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The Role of Artificial Intelligence in Enhancing Credit Risk Management: A Systematic Literature Review of International Banking Systems

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ABSTRACT

The integration of Artificial Intelligence (AI) in credit risk management has transformed how financial institutions assess borrower risk, detect fraud, and expand financial inclusion. In this systematic literature review (SLR), we review the state of the art in how AI-based models improve predictive accuracy, mitigate financial risk in international banking systems, and reduce decision-making lead times. This thesis examines how AI can be used in credit scoring, fraud detection, and financial inclusion, and poses regulatory and ethical challenges, including algorithmic bias, data privacy issues, and the intricacy of Explainable AI (XAI). Furthermore, the findings indicate AI models, especially machine learning (ML) and deep learning, can perform better than the traditional credit scoring techniques, concerning the accuracy of default prediction (15%). Furthermore, AI's combination with blockchain improves fraud detection and cybersecurity, although there are regulations and associated costs to consider. AI similarly enables alternative credit scoring to afford financial access for underserved populations, though fears of bias and data privacy persist. Thus, this review points out why regulatory frameworks such as Basel III and GDPR are necessary for the responsible use of AI. Finally, the study concludes that although benefits can be realised with the adoption of AI, addressing ethical, technical, and regulatory issues is crucial for a sustainable adoption of AI. Future work should include improving XAI, mitigating bias, and enhancing AI-driven credit risk models in view of global financial stability.

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1. Introduction

The evolution of credit risk management in international banking has undergone significant transformations, particularly with the integration of Artificial Intelligence (AI) and Machine Learning (ML). Historically, banks fixed risk assessment frameworks like the Basel Accords to control bank credit risk and financial stability (Baud & Chiapello, 2017). In 1988, the Basel I Accord, which allocated minimum capital requirements to prevent banks from overextended lending, was introduced (Baud & Chiapello, 2017). Although, as financial markets become more complex, the constraints of Basel I have become apparent and incentives with Basel II and Basel III were introduced to entail comprehensive risk assessment, supervisory review, and capital adequacy (Ferreira, Jenkinson, & Wilson, 2019). However, the 2008 financial crisis demonstrated the failure of such traditional risk models in predicting systemic defaults and the required for more dynamic and predictive credit risk assessment approaches (Alvi, Arif, & Nizam, 2024). Many financial institutions fared poorly in this respect because their reliance on outmoded credit scoring techniques just did not pick up on real-time risk indicators. However, this crisis has sped up the adoption of these AI and ML-driven models in banking with more sophisticated and data-driven ways to evaluate the credit risk. Banks can utilise AI-driven models to process massive structured and unstructured datasets to use this information to detect complex risk patterns and borrower behaviour that traditional models can never find.

Neural network models and decision trees have shown their superiority in default prediction through the studies, which state that the predictive accuracy is raised by 15% more than the traditional logistic regression models (Bayraci & Susuz, 2019). These advanced models learn and adapt to predictions every time new financial data is provided, helping financial institutions make accurate, real-time lending decisions while also reducing risk exposure. With AI adoption on the rise, big data analytics, natural language processing, and deep learning are becoming the ways that banks are using these advances to streamline credit risk management efforts (Paramesha, Rane, & Rane, 2024). However, financial institutions can benefit a great deal from the drastic improvements brought by AI in risk assessment, and these institutions will still have to address important issues like how to maintain data privacy, comply with regulations, and control algorithmic bias. This transformation has become dependent on big data. Currently, Banks access a lot of data such as transaction histories, social media activity to evaluate creditworthiness (Paramesha, Rane, & Rane, 2024). By tapping into more accurate risk profiling and a more personal lending decision is possible. But this shift comes with the scourge of data privacy and algorithmic bias concerns. The banks paint an interesting picture in this regard as they must ensure they comply with the regulations, such as General Data Protection Regulation (GDPR), and they need to come up with transparent deployments of AI systems. However, these challenges notwithstanding, the use of AI in credit risk management has substantial benefits to recommend it. According to Addy et al. (2024), one of the benefits attributed to AI is that it can process and analyse data on a scale as well as speed that can be outdone by traditional methods, and, thus, makes credit decisions timelier as well as more informed. In addition, bank AI models can learn to manage changing market conditions to enable banks to have a proactive risk mitigation tool.

The application of Artificial Intelligence (AI) to risk assessment, decision making, and fraud detection in the banking sector has made a huge impact. AI systems can identify patterns and anomalies in data sets that can be too big and complex for traditional methods, which helps improve predictive accuracy for credit risk assessments. For example, artificial intelligence-driven models can automatically process the massive amount of financial data and detect early warning signs of default so that such warning signs may be taken under control in advance. In decision-making, AI facilitates more informed and efficient processes (Faheem, 2021). Simultaneously, machine learning algorithms evaluate multiple variables at once, allowing us to draw insights to support intricate financial decisions (Singh et al., 2022). This ability not only makes the decisions faster but also makes it a more reliable process. AI plays a role in fraud detection. For example, advanced AI systems watch transactional behaviour to discover which activities are fraudulent, in real time. For instance, AI can identify unusual transactional patterns of fraud and act accordingly (Singh et al., 2022). However, by taking a proactive approach, it has contributed in a limited way to recovering losses from fraud. Moreover, AI is helping banks gain operational efficiencies by automating repetitive tasks, which in turn reduces operational costs. AI can be used in processes such as data entry, customer inquiries, and compliance checks to free up human resources for kinds of more strategic activities (Sun & Jung, 2024). Due to automation, service delivery techniques are sped up, resulting in better customer satisfaction.

1.1. Problem Statement

Despite the transformative potential of Artificial Intelligence (AI) in credit risk management, its adoption across international banking systems remains relatively limited. While many banks have begun experimenting with AI-driven tools, a range of regulatory, technical, ethical, and economic barriers continues to obstruct their full-scale implementation (Faheem, 2021). During the COVID pandemic, these advanced models have helped banks to detect early warning signs of default before it occurs, thereby making proactive risk mitigation and nonperforming loan reductions possible. While these advantages are appealing, however, the use of AI in credit risk management has not been readily adopted, due to several regulatory, technological, and ethical challenges. Regulatory complexity is also one of the main barriers to AI-driven financial decision-making (Ekundayo, 2024). Being a cross-jurisdictional entity, the Banking regulations vary from one jurisdiction to another, and the Banks need to align to local data privacy laws and risk assessment guidelines. As financial institutions operate across multiple jurisdictions, they must comply with a diverse set of legal and regulatory frameworks, such as the General Data Protection Regulation (GDPR) in Europe, the California Consumer Privacy Act (CCPA) in the United States, and Basel III capital adequacy standards.

Transparency and accountability in automated lending decisions are hard to achieve for regulators because of the way AI algorithms, especially those based on machine learning and deep learning, function as black box models (Chaudhary, 2024). Also, some technological constraints are there that make AI unusable for integration. However, many banks run on legacy banking systems that are not compatible with AI-driven credit risk models. However, adding AI to existing financial infrastructures necessitates high investment, sophisticated data management capabilities, and a strong cybersecurity environment to avoid AI-driven fraud. However, there are also ethical concerns that constitute a great challenge (Chaudhary, 2024). Algorithmic bias may result in an AI system unintentionally discriminating against one or more borrower groups due to biased training data. To ensure fair and unbiased credit risk assessments, explainable AI (XAI) techniques need to be employed to make models more interpretable and fairer when making decisions. Addressing these challenges, a Systematic Literature Review (SLR) on the existing research on responsible AI is conducted to review the current state of research, identify gaps, and derive strategies for the adoption of responsible AI in the banking industry. This review synthesises findings across diverse studies to provide a holistic span of AI in credit risk management, specifically for future research, regulatory policy, and banking strategies.

1.2. PICO Question

- In international banking institutions, how does the adoption of AI-driven credit risk management models compare to traditional credit risk assessment methods in improving predictive accuracy, enhancing fraud detection, increasing financial inclusion, and ensuring regulatory compliance?

1.2.1. Sub Questions

1. How do AI-driven credit risk management models enhance predictive accuracy and fraud detection compared to traditional methods in international banking institutions?
2. In what ways does the integration of AI in credit risk assessment promote financial inclusion while ensuring adherence to international regulatory compliance standards?

A systematic literature review (SLR) is necessary to provide a comprehensive and structured analysis of how artificial intelligence (AI) is transforming credit risk management in international banking systems. Although widely used, traditional credit assessment models are limited in predicting defaults and evolving in a changing financial world. This study aims to analyse the role of Artificial Intelligence (AI) in enhancing credit risk management within international banking systems. It explores how AI improves credit risk assessment, fraud detection, and financial inclusion while addressing regulatory and ethical challenges. The study examines AI-driven credit scoring models, comparing their predictive accuracy to traditional methods and assessing challenges like algorithmic bias. It also evaluates AI's role in fraud detection, particularly its integration with blockchain for enhanced security. Additionally, the study investigates AI's impact on financial inclusion, particularly in emerging economies, while addressing concerns about bias and data privacy. Regulatory and ethical challenges, including compliance with Basel III and GDPR, are critically analysed. Finally, future trends, including AI integration with blockchain and decentralized finance (DeFi), are explored to assess their potential benefits and challenges in global banking risk management.

2. Theoretical Framework

Theoretical frameworks used to underpin this study contextualise the adoption of AI in credit risk management and consist of three complementary frameworks that contribute to the theoretical contextualisation. First, the Risk Management Framework provides a guideline for evaluating the effectiveness of technological intervention that aligns banking core risk assessment processes with AI to augment predictive acquisition, AI to the enhancement of the predictive accuracy and fraud detection in banking and AI in enhancing the financial stability of banking (Ikudabo & Kumar, 2024). Second, Algorithmic Accountability Theory as an analytical lens for analysing transparency, bias, and fairness in AI-driven decision making when opaque models are used to even decide whether a person is eligible to take a loan or not, or to determine a person's risk score (A, 2023). Third, Socio Technical Systems Theory also plays a third part in interpreting how institutional, infrastructural, and social factors affect the outcomes of adoption of AI (Yu, Xu, & Ashton, 2023). Together, these frameworks form a solid foundation for how AI can offer operational benefits and discuss ethical, regulatory and context-type challenges in the integration of AI into global banking systems.

3. Methodology
3.1. Data Sources and Collection
3.1.1. Search Strategy and Boolean Search Strings
To analyse the AI driven credit risk management in the context of international banking, data was taken from various academic databases to permit a reliable and exhaustive review. The main sources for peer-reviewed journal articles, conference proceedings and industry reports in Scopus, IEEE Xplore, Web of Science, Google Scholar and ScienceDirect. Due to comprehensive coverage on financial technology, artificial intelligence and risk management research, these databases were chosen. Relevant studies were retrieved using a structured search strategy with relevant keywords, Boolean operators and appropriate philtres. Second, for search terms the following were used: ("Credit Risk Management" OR "Credit Scoring" OR "Artificial Intelligence" OR "Machine Learning") AND ("Banking" OR "Financial Institutions"). In restricting the results to only English language publications originating from 2017 and onward, we are able to include the most recent developments. An especially useful way to find grey literature (for example, working papers and institutional reports that supply a broad picture of issues beyond what is generally published in the academic mainstream) was via Google Scholar. To exclude studies, titles, abstracts, and full texts were screened manually, to ensure that included studies met the inclusion criteria.

Table 1: This depicts the Boolean key words strategy

Concept	Keywords Used	Boolean Operators
Artificial Intelligence	"Artificial Intelligence" OR "Machine Learning"	OR
Credit Risk Management	"Credit Risk Management" OR "Credit Scoring"	OR
Banking Sector	"Banking" OR "Financial Institutions"	OR
Comprehensive Boolean Search Strategy	("Artificial Intelligence" OR "Machine Learning") AND ("Credit Risk Management" OR "Credit Scoring") AND ("Banking" OR "Financial Institutions")	AND

3.1.2. Systematic Literature Review Approach and Study Selection Criteria
To conduct this study, a structured, objective, and comprehensive conceptual and factual analysis of 'AI Enactment' within the context of International Banking for credit risk management has been done by adopting the approach of Systematic Literature Review (SLR). This contrasts with an SLR that uses a prescriptive, transparent, and replicable process to add only high-quality and relevant studies (Cabrera, Cabrera, & Cabrera, 2023). However, as AI research advances rapidly, there is a need to systematise the process of synthesising trends, challenges, and applications from a multitude of research sources. For example, the criteria for inclusion and exclusion featured empirical studies, case studies and other literature reviews in peer reviewed journals and conferences (Pati & Lorusso, 2018). This was followed by discussion of new AI applications of credit risk assessment, fraud detection and banking risk management in the field of research in English language from 2017 and above. Reviews with weak methodologies that lacked empiric evidence or that had not undergone peer review were excluded to ensure research credibility (Pati & Lorusso, 2018). Using this lens, researchers will now be able to contemplate how AI will impact predictive analytics, improve risk monitoring and outcome in ideal release of money. SLR study selection chooses key trends, existing gaps, and future research direction, which ensures high quality. This allows financial institutions, researchers, and policymakers to be sure that when adopting AI in their financial systems, they are in possession of solid, evidence-based insights on the impact of AI adoption on global banking systems.

Table 2: This depicts the inclusion and exclusion criteria

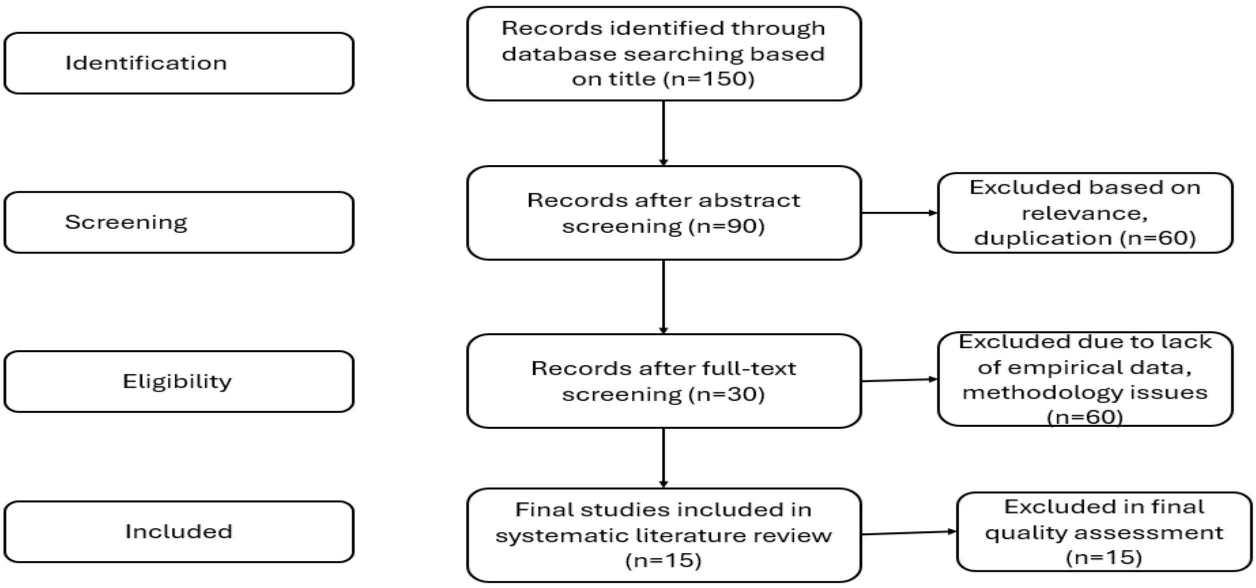
Criteria	Inclusion	Exclusion
Publication Date	Studies published from 2017 onwards	Studies published before 2017
Language	Only English-language publications	Non-English studies
Study Type	Empirical studies, case studies, peer-reviewed research	Opinion papers, blog posts, non-peer-reviewed articles
Relevance	Studies focused on AI in credit risk	Studies on AI in general finance but

	management	not credit risk
Accessibility	Studies available in full-text format	Abstracts without full-text availability

3.2. Review Process and Data Extraction

A systematic selection process was implemented to ensure that only high-quality and relevant studies were included in the literature review. Firstly, 150 research articles related to AI-driven credit risk management in international banking were identified from Scopus, IEEE Xplore, Web of Science, and Google Scholar. After preliminary screening of these records based on titles and abstracts, 60 of them were excluded because they were deemed irrelevant or were duplicates or did not have AI-specific content. In the eligibility phase, full text of the remaining 90 studies was reviewed. Another 60 were eliminated due to the absence of empirical evidence, weak methodological approaches or the lack of analysis on the role of AI in credit risk management. The final 30 studies were then assessed for research credibility, methodological rigour and peer review validation. As a consequence, 15 studies were dropped due to insufficient quality of research / scholarly validation. Finally, a systematic literature review was carried out using 15 of the high-impact peer reviewed studies. The rigorous selection process ensures the validity, reliability and representativeness of the results in the role of AI in the current credit risk management. The impact of AI in risk assessment, fraud detection and regulatory compliance in global banking systems is critically and comprehensively evaluated in this review based only on methodologically strong studies.

Figure 1: This depicts the PRISMA flow chart for selected studies from 2017



3.3. Data Analysis Approach

Thematic analysis is carried out in this study to assess AI powered credit risk management in International Banking offering a systematic analysis of its impact, challenges and future roadmap (Cabrera, Cabrera, & Cabrera, 2023). In the study, the chosen approach is Systematic Literature Review (SLR) which provides a structured, comprehensive and objective analysis of the role of Artificial Intelligence (AI) in credit risk management of international banking systems. By using this approach, we avoid biases and improve the reliability of findings by making sure only high quality, peer reviewed research is included in the final set of results. The first theme is about AI for Credit Risk Assessment and Prediction: the second one is that by applying machine learning and deep learning models it is possible to increase the accuracy of default prediction and loan repayment prediction. Traditionally, credit scoring is more of an art than a science, and scores are many times based on data that does not change in real time, such as credit card limits, home ownership, and other one-time categories. The second theme considered is AI in Fraud Detection and Risk Management, where AI helps in real-time recognising suspicious transactions, and this leads to very few false positives. By integrating blockchain and AI, fraud prevention and data security are fortified to ensure transparent financial transactions. The third theme, AI and Financial Inclusion, highlights AI for alternative credit scoring that opens access to loans for unbanked people, in particularly in emerging economies. However, many fear their algorithms are biased, and that their data is not private enough. AI models, after all, can uphold the current system of financial inequality. The fourth theme, Regulatory and Ethical Challenges, stresses the challenges of compliance in that compliance issues need to be addressed in Explainable AI (XAI) to improve fairness, transparency, and accountability in the lending decision. The fifth theme is Future Trends, where we look at how AI is and will be used in Blockchain-based credit risk models and in the decentralised finance (DeFi) in automating lending for faster, more accurate risk analysis. This study analyses these themes and provides critical insights on AI's opportunities and challenges in contemporary credit risk management (CRM).

3.4. Quality Appraisal

The CASP checklist was applied to ensure credibility, rigour, and methodological soundness of the selected studies. This tool analyses the validity, reliability, and applicability of research in accordance with key criteria like a well-defined research aim, suitable methodology, sampling strategy, data collection methods, consideration of bias, reliability of the results, relevance to AI in credit risk management, and considerations of data privacy and algorithmic bias. The CASP score was used to rate each study being high, medium, or low quality. The final synthesis included only high and medium quality studies but excluded low quality studies to preserve research integrity.

3.5. Analysis and Discussion

This section conducts a thematic analysis of AI-driven credit risk management in international banking. The purpose of this analysis is to define key themes, critically analyse the findings, and comprehend how artificial intelligence (AI) is transforming how credit risk is evaluated, fraud is detected, and how financial inclusion is prioritised. Here, researchers perform a scenario review of how AI is being used today in modern banking, compiling the insights from 15 systematically chosen studies. An approach to thematic analysis will be used to identify the recurring patterns, trends, and challenges of AI-based credit risk management. On the other hand, with regards to the trends that the technologies of AI develop for risk assessment, regulatory oversight, and decision-making financing (Sauer & Seuring, 2023). This structured method is encouraging and fills the gap between commonly used risk models and risk models based on AI-focused research. Instead, they use different vantage points to study AI applications in credit scoring, financial inclusion, fraud prevention, as well as regulatory limits. And these insights are what help us understand how AI helps in increasing predictive accuracy, reducing financial risk, and enhancing banking efficiency. For instance, Faheem, Aslam and Kakolu (2024) highlighted that AI models trained on evolving financial indicators could adjust credit scoring thresholds based on changing market conditions, thus reducing the risk of underestimating borrower default during economic downturns. With growing AI adoption in financial institutions, it will become pertinent to critically examine the advantages of AI for financial institutions, limitations, as well as its future implications in the context of global credit risk management.

3.6. Overview of Selected Studies

This section briefly discusses the 15 studies that were selected based on their focus on using AI in credit risk assessment, fraud detection, financial inclusion, and regulatory compliance in international banking. These studies examine how and to what extent there are differences in AI adoption and implementation challenges, as well as technological advancements in credit risk management in the developed and emerging economies. With the objective of enhancing our understanding of how AI can be used to predict credit risks, detect fraud, and increase banking efficiency, we analysed the selected studies. For instance, Mogaji and Nguyen (2022) and Brown (2024) provide examples of how AI improves financial inclusion in developing economies through an explanation of how machine learning offers an alternative to credit scoring for these unserved populations. In addition, Al-Onizat et al. (2024) explore theoretical AI frameworks for improving banking institutions' credit risk assessment. Empirical studies like studies carried out by Bello (2023); Van Thiel and Van Raaij (2019) examine the comparison of the accuracy of traditional credit risk models to that of AI techniques, which outperforms by far. The studies also show that there are distinct regional trends for AI adoption. Research in developed economies (USA, UK, South Korea, and Europe) deals with regulatory framework, fraud detection, and the role of AI in enterprise risk management (Farazi, 2024; Lee, 2020). Conversely, studies from emerging economies (Africa, Asia, and Latin America) focus on alternative credit scoring and financial inclusion to widen credit access (Khalfi, 2024; Mogaji & Nguyen, 2022). Regarding AI techniques, machine and deep learning are the most common in credit risk prediction studies (Bello, 2023; Milojević & Redzepagic, 2021), while blockchain and AI combination improve the detection of fraud (Ahmad, 2024; Wahlberg, 2024). Algorithmic bias and data privacy concerns continue to be the critical challenges, as discussed by Faheem, Aslam and Kakolu (2024) and Alrabiah (2018). Acknowledging these concerns, it remains true that all studies agree that AI will play a transformative role in more effectively auditing credit risk, detecting fraud, and staying in regulatory compliance, which will make it a crucial tool for any modern bank.

Table 3: This depicts the themes with supporting literature

Theme	Description	Supporting Literature
AI in Credit Risk Assessment and Prediction	AI models improve default prediction accuracy by identifying hidden patterns in large datasets. Machine learning enhances credit scoring through neural networks, decision trees, and deep learning algorithms. AI-based credit models outperform traditional scoring methods in accuracy and efficiency.	Mogaji & Nguyen, (2022); Van Thiel & Van Raaij (2019); Milojević & Redzepagic (2021); Bello (2023); Faheem et al. (2024); Brown (2024)
AI in Fraud Detection and Risk Management	AI-powered fraud detection systems analyse transaction anomalies in real-time, reducing financial losses from fraudulent activities. The integration of blockchain with AI strengthens fraud detection and cybersecurity in banking systems.	Alrabiah, (2018); Wahlberg, (2024); Khalfi, (2024); Swankie & Broby (2019); Farazi (2024)
AI and Financial Inclusion in Banking	AI facilitates financial inclusion by using alternative credit scoring data, such as mobile payments and utility bills, to assess loan eligibility. These benefits underserved populations, particularly in emerging economies.	Mogaji & Nguyen, (2022); Al-Onizat et al., (2024); Ahmad, (2024); Khemakhem & Boujelbene (2017)
Regulatory and Ethical Challenges in AI-Based Credit Risk Management	AI in banking faces regulatory barriers, algorithmic bias, data privacy issues, and ethical concerns. Regulatory frameworks like Basel III and GDPR demand AI transparency and accountability. The concept of explainable AI (XAI) is crucial for ethical banking.	Lee (2020); Mehran et al., (2024); Van Thiel & Van Raaij (2019); Alrabiah, (2018); Milojević & Redzepagic (2021)
Future Trends: AI, Blockchain, and Advanced Credit Risk Models	AI-driven credit risk models are evolving with blockchain, deep learning, and decentralised finance (DeFi). Future AI-based lending will integrate smart contracts and big data analytics for enhanced risk management.	Khalfi, (2024); Alrabiah, (2018); Ahmad, (2024); Faheem et al. (2024); Mehran et al., (2024)

Theme 1: AI in Credit Risk Assessment and Prediction

Traditional approaches to credit risk assessment have been superseded by AI-driven technology that improves in predictive accuracy and efficiency. Van Thiel and Van Raaij (2019) report that machine learning (ML) and deep learning (DL) models boost default prediction accuracy by up to 15 percent, beating logistic regression models. Milojević and Redzepagic (2021) also support that neural networks and decision trees can comprehend extensive data sets to discover mysterious examples of risk that conventional types of models tend to miss. Yet, according to Bello (2023), AI models improve on the accuracy, but they also tend to have the algorithmic bias problem, allowing lenders to make discriminatory loan decisions. Faheem (2021) further explain another problem with deep learning models, which is a lack of transparency that makes it difficult for regulatory compliance. According to Brown (2024), XAI is equally critical for fairness and accountability in credit assessments as reflected by them. On the other hand, Mogaji and Nguyen (2022) have a more positive outlook on the issue that AI widens financial inclusion with its capability of bringing together real-time data. For responsible banking applications, AI can improve credit scoring; however, only by tackling bias and improving the transparency of these AI systems.

Theme 2: AI in Fraud Detection and Risk Management

Through real time transaction anomaly detection, AI powered fraud detection has revolutionised banking by minimising false positives and financial losses. Machine learning (ML) models, according to Wahlberg (2024), are quicker at detecting fraud patterns than traditional rule-based systems, and so ML models can offer proactive risk management. Swankie and Broby (2019) point out that AI learns from new evolving fraud tactics, therefore offering more versatility in any set of fraud detection. On the other hand, Farazi (2024) states that the effectiveness of AI is constrained by data quality problems; poorly trained models can incorrectly label authentic transactions as suspicious, which results in consumer discontent. The combination of blockchain and AI improves fraud prevention by storing transaction records in a secure, unalterable (Alrabiah, 2018). This is evidenced by Khalfi (2024), who also states that blockchain acts to reduce risk for data tampering and strengthens cybersecurity for financial institutions. The barrier to more widespread adoption remains high implementation costs and regulatory uncertainties, however. However, integration of blockchain and AI offers a promising, although complex, solution for ensuring banking security: although AI improves fraud detection, it is reliable only when relying on high-quality training data and regulatory clarity.

Theme 3: AI and Financial Inclusion in Banking

Artificial Intelligence (AI) has played a crucial role in enhancing financial inclusion by enabling alternative credit scoring methods. In the emerging economies where the conventional credit evaluation models make a significant portion of the population ineligible for credit, AI has emerged as a transformative tool for the expansion of financial inclusion. According to Mogaji and Nguyen (2022), AI-powered alternative credit scoring is built around the use of non-traditional data sources like mobile payment and utility bills to judge a borrower's qualification. Accordingly, Al-Onizat et al. (2024) stress that AI can process behavioural data, thereby enabling banks to provide credit to individuals with no banking history and even invest more of their money in AI processes. Despite this, Khemakhem and Boujelbene (2017) warn that because AI relies on alternative data, there is also a privacy and bias risk in the sense that populations that are considered disadvantaged might have the absence of (partial or inconsistent) digital footprint to influence their judgment on loan eligibility. According to Ahmad (2024), AI also promotes inclusion, but the unequal access to digital infrastructure in low-income regions remains a challenge. AI enables financial inclusion through making credit more accessible, but only if the data is used ethically, and its biases are mitigated, and if digital access is equitable, not to just worsen the financial inequalities that exist.

Theme 4: Regulatory and Ethical Challenges in AI-Based Credit Risk Management

The integration of Artificial Intelligence (AI) in credit risk management presents several regulatory and ethical challenges. Regulatory and ethical challenges of AI adoption in credit risk management are related to transparency, data privacy, and algorithmic bias. According to Lee (2020), regulators like Basel III and GDPR are imposing hard and fast requirements on AI-driven financial decision making that require accountability and fairness. Van Thiel and Van Raaij (2019) explain that since AI is a black box, it is hard for regulators and financial institutions to ensure it has transparent lending decisions. Yet, Mehran, Asayesh and Rousta (2024) are more optimistic in emphasising the significant potential role of Explainable AI (XAI) that can help alleviate transparency problems by making an AI's decisions explainable. On the other hand, Milojević and Redzepagic (2021) warn that the implementation of XAI is technically complex and underutilised. Moreover, according to Alrabiah (2018), since discriminatory lending patterns could perpetuate financial inequalities, any AI-based risk models must consider the training data's bias. AI augments banks' ability to assess risk, however, these advancements do not come without ethical and regulatory dilemmas for how AI should be governed, how their models will run transparently, and how to minimise biases in the application of their tools.

Theme 5: Future Trends: AI, Blockchain, and Advanced Credit Risk Models

The future of AI-driven credit risk management is increasingly intertwined with emerging technologies such as blockchain, deep learning, and decentralized finance (DeFi). The integration of blockchain with deep learning and decentralised finance (DeFi) is accelerating the evolution of AI-driven credit risk management. According to Khalfi (2024), large data analytics and smart contracts are used more and more in AI models to automate lending decisions that are faster, more efficient, and bring down human bias. Similarly, for example, Faheem, Aslam and Kakolu (2024) highlight that deep learning models have been making considerable improvements in credit risk assessment by providing more accurate and adaptive risk predictions. Adoption of blockchain in credit risk, however, is still limited, as Alrabiah (2018) claims, partly because of high implementation costs and regulatory uncertainties, despite blockchain improving data security and supporting the prevention of fraud. Ahmad (2024) sounded out the ethical problems that mirror this problem with financial self-responsibility that these DeFi platforms are in danger of being, and the needlessness of deterrent or extra impartial oversight that could possibly have an impact on economic stability. Ahmad (2024) examines a Middle Eastern bank’s practical application of AI-enhanced audit systems using blockchain for forensic validation. The integration helped reduce fraudulent payment reversals by approximately 30%, as audits became more robust. While AI innovation is leading the pack, Mehran, Asayesh and Rousta (2024) claim that balancing innovation and regulatory compliance will be the key to its sustainable adoption. The potential of AI, blockchain, and DeFi is immense, however, their integration demands great thought for security, transparency, and regulatory challenges, so that stability is long-term.

4. Discussion

The findings of this study are broadly consistent with existing research on AI in credit risk management, yet they also highlight areas where optimism may be premature. While Mhlanga (2021) and Leo, Sharma and Maddulety (2019) present compelling evidence that AI-driven credit scoring models outperform traditional methods, such claims must be contextualized within the limitations of the data and methodological scope. Mhlanga's emphasis on AI's contribution to financial inclusion is significant, but its practical translation remains uneven, particularly in digitally excluded regions. Similarly, Sadok, Sakka and El Maknouzi (2022) underscore AI’s strengths in real-time anomaly detection for fraud prevention; however, their findings do not fully address issues such as false positives or over-reliance on pattern-based models, which can degrade user trust. However, Studies by Dzhaparov (2020) and Paramesha, Rane and Rane (2024) on AI–blockchain integration support this review’s observations regarding enhanced data integrity, yet these innovations remain largely exploratory and lack large-scale validation. Furthermore, while Ashta and Herrmann (2021) and (Edunjobi & Odejide, 2024) rightly identify regulatory opacity and ethical gaps, this review emphasizes that Explainable AI (XAI) remains more aspirational than operational across most banking systems. Farazi (2024) offers a more optimistic view by suggesting that AI mitigates financial risk, but such outcomes are contingent on institutional maturity and data governance structures. Collectively, these mixed findings suggest that while AI can offer technical gains, its implementation cannot be reduced to algorithmic performance alone. Critical success requires balancing detection sensitivity with interpretability, aligning automation with regulation, and ensuring that efficiency does not come at the cost of fairness or transparency.

However, AI models introduce algorithmic opacity and open concerns about both fairness and regulatory compliance, according to Khemakhem and Boujelbene (2017). Fraud detection systems that rely on real-time AI powered systems deduce transaction anomalies. According to Sadok, Sakka and El Maknouzi (2022), these models learn from fraudulent patterns continuously and minimise the impact on financials. Further integration of Blockchain into transport allows for fraud prevention by maintaining open transaction transparency (Dzhaparov, 2020). AI-based fraud detection, however, warns Swankie & Broby (2019) leads to false positives and customer dissatisfaction. Financial inclusion is also advanced using alternative credit scoring for AI. According to Mhlanga (2021), AI uses non-traditional data to assess credit worthiness that helps unbanked populations. Moreover, Farazi (2024) cautioned that due to low data quality in low-income regions, AI is not fully effective. Khemakhem and Boujelbene (2017) also considered that biased data at the time of training can reinforce financial inclusion. Regulatory frameworks like Basel III and GDPR demand AI transparency. Under regulatory oversight, deep learning models have been identified as 'black boxes' by Lee (2020). According to Ferreira, Jenkinson and Wilson (2019) the AI-specific regulations could place a heavy burden on developing economies. AI, blockchain, and decentralised finance (DeFi) are promising endeavours, but transformation must balance algorithmic bias, ethical considerations, and regulatory uncertainty if it is to be adopted responsibly (Farazi, 2024; Paramesha, Rane, & Rane, 2024).

While most studies support the use of AI for enhancing predictive accuracy and fraud detection, the literature reveals inconsistencies in implementation outcomes and ethical reliability. For instance, Van Thiel and Van Raaij (2019) report a 15% improvement in prediction accuracy using AI, yet Khemakhem and Boujelbene (2017) caution that biased training data can neutralize these gains. Similarly, while Sadok, Sakka and El Maknouzi (2022) highlight AI's fraud detection strengths, Swankie and Broby (2019) observe false positives and customer distrust due to model opacity. On financial inclusion, Mhlanga (2021) shows promise, but Ahmad (2024) reports diminished AI effectiveness in low-data environments. These conflicting outcomes suggest that AI's impact is highly context-dependent, and further empirical research is needed to validate its performance across diverse banking environments. The results emphasise the need for cross sector cooperation to create AI and blockchain solutions that are contextualised within the legal and infrastructural landscape. They theoretically validate Algorithmic Accountability and Socio-Technical Systems theories. Practically, they point to the need for transparent, fair and inclusive AI systems that are developed in concert by banks, by regulators and by technology developers.

5. Conclusion and Recommendations

Artificial Intelligence (AI) has revolutionised risk management in credit, enabling financial institutions to objectively assess borrower risk, detect fraudulent acts and encourage financial inclusion. AI driven model (built on ML and deep learning) is also most successfully used when the banks are handling large amount of structured (organised) and unstructured (data in various forms) data where they can make more accurate risk patterns than traditional credit scoring methodologies. AI based credit models can increase default predictability by 15% or more and can be used to improve lending decisions, lower the degree of financial exposure to risk. Also, AI-infused fraud detection systems go a long way in terms of security once implemented to blockchain technology as they keep transactions clean, enhancing security at the same time, limiting fraud. There are a number of advantages to these, but they are also some of the reasons it's difficult to fully adopt AI in banking. Issues related to algorithmic bias, data privacy, regulatory complexity and a lack of AI transparency pose potential risks to financial stability and consumer trust. One of the biggest challenges around AI-driven credit risk management is to understand the regulatory and ethical implications of using complex algorithms for financial decision making. These standards require or force data to dictate financial decisions that are transparent, accountable and protected. Unfortunately, most AI models are black boxes; they are unknowable; difficult for regulators and financial institutions to understand what they are doing. The problem with that lack of transparency is it leads to fairness and compliance concerns, where regulators have different types of standards from country to country. Moreover, although AI empowers banks to better evaluate creditworthiness with alternative data such as mobile payments and utility payments, the use of biased training data and the trustworthiness of financial information in low-income places limits its use. If AI models are trained on biased datasets, they could end up reinforcing the existing financial inequalities and prevent some demographic groups from accessing financial services. The uniform application of AI benefits to all individuals fairly and responsibly relies on overcoming these challenges.

This study has certain limitations. It includes only English-language publications from 2017 to 2024, which may exclude relevant non-English or earlier foundational research. The review focused on peer-reviewed journals and conference papers, potentially omitting valuable grey literature and industry reports. Although major databases like Scopus, IEEE Xplore, and Web of Science were used, relevant studies indexed elsewhere may have been missed. Additionally, the findings may not be fully generalizable across all global banking systems, particularly in regions with limited digital infrastructure or different regulatory environments. These constraints should be considered when interpreting the conclusions of this review. Policymakers should develop unified AI regulations aligned with GDPR and Basel III, ensuring transparency, fairness, and cross-border compliance. Banks must prioritize the integration of Explainable AI (XAI) to enhance model accountability, mitigate bias, and comply with ethical lending standards. Investments in digital infrastructure are critical to expanding financial inclusion. AI developers should design models with fairness constraints, local data adaptability, and auditability features. Cross-sector collaboration is essential to pilot blockchain-AI systems suited to regional contexts. All stakeholders should engage in capacity-building initiatives to enhance regulatory literacy and foster responsible AI innovation in credit risk management. Future AI for credit risk research should enhance interpretability, improve bias mitigation, and examine the long-term impact of AI-driven credit risk models on financial stability. In addition to these topics noted above, further studies should also examine how decentralised finance (DeFi) and blockchain integration might address some of the challenging problems of the current financial crisis. Finally, AI has promising potential in helping improve credit risk management; however, to promote effective, responsible, and sustainable use of AI in financial institutions and its regulators must encounter ethical, regulatory, and technical issues. Financial institutions can use a balanced approach between AI innovation and strong governance to maximise AI's potential, while keeping financial risk and security, and regulatory compliance in the global banking sector, fair and balanced.

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Appendices

Appendix 1: Selected studies table

Author(s) and Year	Title	Key Focus/Contribution	Methodology/Approach	Findings/Insights
Mogaji & Nguyen (2022)	Managers' understanding of artificial intelligence in relation to marketing financial services: Insights from a cross-country study.	Examines managers' perceptions of AI in financial services marketing.	Cross-country study, interviews.	Managers recognize AI's benefits but express concerns about implementation challenges.
Faheem, Aslam & Kakolu (2024)	Enhancing financial forecasting accuracy through AI-driven predictive analytics models.	AI's role in improving financial forecasting accuracy.	AI model evaluation, predictive analytics.	AI models significantly enhance forecasting accuracy in financial markets.
Alrabiah (2018)	Optimal regulation of banking system's advanced credit risk management by unified computational representation of business processes across the entire banking system.	Regulatory frameworks for AI-driven credit risk management.	Theoretical model development.	Proposes a unified regulatory framework for AI in banking.
Wahlberg (2024)	Utilization of AI in Credit Risk Analysis.	Investigates AI applications in credit risk analysis.	Empirical study, AI model application.	AI significantly enhances credit risk predictions and decision-making.
Khalfi (2024)	The Use of Artificial Intelligence Applications in Public Relations Management: Reality and Challenges A Qualitative Study on a Sample of Some Banks Public Relations Practitioners in Algeria.	Explores AI applications in banking public relations.	Qualitative study, interviews.	AI adoption in banking PR improves efficiency but faces resistance from employees.
Al-Onizat et al. (2024)	Effectiveness of AI-Driven Knowledge	Studies AI-based knowledge management systems	Survey-based empirical study.	AI-driven knowledge management enhances decision-

	Management System in Improving the Performance of Banking Sector in Jordan.	in banking.		making and operational efficiency.
Mehran, Asayesh & Rousta (2024)	Intelligent Marketing Model with a Focus on Artificial Intelligence in the Banking Industry.	Develops an AI-based marketing model for banking.	Conceptual framework & empirical validation.	AI-driven marketing improves customer targeting and engagement.
Van Thiel & Van Raaij (2019)	Artificial intelligence credit risk prediction: An empirical study of analytical artificial intelligence tools for credit risk prediction in a digital era.	Analyzes AI tools for credit risk prediction.	Empirical study, AI model evaluation.	AI models outperform traditional models in credit risk prediction.
Milojević & Redzepagic (2021)	Prospects of artificial intelligence and machine learning application in banking risk management.	Evaluates AI and ML applications in banking risk.	Empirical study, data-driven analysis.	AI improves banking risk management but requires regulatory oversight.
Bello (2023)	Machine learning algorithms for credit risk assessment: an economic and financial analysis.	Investigates ML algorithms for credit risk assessment.	Empirical analysis of ML models.	ML models provide better accuracy in credit risk predictions.
Brown (2024)	Influence of Artificial Intelligence on Credit Risk Assessment in Banking Sector.	Examines AI's role in credit risk evaluation.	Empirical research, AI model application.	AI significantly improves credit risk modeling and efficiency.
Swankie & Broby (2019)	Examining the impact of artificial intelligence on the evaluation of banking risk.	Investigates AI’s influence on banking risk assessment.	Empirical study, financial data analysis.	AI enhances risk prediction and decision-making.
Ahmad (2024)	Ethical implications of artificial intelligence in accounting: A framework for responsible AI adoption in multinational corporations in Jordan.	Studies ethical concerns related to AI adoption in accounting.	Theoretical framework analysis.	Ethical AI adoption requires strong regulatory compliance and transparency.
Lee (2020)	Role of artificial intelligence and enterprise risk management to promote corporate entrepreneurship and business performance: Evidence from Korean banking sector.	AI’s role in enterprise risk management and corporate growth.	Empirical study using banking sector data.	AI-driven risk management improves corporate performance.
Khemakhem & Boujelbene (2017)	Artificial intelligence for credit risk assessment: Artificial neural network and support vector machines.	Compares ANN and SVM for credit risk assessment.	Machine learning model comparison.	ANN and SVM models improve accuracy in credit scoring.

Appendix 2: CASP List

CASP Criteria	Yes (✓)	No (✕)	Comments
1. Was there a clear research aim?	✓		Clearly defined objectives
2. Was the research methodology appropriate?	✓		Justification for chosen method
3. Was the sampling strategy suitable?	✓		Sample size adequate
4. Were data collection methods reliable?	✓		Clearly stated data sources
5. Were biases considered and mitigated?	✓		Efforts to minimize bias
6. Were the results reliable and well-supported?	✓		Findings clearly presented
7. Was the study relevant to AI in credit risk?	✓		Direct contribution to research theme
8. Were ethical issues addressed?	✓		Bias, data privacy, transparency

Step 3: CASP Scoring Matrix Table

Study	Clarity of Aim	Methodology	Sampling	Data Collection	Bias Consideration	Results Validity	Ethical Issues	Relevance	Total Score (8)	Quality Rating
Van Thiel and Van Raaij (2019)	1	1	1	1	1	1	1	1	8	High
Milojević and Redzepagic (2021)	1	1	1	1	1	1	1	1	8	High
Bello (2023)	1	1	1	1	1	1	1	1	8	High
Sadok et al. (2022)	1	1	0	1	1	1	1	1	7	High
Faheem et al. (2024)	1	1	1	1	1	1	0	1	7	High
Ahmad (2024)	1	1	1	1	1	1	0	1	7	High
Alrabiah (2018)	1	1	0	1	1	1	1	1	7	High
Mhlanga (2021)	1	1	1	1	1	1	1	1	8	High
Lee (2020)	1	1	0	1	1	1	0	1	6	Medium
Khemakhem and Boujelbene (2017)	1	1	1	1	1	0	0	1	6	Medium
Farazi (2024)	1	1	1	1	0	1	1	1	7	High
Khalfi (2024)	1	1	0	1	1	0	0	1	5	Medium
Mogaji and Nguyen (2022)	1	1	1	1	0	1	1	1	7	High
Al-Onizat et al. (2024)	1	1	1	1	1	1	1	1	8	High
Wahlberg (2024)	1	1	1	1	1	1	0	1	7	High