations of credit risk evaluation.

Rhzioual Berrada, Barramou, and Alami (2022) conducted a comprehensive review of AI approaches for credit risk assessment, emphasizing how AI and big data analytics are reshaping the way banks evaluate loan applications and manage credit exposure. The study noted that although traditional banking systems rely on predefined rating frameworks, many fail to fully leverage the vast and continuously growing datasets available. The authors reviewed recent advancements from 2016 to 2021, focusing on key developments in AI-driven credit risk modeling. They categorized the literature based on methods involving feature selection, classification, and prediction, and provided a comparative discussion of supervised, unsupervised, and deep learning techniques. Among the AI algorithms evaluated, support vector machines,

CatBoost, decision trees, and logistic regression emerged as frequently applied and empirically validated methods, showing strong predictive performance in identifying credit defaults. The review highlighted how these technologies enable more accurate, scalable, and faster credit decisions, offering strategic benefits in terms of both operational efficiency and risk mitigation. Importantly, the paper emphasized that AI integration allows banks to transition into more agile and intelligent institutions capable of tailoring services and protecting themselves against financial losses. The authors concluded that continued exploration and implementation of AI techniques are critical for banks aiming to modernize credit assessment frameworks while maintaining robust risk controls.

Shittu (2022) presented a comprehensive review of recent advancements in AI-driven credit risk modeling and their implications for optimizing financial services. The study contextualized the limitations of traditional credit risk models—typically grounded in static data and basic statistical techniques—and highlighted how AI technologies have increasingly supplanted these methods with more dynamic, data-rich alternatives. AI models now incorporate machine learning, big data analytics, and real-time data to provide more accurate and granular assessments of creditworthiness. These innovations allow for deeper insights through the use of alternative data sources, including transaction behaviors and non-traditional credit indicators, thereby expanding credit access to underbanked populations. The paper discussed key AI applications such as natural language processing for sentiment analysis, predictive analytics for estimating default probabilities, and reinforcement learning for dynamically adapting credit strategies. Additionally, the integration of explainable AI (XAI) was noted as an important development, enabling improved transparency and regulatory compliance. The paper emphasized that these models not only enhance operational efficiency and reduce human bias in credit decisions but also support proactive and continuous credit risk monitoring. However, the author acknowledged persistent challenges related to data privacy, algorithmic fairness, infrastructure requirements, and regulatory complexity. Despite these barriers, the study concluded that AI's transformative potential continues to reshape the credit risk landscape, offering opportunities to drive innovation, promote financial inclusion, and enhance institutional resilience across the financial sector.

Sadok, Sakka, and El Maknouzi (2022) conducted a comprehensive review of the integration of AI into bank credit analysis, examining its methodological advantages, practical impacts, and emerging regulatory challenges. The authors highlighted that AI models—when paired with increased computing capabilities and access to big data—enable more nuanced and powerful assessments of creditworthiness by detecting weak signals, complex variable interactions, and non-linear patterns that traditional models often overlook. These capabilities not only improve the predictive accuracy of credit assessments but also facilitate broader financial inclusion by enabling banks to evaluate non-traditional data sources and extend credit to underserved populations. At the macroeconomic level, these improvements contribute positively to financial system efficiency and potentially stimulate economic growth. The paper also explored the socio-economic benefits of AI-enhanced credit analysis, particularly in expanding access to finance among borrowers previously excluded from formal credit markets. However, the authors noted significant limitations, including algorithmic bias, lack of transparency, and concerns about fairness, accountability, and data governance. To address these concerns, the article called for the implementation of forward-looking regulatory frameworks, including the certification of AI algorithms and the data they utilize, to ensure ethical and reliable use of AI in banking practices. The review concluded that while AI presents transformative potential for credit analysis, its deployment must be matched with stringent oversight to safeguard against systemic and social risks.

CONCLUSION

The findings from this literature-based investigation affirm that AI has become a pivotal force in reshaping credit risk assessment frameworks, offering measurable improvements in predictive accuracy, adaptability, and operational efficiency over traditional statistical models. Across diverse empirical settings—from emerging markets to digital lending ecosystems—AI techniques such as support vector machines (SVM), artificial neural networks

(ANN), fuzzy logic systems, and hybrid architectures consistently outperform classical methods like logistic regression, particularly in handling nonlinear relationships, high-dimensional data, and class imbalance. Notably, several studies reveal that AI-enhanced models are not only more accurate but also more capable of incorporating alternative and dynamic data sources, thereby extending the reach of credit assessment to underbanked populations and contexts previously excluded from formal financial systems. However, these gains are accompanied by persistent limitations, particularly surrounding interpretability, algorithmic fairness, and data governance—issues that become more pronounced as AI systems are operationalized in regulated financial environments.

What emerges from this synthesis is the dual imperative to advance technical performance while embedding ethical and practical safeguards into AI-driven credit risk models. Future research must prioritize explainable AI (XAI) techniques and regulatory-aligned validation methods to ensure that model transparency and accountability are not sacrificed for predictive power. Moreover, the success of AI in credit risk management depends not only on algorithmic sophistication but also on institutional readiness—data infrastructure, domain expertise, and governance mechanisms must evolve in tandem to fully leverage AI's capabilities. As financial institutions seek to modernize risk assessment practices, this review underscores the importance of a balanced and context-sensitive adoption strategy: one that integrates cutting-edge AI tools while remaining attentive to systemic risks, ethical concerns, and regulatory expectations. In doing so, AI can transition from a disruptive innovation to a responsible pillar of financial risk governance.

CONFLICT OF INTEREST

No conflict of Interest declared by the author(s.

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