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COMPARATIVE ANALYSIS OF ARTIFICIAL INTELLIGENCE METHODS AND TRADITIONAL CREDIT RISK MODELS: AN EXPLORATORY QUALITATIVE REVIEW

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Abstract:

Artificial intelligence (AI) and machine learning (ML) methods are revolutionizing the credit risk modelling. Traditional statistical methods which have been around for a long time are replaced with AI-based models. Although AI models provide superior predictive performance, their adoption in regulated financial sector is seen with caution. Financial sector regulatory requirements regarding interpretability, stability, fairness, and governance of credit risk models are one of the big challenges to AI & ML adoption. This study is based on an exploratory qualitative review to perform a comparative analysis of AI models and traditional credit risk models. This study examines relevant academic literature, publications, and industry reports. Five key points have been identified as a result of this study: (1) AI models are better than traditional models in terms of performance; (2) explainability and auditability is still the biggest challenge with AI adoption; (3) traditional models are more reliable yet they may not be efficient; (4) regulatory requirements impact model selection; and (5) hybrid modelling approaches are a promising middle ground. The article suggests a multidimensional theoretical framework for assessing credit risk models and emphasizes prospective research avenues in hybrid modelling, fairness-aware AI, and real-time risk monitoring.

Keyword:

Artificial Intelligence, Machine Learning, Hybrid Modelling, Fairness, Auditability, Black-Box, Bias, SLR, Behavioural Patterns, PICO, Ethical Implications.



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Introduction

Credit risk modelling is at the heart of decisions making process about lending, allocating capital, and compliance the rules and regulations. Traditional models have been in place for a long time and are seen as reliable as they are clear, stable, and in line with Basel regulatory requirements (Sousa et al., 2016). AI and ML models have capability to process nonlinear relationships and complex customer behaviours. Traditional models have been in place for decades due to auditability and transparency (Umeorah et al., 2024).

Though AI models provide enhanced processing speed, it is challenging to adopt them in credit risk modelling. Regulatory requirements on AI revolve around fairness, visibility and auditability. On the contrary, financial institutions are struggling to find the right balance between governance and operational feasibility (Alonso Robisco et al., 2022; Masud et al., 2023). The shift toward AI enabled credit evaluation demands a rigorous examination of the predictive decisions making model of AI and the requirements for regulatory compliance. Traditional credit scoring frameworks, have been subject to structured governance under Basel standards, whereas AI deep learning models introduce a "black-box" which challenges the auditability requirements (Esther & Abayomi, 2024; Kowsar et al., 2023). Regulatory bodies are increasingly emphasizing on the requirement of explainable and auditable AI. This ensures that decisions made through AI models are interpretable and transparent for stakeholders. Equal Credit Opportunity Act, USA makes it illegal for lenders to discriminate the applicant unfairly based on race, sex, age or marital status. It makes it imperative for AI models to be interpretable to the stakeholders including the lender and the applicant (Ogbuefi et al., 2023). Furthermore, regulatory guidance such as EU AI Act, GDPR have clauses to ensure that financial institutions implement controls for AI robustness and consistency, such as pre-processing bias mitigation and post-processing calibration, to ensure that outcomes from the processing match the expectations (Abugri & Colley, 2026). These legal requirements ensure that financial institutions have justifications for an outcome of a credit assessment performed through AI model under frameworks such as the GDPR, Fair Credit Reporting Act, and EU AI Act.

Earlier studies have stressed the importance of systematic literature reviews (SLR) to explore the fragmented evidence base. (Shi et al., 2022) performed a PRISMA-based review combining statistical, machine-learning, and deep-machine learning methods with persistent challenges including data imbalance, dataset inconsistency transparency issues of the studies themselves followed by limited applications. Similarly, (Roy & Vasa, 2024) also explored AI/machine learning in fintech versus traditional models in FinTech. Focus of study conducted by (Roy & Vasa, 2024) was on credit assessment procedures and evaluation of AI models' accuracy efficiency fairness within the process. (Ayari et al., 2025) conducted a systematic review of the

recent literature on machine-learning credit-scoring methods to classify, evaluate and describe those practices in terms of their advantages/limitations as well as opportunities for future research.

As previous studies conducted were either focused on challenges inherent in AI and ML with limited application, or the studies compared the AI/ML models versus traditional models in fintech industry. Another research aimed to identify the major ML methods used in credit scoring, assess their strengths and limitations, and highlight notable trends and advancements. It is also critical to note that the existing literature often highlights the trade-off between AI model accuracy, fairness, auditability and interpretability. There remains an opportunity to explore AI/machine learning architectures with regulatory requirements for transparency, fairness and interpretability.

As discussed by (Bücker et al., 2022; Sarkar, 2026), that studies report increasingly on the impact of AI in predictive decision making, the evidence of which remains fragmented due to varied lending context, evaluation criteria defined in AI models. On the contrary, the traditional models retain the advantage of clarity, transparency, auditability, and regulatory compliance. Similarly, (Ali, 2026) noted that most of the research focuses on peer-to-peer lending instead of peer-to-business lending.

The above-mentioned research contributes to the overall knowledgebase, while there is a need for performing a study which compares AI-driven credit risk assessment and traditional credit risk evaluation methodologies. The limitations identified by the researchers provide the opportunity to perform a comparative study of AI credit risk assessment methods and traditional credit risk models. The study evaluates not only predictive accuracy but also interpretability, fairness and suitability to practice credit decisions.

This study is based on exploratory qualitative research methodology, under which existing literature is analysed to generate comparative analysis between AI-based models and traditional credit risk models. The study suggests a multidimensional theoretical framework for assessing credit risk models and emphasizes prospective research avenues in hybrid modelling, fairness-aware AI, and real-time risk monitoring.

Even though clear efficiencies are arising from AI models, the financial sector foresees barriers to AI adoption. Regulators expect transparency, fairness, and auditability of AI models used for credit modelling (Umeorah et al., 2024), At the same time financial institutions are seeking to strike the right balance with governance and efficiency (Alonso Robisco et al., 2022).

Literature Review

This study leverages on exploratory qualitative research approach to examine the existing literature for AI-based risk models and traditional credit risk models. Specifically, the analysis evaluates how the inherent opacity of advanced algorithms like neural networks conflicts with regulatory mandates for model interpretability, which often favour traditional, linear methods despite their limitations in capturing complex behavioural patterns (Ayari et al., 2025). The subsequent sections detail the research design, synthesize findings from academic and industry sources, and evaluate the trade-offs between predictive performance and regulatory compliance across different modelling paradigms.

The qualitative exploratory methodology which is integrated into systematic literature review, supports structured assessment of existing literature on AI-based and traditional credit risk assessment (Černevičienė & Kabašinskas, 2024). The study performs assessment of AI and traditional models in terms of performance, data models, transparency, explainability, fairness, regulatory acceptability, as well as implementation challenges. This approach supports structured qualitative analysis which is ideal for identifying and interpreting recurring themes. Additionally, the inductive nature of exploratory research supports providing a comparison of how AI-based and traditional credit risk assessment systems influence decision-making. Compared to quantitative research which is based on numerical datasets, the qualitative exploratory research facilitates an in-depth analysis thereby revealing how contextual factors shape the implementation of credit models (Jain, 2021). This flexibility offered by these methodological addresses the current analytical gap, and provides visibility on interpretive, context-dependent nature of AI and traditional credit evaluation

The methodology presented in this study comprises two main phases: “Planning,” and “Conducting.” Planning outlines the steps that need to be taken for the review and keeps track of what needs to be done. The second phase, “Conducting,” is the operational phase where steps planned in previous step are executed. The planning phase provides with the details of the process of literature review. It defines the set of rules for search strategy, and selection criteria (Brown, 2024).

Planning

The research adopts a systematic approach to conduct a literature review that examines and produces a comparative analysis of AI-based risk models and traditional credit risk models. The approach supported the study's ability to understand the state and identify gaps and challenges in the field. The systematic literature review (SLR) is a systematic framework for literature review. SLR provides the methodology for identifying, analysing and synthesizing the literature.

This research utilized PICO (Population, Intervention, Comparison, Outcome) criteria to break down the SLR's objectives into searchable keywords and help formulate research questions (Negri-Ribalta et al., 2024). The PICO framework is used in this study for clear and focused research question. PICO is particularly helpful in systematic literature reviews (Frandsen et al., 2020).

The PICO (Population, Intervention, Comparison, Outcome, and Context) framework is widely adopted for developing research questions and providing systematic literature review framework. Espinoza mentions that using PICO for performing literature review provides a systematic approach (Espinoza et al., 2023; Martha & Sandra, 2023). In this study, the financial institutions are Population, the Intervention includes AI and machine learning techniques, whereas the traditional credit risk models are assumed to be Intervention, Comparison comprises evaluation of AI & ML vs. traditional models, and the Outcome discusses the accuracy, explainability, and regulatory compliance for both alternatives (Wang et al., 2021). (Okoli, 2015) mentioned that SLR facilitates a framework under which literature review is conducted as a systematic process for collecting, analysing, and synthesizing relevant academic literature. A systematic literature review provides a structured approach for gathering, examining, and integrating relevant scholarly articles, industry reports, and significant

documents to achieve a comprehensive understanding of a subject (Okoli, 2015). (Kitchenham & Charters, 2007) recommends that the literature review process to be easy to follow, should be repeatable, and should be reproducible. (Papakostas et al., 2021).

Formulating Research Question with PICO

The PICO framework is referred in this study to define the scope of the literature. The review has been broken down into four key components: Population, Intervention, Comparison, and Outcome (Cumpston et al., 2023). For this research on "Comparative Analysis of AI Methods and Traditional Credit Risk Models," the PICO elements are defined as follows:

Based on these PICO elements, a core research question for the literature review is, "How AI & ML can be compared to traditional models in terms of accuracy, efficiency, interpretability, for credit risk assessment in financial institutions?"

Search Strategy

The literature review requires a consistent strategy for identifying relevant literature. While defining the search strategy for this study, keywords and search strings were used for searching relevant literature in various academic databases.

Databases: Several academic databases (e.g., Scopus, Web of Science, IEEE Xplore, ACM Digital Library, Google Scholar) were referred while conducting this study. The following keywords were used for searching the literature.

Keywords: Examples included:

("Artificial Intelligence" OR "Machine Learning" OR "AI" OR "ML") AND ("credit risk" OR "credit scoring" OR "financial risk") AND ("traditional models" OR "statistical models" OR "econometric models") AND ("comparison" OR "comparative analysis" OR "performance" OR "accuracy" OR "efficiency" OR "interpretability" OR "fairness").

"PICO framework" AND "systematic literature review" AND "finance" OR "credit risk".

Inclusion/Exclusion Criteria: In order to select relevant literature from the sources, inclusion and exclusion criteria were defined under the following:

Publication Type: Peer-reviewed journal articles, conference papers, and reputable review articles.

- Language: English.
- Date: Literature published within the last 5-10 years.
- Relevance: Literature alignment with the research topic.
- Exclusion: Literature not aligned with research topic.

Study Selection

Studies identified as a result of above criteria were systematically reviewed under the following approach.

Initial Screening: Abstracts were assessed based on inclusion/exclusion criteria.

Review of academic resource: Relevant articles were screened for material supporting the research topic.

Expanding the research: Citations in selected literature were reviewed for further examining relevant literature.

Data Extraction

Relevant information was extracted systematically along with details for academic citation. For literature selected, extracted details included:

Authors, year of publication, journal/conference.

- Credit risk analysis - AI/ML models and traditional models' comparison.
- Context.
- Findings.
- Study limitations and future research opportunities.

Data Synthesis and Analysis

Once the literature is selected, the extracted information is synthesized. This involves organizing and interpreting the extracted information to seek answer to the research topic. During synthesization process, following activities were performed:

Critical Appraisal: Selected research material is analysed for relevance with research topic.

Thematic Analysis: Themes and patterns originating from the selected literature are noted (Nowell et al., 2017).

Comparative Analysis: Findings reported as a result of analysis are consolidated to provide a comparative analysis of AI/ML versus traditional methods.

Gap Identification: Identify areas of improvement for the current research.

Conducting

Literature review was conducted using the PICO framework which identified several key themes related to adoption of AI in credit risk modelling. These themes emerged as a result of comparison of AI-driven models with traditional models. The following section discusses the themes which were noted during the literature review.

Comparative Analysis of AI/ML vs. Traditional Models

Comparison of AI & ML models with traditional credit risk modelling is discussed by various researchers and has been elaborated in their reports and studies. This theme dominantly emerged from observed as it was discussed repeatedly during the literature review. It was commonly noted in the literature that evaluated the efficacy, accuracy, and predictive capabilities of AI and ML models in comparison to traditional statistical methods for credit risk assessment. The literature reviewed during the study emphasizes the processing capacity and capability of AI/ML models. These models can process huge data sets with structure and

unstructured data. Traditional credit models take a lot of time (Wang, 2024). AI & ML models support in identifying patterns as well as variations in the data. Utilizing AI & ML models have capability of performing risk assessment modelling at such discrete data sets (Bari, 2024). Additionally, deep learning models have enhanced these capabilities by processing unstructured data at processing speed which is far above the traditional credit modelling techniques. However, due to nature and complexity of deep learning models, such models are faced with lack of interpretability, explainability challenges (Bari, 2024). Researchers have emphasized on explainable AI techniques so compliance requirements can be achieved (Esther & Abayomi, 2024). Even though AI & ML improve efficiency and effectiveness, complex algorithms are challenging to explain and audit, this is still a major worry for banks and regulators strong regulatory rules are needed for model governance and auditability (Bari, 2024).

Explainability, Interpretability, and Transparency

During the literature view, it was noted that researchers focus on lack of explainability in AI models and emphasize on regulatory requirement of explainable AI in high-stakes environments like financial services. Literature review identified that researchers favour support AI models which are understandable, and auditable (Bücker et al., 2022). Researchers have also discussed advanced AI models with deep learning capabilities are complex and thus are not easy to explain or being audited. This lack of interpretability results hinders in regulatory compliance as well as seeking the stakeholders' trust (Bari, 2024). These requirements have pushed AI & ML developers to come up with explainable and auditable models.

Fairness, Bias, and Ethical Considerations

The literature consistently highlighted the importance of fairness, bias within AI models and ethical implications. Researchers typically looked deeply into the importance of having a secure AI development. A key element in AI development lifecycle is fairness in training data for models. Such practices are necessary for AI implementation to guarantee fair outcomes for all applicants (De Castro Vieira et al., 2025). Studies also reveal that algorithmic discrimination is among the key problems, coupled with bias in training data. Researchers emphasize on the need of bias detection protocols (Masud et al., 2023). Additionally, it has been revealed from the literature review that explainable and auditability AI tools which guarantee fairness and free of bias are increasingly accepted for maintaining compliance with regulatory frameworks, which require financial institutions to substantiate credit decisions to prevent ambiguous or inequitable lending practices (Mujo, 2025).

Regulatory Compliance and Governance

This theme has come out as regulatory frameworks and governance requirements have resulted in delays in adopting AI & ML in credit risk modelling. It addresses how regulatory expectations for transparency and auditability influence the choice and implementation of credit risk models (Bravo et al., 2023). Regulatory frameworks, however, present an opportunity to resolve this tension by enabling the deployment of advanced models alongside the necessary explanations to satisfy regulatory scrutiny (Ye & Chen, 2025). Recent enhancements in AI frameworks support and demonstrate AI & ML models to make these

explainable and auditable. This may support in resolving the challenge of lack of transparency in AI & ML models (Ye & Chen, 2025).

Hybrid Modelling Techniques

An emerging theme is noted during literature review, which mixes the traditional methods with AI/ML techniques or explores alternatives to utilize best features of both. The goal of this approach is to get accurate model for credit risk modelling which is understandable and reliable (Wang, 2024). Studies in this domain recommend framework which integrate linear regression or logistic regression components of traditional credit risk assessment with AI modelling. Such approach provides balance of accuracy with the clear decision boundaries required by regulators. (Bari, 2024; Dumitrescu et al., 2022). These hybrid models can simultaneously process huge amount of data with accuracy and speed but also identify the underlying contextual aspects available in traditional risk models. The above approach provides a consistent and reliable decision-making process in credit risk management (Schmitt, 2024).

Comparative Analysis of Literature on AI Methods and Traditional Credit Risk Model Performance

This section discusses the outcomes of this research. The section provides details of findings noted while exploring on how AI models can be compared to traditional statistical methods for credit risk. It is envisaged that ML algorithms provide speed with accuracy at predicting outcomes of credit risk analysis as compared to standard linear models. AI & ML models have the capability to identify complicated, non-linear relationships in huge data set (Dil & Ramchand, 2025). Hybrid frameworks that offer functionalities of AI models along with traditional credit risk modelling have shown to be effective (Bari, 2024) (Shahnawaj et al., 2025). Conventional credit risk methods have limitation when it comes down to analyse unstructured data. These models need to be adjusted due to fluctuating market conditions which put constraints on their performance and effectiveness. The above points suggest to opt for implementation of more adaptable and hybrid approaches (Wang, 2024).

The literature review shows that there are a few main topics that show how difficult it is to use AI in credit risk modelling.

Comparative Analysis: During the literature review, it has been noted that AI and ML models provide superior predictive accuracy and processing capacity for complex, non-linear datasets (Bari, 2024). Whereas, traditional models, are unable to timely process unstructured data and non-linear patterns, which makes them less effective. (Wang, 2024). The adoption of AI often slows down due to firm's indecisiveness, unclear legal frameworks, and the lack of sandboxes for regulatory validation. These factors make it challenging to migrate to AI modelling techniques (Masud et al., 2023).

Explainability, Interpretability, and Openness: One major challenge that has been found is that many powerful AI models are "black boxes." AI models enhance the capabilities by processing huge data with speed and accuracy. However, it has been witnessed that AI models often lack explainability and auditability. Lack of clarity and interpretability on the processing and decision making algorithms, has prevented the stakeholders in the financial services industry from adopting AI modelling techniques for credit risk (Chackrvarti, 2025). Regulators need

clarity and supporting logs on how the system processes and makes decisions based on machine learning algorithms. This scenario has led to development of explainable AI models, so the gap between predictive capability and interpretability can be closed by giving information about model predictions (Shiam et al., 2024). At the same time this has also led to the development of hybrid architectures whereby traditional credit risk modelling components are combined with AI & ML algorithms. These hybrid architectures have witnessed the balance between regulatory compliance and predictive accuracy. Masud sees these hybrid models as a solution for organizations that want to update their risk modelling techniques (Masud et al., 2023; Shiam et al., 2024).

Fairness, Bias, and Ethical Considerations: AI & ML models undergo the training process during their development process. Any bias in training data will impact the learning outcomes of the AI model. Consequently, the decisions made by AI model could be unfair or biased. (Chackrvarti, 2025) and (Ngozi et al., 2023) have mentioned their concerns related to ethical implications of AI in credit decisions, which arise from issues arising from algorithmic discrimination. These biases originate from biases in training data. (Chackrvarti, 2025; Ngozi et al., 2023). AI Frameworks and regulations focus on requirements of transparency, auditability, and fairness in AI models' credit decision making process. Traditional credit analysis provide the required interpretability that corresponds with established regulatory frameworks (Chackrvarti, 2025).

Regulatory Compliance and Governance: Regulatory requirements for fairness, auditability, and lack of bias in credit decisions impacts selection of AI models (Chackrvarti, 2025). Traditional credit analysis models are easier to comprehend and are auditable. This makes them traditional models more compatible with the regulatory frameworks. On the same note, firms are willing to adopt AI models which are supported by sufficient documentation on algorithms and are auditable as per the regulatory requirements. Specifically, regulatory frameworks like Article 22 of the EU General Data Protection Regulation require rights of explanation for automated profiling and decision making. Financial regulators are on the path to develop guidance to put these rules to practice. Regulators are working towards developing rules to balance the innovation with data protection (Gajula, 2025).

Hybrid Modelling and Advanced Techniques: The study shows that hybrid modelling methods are becoming more popular (Shiam et al., 2024). These models combine the traditional statistical methods and AI/ML methods to get higher accuracy and acceptance from regulators (Masud et al., 2023; Shiam et al., 2024).

Review of literature on comparative analysis of AI methods and traditional credit risk model literature confirmed the above findings. AI models have capacity of performing predictive analysis with speed and accuracy, in addition to the capability of processing unstructured datasets (Alonge et al., 2023; Bari, 2024). The balance between efficiency and regulatory adherence remains a key concern (Mujo, 2025).

Conclusion

The study was conducted to seek answer to the research question: How AI & ML can be compared to traditional models in terms of accuracy, efficiency, interpretability, for credit risk assessment in financial institutions?

Explorative qualitative research methodology was utilized to examine academic journals, research papers and industrial sources for the presence of data sources. We conducted an extensive literature study using the PICO method. What was important about the PICO method is that it gave useful guidance for identifying and looking at relevant studies (Frandsen et al., 2020).

The PICO framework of this study was delineated as follows: the Population comprised financial institutions engaged in credit risk assessment; the Intervention integrated Artificial Intelligence and Machine Learning techniques (e.g., neural networks, ensemble methods); the Comparison employed traditional statistical models such as logistic regression; and the Outcome focused on predictive accuracy, interpretability, and adherence to regulatory standards.

It has been noted that previous research emphasized that the processing capacity and capability of AI/ML models has outperformed the traditional models. AI models process huge amounts of data whether structured or unstructured. This processing speed provides an edge to the AI models over traditional credit models.

As AI models are becoming smarter with deep learning capabilities, researchers are emphasizing explainable AI techniques. Deep learning AI models result in black box processing which raises concerns for regulatory compliance requirements. As AI models are growing, legal frameworks are also developed in accordance with the capabilities of AI models. These requirements encompass transparency, fairness, interpretability, auditability, robustness of AI models. Model bias and training data bias is also addressed in relevant laws such as EU AI Act. Additionally, GDPR and other relevant regulations addressing data privacy become relevant as AI models process personal data of the applicants. A key element noted during the AI development is fairness in training data which is critical to minimize the model bias risk at the initial stage of model training. Hybrid modelling has come out as a possible solution to minimize the risk of model drift and bias. The goal of this hybrid approach is to utilize the best features of both traditional models as well as AI models as it supports the key requirements of transparency, fairness, bias detection, interpretability and auditability.

Though the benefits of AI are undeniable, there is a need to ensure that AI models are aligned with goals and objectives of the financial institution while complying with applicable laws and regulations. In conclusion, the benefits arising from of AI & ML in credit risk assessment are undeniable. AI models offer predictive accuracy and the ability to process complex datasets compared to traditional models (Carr & Peterson, 2024; Wang, 2024).

On the other hand, adoption of AI in financial sector is restrained due to the challenges related to model interpretability, probability of algorithmic bias, and adherence to regulatory standards (Mujo, 2025; Ye & Chen, 2025). Two important areas for future research are growing popularity of hybrid modelling methods and the ongoing development of explainable AI techniques. Financial institutions continue to explore right combination of AI's better ability to make predictions and the need for fairness, openness, and regulations when making financial decisions (Bari, 2024; Shahnawaj et al., 2025). This ongoing development shows how new technologies, ethics, and rules all work together to shape the future of credit risk management.

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