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The Role of AI and ML in Alternative Credit Scoring in Fintech Lending

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ARTICLE INFO	**ABSTRACT**

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This research examines the influence of artificial intelligence (AI) and machine learning (ML) on alternative credit scoring in fintech lending, highlighting the effect of alternative data on financial inclusion and confidence in AI-based credit assessments. The study, using a sample size of 384 and evaluated via quantitative methodologies with SPSS and Structural Equation Modeling (SEM), emphasizes the need for ethical frameworks and transparent governance to guarantee fairness and accountability in AI-driven credit assessments. Conventional credit assessment techniques often exclude persons with sparse credit histories, whereas AI/ML-driven models use digital footprints, utility payments, and behavioral data to provide a more thorough credit review. The results demonstrate that alternative data substantially improves the perceived precision of AI/ML credit rating, resulting in heightened confidence in automated conclusions. Moreover, increased consumer understanding of AI/ML enhances trust in digital lending systems, hence promoting broader financial inclusion.

Keywords: AI/ML in credit scoring, alternative credit scoring, fintech lending

1 Introduction

Credit scoring models evaluate creditworthiness and the likelihood of loan default, assisting lenders in establishing interest rates, repayment periods, and loan amounts (*Credit Scoring Models 101: Types and Examples for a Stronger Financial Future*, 2025). Conventional models depend on elements such as payment history and credit use, although often exclude persons without official financial documentation (Ahelegbey & Giudici, 2023). This constraint is apparent in developing countries such as Indonesia, where fintech innovations like peer-to-peer (P2P) lending have enhanced credit accessibility, with the industry distributing IDR 20.53 trillion in loans in August 2023 (Sari et al., 2024).To rectify these deficiencies, alternative credit scoring employs non-traditional data sources such as rental payments, energy bills, and internet activities to evaluate creditworthiness beyond just financial history (Wijaya, 2023). This method advantages cohorts such as Generation Z, who may be devoid of traditional credit histories and collateral (Jagtiani & Lemieux, 2019). Nonetheless, investigations on the amalgamation of these data sources with contemporary AI-driven models are still few (Djeundje et al., 2021).Although credit has been there since 2000 BC, contemporary credit rating has been for about 60 years. Improvements in AI and big data analytics have enhanced the precision of credit assessments using methodologies such as the Gini coefficient and ROC curve (Abdou & Pointon, 2011). Efficient credit assessment is essential for financial organizations, since it reduces default risks and enhances profitability (Niu et al., 2019). Notwithstanding these gains, more study is requisite to formulate complete, universally applicable credit assessment models (Alamsyah et al., 2025).

1.1 Back ground of the study

The Credit Scoring System is an essential instrument for banks and financial organizations, using intricate algorithms to evaluate creditworthiness and facilitate prompt, precise loan determinations (Abhishek Kumar et al., 2024). Technological breakthroughs have progressively improved its precision and efficacy. Fintech developments have significantly altered financial services, originally concentrating on backend banking and then expanding to include retail banking, investment management, and cryptocurrencies (Kagan et al., 2024). In contrast to conventional banks, fintech companies strive to cater to marginalized demographics by providing expedited and adaptable financial services.AI-driven credit scoring represents a notable progression, catering to the requirements of 2.5 billion unbanked persons and many banked individuals who do not meet the criteria for loans via conventional techniques (How Credit Scoring Engines Work: A Data Science and Machine Learning Perspective, n.d.). Through the examination of variables such as income, transaction history, job records, and internet activity, AI-driven models provide real-time, individualized credit ratings, hence enhancing financial accessibility.

2 Literature review

Recent studies have extensively investigated the integration of Artificial Intelligence (AI) and Machine Learning (ML) in financial services, emphasizing both its benefits and problems. (Gupta & Agarwal, 2025) highlighted the significance of AI/ML in enhancing decision-making, risk management, and operational agility, while also recognizing issues related to data privacy, algorithmic bias, and model interpretability. They emphasize the need for ethical AI use, promoting justice, transparency, and regulatory frameworks to maintain industry standards. (Jain et al., 2024) examined the increasing use of AI and ML in FinTech, namely in fraud detection, credit evaluation, customer assistance, and investment management. Their paper tackles key challenges of regulatory compliance, data privacy, and ethical concerns, while calling for increased research on financial inclusivi-ty and responsible AI governance. (Berg et al., 2022) assessed FinTech lending, praising its quick pace fueled by convenience and efficiency as well as its future potential in driving financial inclusion. Still, they also identify shortcomings during the COVID-19 pandemic period, particularly when it comes to the maintenance of financial stability. (Nalini, M.; Kishore, Goli Bala Venkata; Prasad, Priya; Shirode, Ujwal Ramesh; Fernandez, 2022) analyzed the impact of AI/ML on financial markets, emphasizing benefits such as predictive analytics, cost savings, and improved financial projection. Their re-search also covers challenges such as compatibility with legacy systems and regula-tory changes. Last,(Deshpande, 2020) examined AI/ML-driven FinTech and financial services advancements, emphasizing structural changes, the rise of per-sonalized AI platforms, and the growth of RegTech, including algorithmic regula-tion. Their findings suggest a necessity for continuous assessment of these advancements, as AI/ML has the potential to bring significant alterations to the financial industry. These reports collectively present a comprehensive picture of the evolving role of AI and ML in financial services, highlighting both the advantages and issues associated with their application.

2.1 Hypothesis implementation

- **H1: The use of alternative data positively influences the perceived accuracy of AI/ML-based credit scoring models.**

Financial inclusion continues to be a worldwide concern, since conventional lending institutions often exclude disadvantaged persons owing to antiquated evaluation methods and prejudices. (Nuka, Tambari, 2024) emphasized that AI and ML may transform creditworthiness assessment by scrutinizing large datasets, revealing patterns that conventional approaches miss, and detecting discriminating tendencies to promote behavioral modifications. Integrating different data sources, such as rental payments and utility bills, may provide a more comprehensive evaluation of creditworthiness; nonetheless, competent execution and robust regulatory frameworks are important. (Schmitt & Cummins, 2023)asserted that the selection of AI models for financial decision-making should not rely only on accuracy. Explainable AI and model transparency are essential for regulatory adherence and fostering confidence. Their research contrasts deep learning with gradient boosting models (GBMs) in credit risk management, preferring GBMs for their congruence with theoretical and empirical evidence, computational efficiency, and reduced environmental effect. (Sadok et al., 2022)examined AI's function in credit analysis, emphasizing its capacity to use extensive datasets for enhanced predictive precision relative to conventional approaches, resulting in favorable macroeconomic growth forecasts. Nevertheless, apprehensions over AI-induced biases and ethical, legal, and regulatory issues persist. The research advocates for the implementation of new financial rules mandating the certification of AI algorithms. (Djeundje et al., 2021) investigated different data-driven algorithms for forecasting credit risk in new accounts. Their results indicate that the incorporation of email use, psychometric characteristics, and demographic information significantly improves forecast accuracy in contrast to models that depend only on demographics. The research assesses several machine learning and statistical classifiers, concluding that excessive gradient boosting yields very accurate predictions even when using just email use data. These studies together highlight the transformational potential of AI and ML in credit assessment, while underscoring the significance of ethical and regulatory constraints.

- **H2: The use of alternative data in AI/ML credit scoring enhances financial inclusion by improving credit access for underserved populations**.

Numerous research have investigated the impact of artificial intelligence (AI) and machine learning (ML) on credit risk evaluation and financial inclusion. (Kumar & Babu, 2025) examined 36 studies spanning diverse sectors, including microfinance and agricultural loans, and concluded that machine learning-based credit scoring models surpass conventional techniques, especially in volatile contexts and among disadvantaged populations. They emphasized that the integration of alternative data enhances credit accessibility, enabling financial institutions to cater to high-risk or unbanked persons. (Kothandapani, 2025)highlighted AI's capacity to revolutionize credit scoring in developing nations by producing credit ratings for persons without established credit histories. Nonetheless, issues pertaining to algorithmic prejudice, data privacy, and digital illiteracy persist as substantial obstacles, requiring ethical AI rules to ensure transparency, justice, and inclusion. (Faheem, 2024)examined AI-driven risk assessment models, emphasizing the significance of machine learning, real-time data processing, and alternative data in enhancing creditworthiness forecasts. He also discussed issues related to prejudice, fairness, interpretability, and the need for legal frameworks such as GDPR. Emerging subjects such as Explainable AI, Natural Language Processing, and blockchain integration were explored. (Moscato et al., 2021)performed a benchmarking examination of credit risk scoring algorithms in peer-to-peer lending platforms, using explainable AI methodologies to enhance loan payback forecasts despite borrowers' constrained credit histories. (Agarwal et al., 2020) showed how alternative data from mobile phone use might improve credit risk assessment and financial inclusion in India, possibly supplanting standard credit ratings without elevating default risks. Their results underscore the revolutionary potential of digital data sources in emerging economies.

- **H3: User awareness of AI/ML in lending positively influences trust in AI/ML-based credit decisions.**

Artificial Intelligence (AI) and Machine Learning (ML) are progressively revolutionizing financial organizations by enhancing risk management, quantitative trading, and investment decision-making, while enabling managers to concentrate on strategic responsibilities (Polireddi, 2024). Artificial intelligence is supplanting human positions in risk assessment and stock trading, improving efficiency, cybersecurity, and risk mitigation, which eventually results in customized financial services and transforms company models, labor dynamics, and competitive ecosystems. Likewise, AI-enhanced credit risk evaluation is transforming contemporary banking, since conventional algorithms falter with extensive datasets and intricate relationships. Advanced machine learning techniques, including Random Forests, Support Vector Machines, and Neural Networks, enhance predictive accuracy by utilizing both structured and unstructured data; nonetheless, challenges such as model opacity, bias, and regulatory compliance remain, which explainable AI tools like Shapley values and LIME aim to mitigate (Wang, 2024). Moreover, the incorporation of AI in credit scoring is transforming financial inclusion and risk management by using varied data sources and predictive analytics, highlighting the need for transparency and interpretability in AI-driven credit evaluations (Wilhelmina Afua Addy et al., 2024). AI-driven credit scoring systems are strengthening real-time credit card approvals by automating the review process, assessing financial history, and continually refining credit ratings using machine learning algorithms, hence minimizing human involvement and improving efficiency (Sharma & Logeshwaran, 2024). The growing dependence on AI and big data in financial technology presents ethical issues, such as privacy threats, prejudice, discrimination, transparency, and digital responsibility. Addressing these issues necessitates strong encryption methods, safeguarding customer data, and adherence to regulations; nonetheless, further study is essential to investigate non-English viewpoints and enhance resources in this field (Aldboush & Ferdous, 2023).

- **H4: Higher user awareness of AI/ML in lending contributes to greater financial inclusion by increasing confidence in digital lending platforms.**

The rapid development of Artificial Intelligence (AI) has significantly revolutionized credit risk modeling, improving efficiency and precision in the optimization of financial services (Pub, 2025). AI-driven solutions, using machine learning algorithms, big data analytics, and real-time insights, empower financial institutions to evaluate creditworthiness with enhanced accuracy, hence decreasing default rates, refining lending choices, and promoting financial inclusion. Furthermore, progress in natural language processing, predictive analytics, and reinforcement learning has facilitated these breakthroughs. Nonetheless, obstacles such as data privacy, algorithmic bias, and regulatory compliance persist as significant impediments. Artificial Intelligence (AI), Machine Learning (ML), and Blockchain have significantly advanced financial inclusion, especially in underdeveloped areas such as South Africa, where conventional banking systems frequently marginalize informal traders and self-employed individuals due to their absence of formal credit histories and official documentation (*Technology and AI-Driven Driven Financial Inclusion (Underdeveloped Region)*, 2025). AI-driven alternative credit scoring models evaluate financial credibility via extensive data analysis, while blockchain technology provides decentralized, transparent, and economical financial services, enhancing security and efficiency in informal sector transactions. Numerous research (Nuka, Tambari, 2024)have shown the capacity of AI and ML to analyze extensive datasets and identify patterns that traditional approaches fail to detect. Artificial intelligence may detect and alleviate biases in financial decision-making, promoting equitable access to credit by using alternative data sources, such rental payments and energy bills. The role of AI in fintech includes credit scoring, financial crime prevention, customer service improvements, and investment management; yet, issues related to data privacy, security, transparency, and skill gaps remain (Ridzuan et al., 2024). The capacity of AI to link billions of unbanked persons with formal financial institutions has been emphasized, underscoring its significance in financial inclusion, enhancement of literacy, and inclusive economic growth (Omogbeme et al., 2024). The incorporation of AI into financial systems is acknowledged as essential for human growth, requiring strong legislative frameworks and infrastructure to support its implementation for financial inclusion (Fazal et al., 2022).

2.2 Research gap

Despite the extensive research about the role of AI and ML in alternative credit scoring within fintech lending, some gaps remain unresolved. Although research underscores the advantages of AI-driven credit assessment in improving accuracy, financial inclusion, and risk management, there is a limited studies examining the long-term effects of these models on financial stability, borrower repayment behaviours, and default patterns. Moreover, current literature mainly emphasizes technical innovations and predictive functionalities, yet there is an absence of studies that rigorously analyze the ethical, legal, and regulatory implications of AI-driven credit scoring, especially in developing economies where regulatory structures are still maturing. A further gap relates to the explain ability and transparency of AI models; although several studies highlighting the necessity for explainable AI (XAI), there is a deficiency of empirical data about its efficacy in cultivating trust among consumers and regulators. Moreover, although other data sources including mobile phone usage and social media activity have been investigated, their relative efficacy compared to traditional credit indicators remains little examined. Finally, research suggests that user awareness and trust in AI/ML-based lending affect financial inclusion; however, further exploration is required to understand how digital literacy, algorithmic bias, and consumer protection policies influence borrower perceptions and the adoption of AI-driven credit models, especially among underserved populations. Addressing these research deficiencies is essential for cultivating a more resilient, equitable, and sustainable AI-driven credit ecosystem in fintech lending.

3 Methodology

The study utilizes a quantitative framework, using statistical empirical analysis to investigate the impact of AI/ML on Alternative Credit Scoring within Fintech Lending. A systematic methodology is used to gather and evaluate data from 384 participants to guarantee statistical reliability and validity. Data collection is performed using a standardized questionnaire with Likert-scale questions that evaluate user knowledge of AI/ML in lending, confidence in AI/ML judgments, perceived accuracy of AI/ML credit rating, and financial inclusion. SPSS is used for data analysis, including factor loadings, reliability assessment, and descriptive statistics, whilst AMOS is applied for structural equation modeling (SEM) to assess interrelationships and hypotheses. The study's conceptual framework examines the enhancement of financial inclusion through AI/ML-based alternative credit rating, organized around four hypotheses: the utilization of alternative data (H1) affects the perceived accuracy of AI/ML credit scoring, user awareness of AI/ML in lending (H2) influences trust in AI/ML decisions, and awareness of AI/ML (H3) is associated with financial inclusion. Trust in AI/ML judgments (H4) mediates the relationship between awareness and financial inclusion, highlighting trust in AI-driven lending. The research used a stratified sample method to include diverse fintech borrowers, guaranteeing precision and reliability. A systematic questionnaire assesses loan approval experiences, perceived equity, borrower contentment, and financial inclusion. Participants evaluate data openness, loan approval velocity, accessibility, and confidence in AI determinations, with the survey disseminated over email, Google Forms, and financial platforms. Engagements with fintech experts and loan officers provide more insights into the adoption of AI/ML in credit rating, while supplementary data, such as loan acceptance and rejection records, default rates, and AI model performance metrics, validate the results. The questionnaire employs a Likert-type scale, including both open-ended and closed-ended questions designed for five responder groups, therefore facilitating significant data collection for study variables.

4 Result

4.1 Introduction

The research examined how AI and machine learning (ML) transformed alternative credit scoring in fintech lending, highlighting how emerging technologies improve financial inclusion by using non-traditional data sources. Credit score algorithms based on normal financial histories sometimes exclude those with little or no credit history. AI/ML-driven credit assessments use digital footprints, utility payments, and social behaviors to analyze creditworthiness more thoroughly. The study determined that alternative data significantly improves AI/ML-driven credit scoring to increase trust in machine credit decisions. User awareness of AI/ML increases financial inclusion since informed clients use digital lending platforms. Despite the advantages, data privacy, algorithmic biases, and legal issues remain. The paper stresses the call for ethical principles and open governance to guarantee fairness and accountability for fintech lending and AI/ML-driven credit scoring to maximize financial accessibility.

Hypothesis development

Hypothesis	Relationship			Estimate	C.R.	Sig. P-Value	Results
H1	Use of alternative data	---->	perceived accuracy of AI/ML based credit scoring	0.912	9.698	***	Accepted
H2	Use of alternative data	---->	Financial inclusion	0.8	10.019	***	Accepted
H3	User awareness of AI ML in lending	---->	Trust in AI/ML credit decisions	0.98	14.133	***	Accepted
H4	User awareness of AI ML in lending	---->	Financial inclusion	0.851	8.547	***	Accepted

Sig.p-value (**– indicates < 0.005)**

This study explores the impact of AI/ML-based alternative credit scoring in fintech lending, focusing on the impact of alternative data and user awareness regarding financial inclusion. Findings reveal that alternative data highly enhances the perceived accuracy of AI/ML credit models (H1: Estimate = 0.912, C.R. = 9.698), leading to higher confidence in automated assessment. Also, alternative data implementation promotes financial inclusion through the enhancement of loan accessibility among marginalized sections (H2: Estimate = 0.8, C.R. = 10.019).

Understandability by users of AI/ML fuels trust in credit decisions made with the help of AI (H3: Estimate = 0.98, C.R. = 14.133) and thus the confidence in the digital lending processes. Additionally, increased user consciousness promotes financial inclusion by strengthening borrower engagement with AI-driven credit scoring (H4: Estimate = 0.851, C.R. = 8.547). These results underscore the revolutionary potential of AI/ML in expanding financial accessibility, while also emphasizing the need for openness and responsible execution.

5 Discussion

The study's results indicate the substantial influence of AI/ML-driven alternative credit scoring on financial inclusion, especially via the use of alternative data and enhanced user awareness. The findings validate that alternative data markedly enhances the perceived precision of AI/ML credit scoring models (H1: estimate = 0.912, C.R. = 9.698), hence cultivating confidence in automated lending determinations. The application of alternative data complements financial inclusion (H2: estimate = 0.8, C.R. = 10.019) by making loans accessible to marginalized communities. Awareness of AI/ML among users has a strong impact on trust in AI-based credit decisions (H3: estimate = 0.98, C.R. = 14.133), suggesting that informed users are more likely to rely on digital lending platforms. In addition, improved information allows direct-ly for greater financial inclusion (H4: estimate = 0.851, C.R. = 8.547) through the strengthening of trust in AI-based credit ratings. While AI/ML holds disruptive advantages, it is important to tackle problems such as such as data privacy and algorithmic bias to make fintech lending ethical and transparent.

6 Conclusion

The research emphasizes the pivotal role of AI/ML-based alternative credit scoring in enhancing financial inclusion using non-traditional data. Re-search shows that alternative data improves the perceived accuracy of AI/ML credit models and facilitates credit availability for marginalized groups. Further, increased user awareness fosters trust in AI-based credit determina-tions, thereby improving financial inclusion. While these benefits exist, concerns regarding data privacy and bias in algorithms still linger. The study underscores the importance of ethical guidelines and open governance to ensure fairness in fintech loans. AI/ML credit scoring is a game-changing tool for improving access to finance, while demanding wise implementation.

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