

## Credit Risk Prediction Model Using Artificial Intelligence in Digital Financial Systems

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### ABSTRACT

This study adopts a qualitative approach to examine how AI-based credit risk models are conceptualized and applied in digital finance, with a focus on emerging economies. The novelty of this study lies in: Exploring the human dimensions of AI adoption, including trust and interpretation by credit practitioners; Highlighting ethical and governance issues such as bias, fairness, and data privacy; Identifying hybrid models that combine AI with human oversight in risk decisions; and Offering policy insights for the responsible integration of AI in digital credit systems. This study uses a qualitative exploratory approach to investigate how Artificial Intelligence (AI) is conceptualized, implemented, and perceived in the context of credit risk prediction in digital financial systems. Through a qualitative, multi-case approach involving interviews and document analysis, it finds that AI offers substantial potential to improve credit risk models, particularly through the use of alternative behavioral data. These findings highlight the need for a balanced credit assessment framework where AI supports, but does not completely replace, human expertise.

**Keywords:** Credit Risk; Artificial Intelligence; Digital Financial Systems; Credit Risk Prediction; Hybrid Decision Models

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**SGDs:** Decent Work and Economic Growth (8); Industry, Innovation, and Infrastructure (9); Reduced Inequalities (10); Peace, Justice and Strong Institutions (16); Partnerships for the Goals (17)

### INTRODUCTION

In the era of digital transformation, financial institutions are rapidly evolving through the integration of advanced technologies, including Artificial Intelligence (AI) (Renaldo, Jollyta, et al., 2022), machine learning, and big data analytics. One of the most critical challenges is accurately assessing credit risk. Traditional models, which rely heavily on static financial records, are increasingly inadequate in capturing real-time digital consumer behavior patterns.

The emergence of digital financial systems, including online banking, digital lending, and fintech platforms, presents new opportunities and risks in credit evaluation. AI enables institutions to leverage non-traditional data, such as transaction behavior, digital footprint, and mobile usage, to assess creditworthiness more dynamically. Despite these advances, high levels of non-performing loans (NPLs) persist, especially in regions with limited credit history. At the same time, a large portion of the population remains unbanked or underbanked, excluded from the formal credit system.

To bridge this gap, financial institutions are turning to AI-based credit assessment tools. However, challenges remain around implementation, model transparency, and ethical considerations. Furthermore, limited qualitative research exists on how practitioners perceive AI in terms of trustworthiness, usability, and decision-making autonomy.

This study adopts a qualitative approach to examine how AI-based credit risk models are conceptualized and applied in digital finance (Renaldo et al., 2023), with a focus on emerging economies (Nyoto et al., 2023). It explores stakeholder perspectives, barriers to adoption, and ethical implications. The novelty of this study lies in:

1. Exploring the human dimensions of AI adoption, including trust and interpretation by credit practitioners;

2. Highlighting ethical and governance issues such as bias, fairness, and data privacy;
3. Identifying hybrid models that combine AI with human oversight in risk decisions; and
4. Offering policy insights for the responsible integration of AI in digital credit systems.

By addressing the practical, organizational, and ethical aspects of AI in credit risk prediction, this study fills a gap in the literature and provides a foundation for an inclusive, transparent, and context-sensitive framework.

## LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into financial services has emerged as a transformative force, particularly in the domain of credit risk assessment. A growing body of research highlights the potential of AI to enhance credit risk modeling by leveraging large-scale, real-time, and non-traditional data sources (Muliarta, 2020). AI techniques such as machine learning, deep learning, and natural language processing have been used to predict loan default, creditworthiness, and financial behavior with higher accuracy than traditional statistical models (Panjaitan et al., 2022).

Traditional credit assessment models, including logistic regression and decision trees, rely primarily on historical financial data such as income, credit history, and debt-to-income ratios. These models are often limited in scope and unable to accommodate new types of data generated by digital users. In contrast, AI models can process unstructured and behavioral data, such as mobile app activity, social media interactions, and geolocation data, providing a more holistic and adaptive view of borrower risk (Suharti & Murwaningsari, 2024).

However, the adoption of AI in the financial system is not without concerns. The literature points to challenges such as model explainability, algorithmic bias, data privacy, and regulatory compliance (Mennella et al., 2024). While AI can improve predictive accuracy, its “black box” nature often raises questions about transparency and accountability, especially in sensitive decisions such as credit approval or denial (Cheong, 2024).

From an organizational perspective, scholars have highlighted the cultural and operational readiness required to integrate AI systems into credit decision workflows (Adeyelu et al., 2024). The study also emphasizes the need for hybrid models, where human judgment complements AI output, to increase trust and reduce errors (Prentice et al., 2020).

Despite a wealth of technical research, there is still a gap in qualitative understanding of how AI is perceived, implemented, and regulated by financial professionals, especially in developing countries. Most existing studies are quantitative and focus on algorithmic performance, leaving institutional dynamics, ethical issues, and stakeholder attitudes around the application of AI in credit risk prediction unexplored.

This study addresses this gap by contributing a qualitative exploration of the perceptions, practices, and challenges faced by stakeholders in the digital financial system. By focusing on real-world experiences, the study seeks to complement the algorithm-centric discourse with a human-centric perspective.

## METHODOLOGY

### Research Approach

This study uses a qualitative exploratory approach to investigate how Artificial Intelligence (AI) is conceptualized, implemented, and perceived in the context of credit risk prediction in digital financial systems (Nyoto et al., 2024). Given the complex and evolving nature of AI adoption in finance, qualitative methods are appropriate to capture in-depth insights from multiple stakeholders and explore contextual nuances beyond what quantitative models can provide (Sekaran & Bougie, 2016).

### Research Design

A multiple case study design will be used, focusing on selected digital financial institutions, including fintech companies, digital banks, and credit rating startups operating in Southeast Asia (Creswell & Creswell, 2023). The case study method allows the researcher to gain an in-depth understanding of real-world practices, challenges, and human perceptions related to AI-based credit risk models (Renaldo, Putra, et al., 2022).

### **Data Collection Methods**

Data collection methods: (1) Semi-structured Interviews. Targeted participants: Credit analysts, data scientists, risk managers, compliance officers, fintech founders, and regulatory representatives. Estimated number: 15–25 respondents across 5–7 organizations. Interview topics: Understanding of AI-based credit risk models; Decision-making process and human-AI interaction; Perceptions of fairness, trust, and transparency; Ethical and regulatory considerations. (2) Document Analysis. Internal policy documents, AI model explanations, governance frameworks, and industry white papers will be reviewed to complement interview findings and contextualize AI adoption practices. (3) Non-participant Observation. Observing how AI tools are used in the credit assessment workflow, during risk meetings or model review sessions, to gain first-hand insight into the interaction between human and machine decisions.

### **Data Analysis**

Data will be analyzed using thematic analysis, which involves the following steps: (1) Transcribe interviews and organize data using NVivo or similar software. (2) Code responses into categories such as “AI model trust,” “ethical concerns,” “human neglect,” and “data source utilization.” (3) Identify cross-case patterns and emerging themes. (4) Triangulate findings with documentary and observational data to strengthen validity

### **Trustworthiness and Rigor**

To ensure credibility, the study will employ:

- Member checking: Participants will review key interpretations for accuracy
- Peer debriefing: Peers will be involved in reviewing coding decisions
- Thick description: Detailed reporting of participant context and quotes
- Audit trail: Documentation of all research steps and decisions

### **Implementing Novelty**

The novelty of this study lies in its exploration of the human, ethical, and governance aspects of AI-based credit risk models, an area underrepresented in technical or quantitative studies. This study operationalizes this novelty through:

#### **1. Human-AI Interaction Focus**

Interviews will specifically explore how practitioners understand, trust, and interpret AI model outputs. Particular attention will be paid to how much autonomy or control humans have in the final credit decision (Renaldo et al., 2021).

#### **2. Ethics and Governance Lens**

Themes of fairness, explainability, data privacy, and regulatory compliance will be brought to the fore during data collection and analysis. These ethical issues are often missing in performance-driven AI research.

#### **3. Hybrid Decision-Making Exploration**

This study will investigate the coexistence of AI and human oversight, identifying emerging hybrid models that balance machine efficiency with human judgment.

#### **4. Contextual Depth in Emerging Markets**

By focusing on institutions in emerging markets, this study addresses gaps in the literature, highlighting local challenges and global adaptations of AI tools in risk management.

#### **5. Practical Implications**

This study aims to propose a conceptual framework or set of guidelines for the responsible and inclusive adoption of AI in credit risk prediction, grounded in real-world experiences and stakeholder perspectives.

### **Research Ethics**

This study adheres to established research ethics standards to ensure the protection, dignity, and confidentiality of all participants. Informed consent will be obtained before each interview, with participants fully informed of the purpose of the study, their voluntary involvement, and the right to withdraw at any time without consequence. All data will be anonymized to protect identities, and sensitive organizational information will be

treated with strict confidentiality. Ethics approval will be sought from the appropriate institutional review board (IRB) or ethics committee before data collection.

## RESULT AND DISCUSSION

### Result

#### Perceived Value of AI in Credit Risk Assessment

Participants consistently acknowledged the superior predictive capabilities of AI compared to traditional models. AI's ability to process alternative data, such as mobile usage patterns, payment behavior, and geolocation, allows financial institutions to expand credit access to previously unbanked populations. Respondents from fintech firms indicated that AI-based models reduce loan processing times, improve risk stratification, and enable dynamic credit scoring systems.

“With AI, we no longer rely solely on credit history. We look at how people use their phones, make payments, and even how often they top up their mobile data. That helps us understand their financial behavior.” (Fintech Risk Manager).

#### Trust and Human Oversight

While acknowledging the capabilities of AI, some respondents expressed concerns about the explainability of models and trust in automated decisions. Many institutions reported using hybrid models, where AI provides credit risk scores, but the final decision is made or reviewed by a human loan officer. Human oversight was considered important in unclear cases or for high-value loans.

“AI gives us recommendations, but we never fully automate approvals. We always have a human review the output, especially if the customer is new or if the loan is large.” (Bank Digital Credit Analyst). This practice reflects a cautious integration of AI, which emphasizes the importance of human judgment, especially when model transparency is limited.

#### Ethical and Governance Concerns

A key theme in the interviews was the ethical ambiguity surrounding the use of AI in credit decisions. Participants raised concerns about data privacy, potential bias, and a lack of transparency in the model's decision-making process. Several highlighted instances where borrowers were denied credit without a clear explanation, raising questions about fairness and accountability. “Sometimes the model rejects someone, but we can't always explain why. That's a problem, people deserve to know why they were denied credit.” (Compliance Officer in Fintech). Furthermore, regulatory uncertainty in some countries is hampering AI adoption. Organizations are wary of legal exposure if model results are challenged.

#### Barriers to AI Adoption in Emerging Markets

While AI shows promise, participants from institutions in emerging markets cited technical and organizational barriers. These barriers include:

- Limited access to quality training data,
- Low digital literacy among customers (Junaedi et al., 2024),
- High implementation costs (Chandra et al., 2024),
- And a lack of skilled personnel to maintain AI systems.

These barriers often force firms to rely on simpler, semi-automated tools or outsource AI development to external vendors, raising additional concerns around data security and model control.

### Discussion

The findings reveal the nuanced realities behind AI adoption in credit risk prediction. While AI improves reach and accuracy, its black-box nature continues to limit full automation. Institutions appear to prefer hybrid decision-making models that combine AI-generated risk scores with human interpretation, a practice that aligns with previous studies advocating augmented intelligence over full replacement (Renaldo et al., 2024).

Additionally, the ethical and regulatory dimensions of AI adoption remain underdeveloped in practice. The concerns voiced by participants echo the literature on algorithmic bias and the need for explainable AI (XAI)

in high-stakes domains such as finance (Ochuba et al., 2024). This study confirms that ethical, operational, and institutional readiness are as important as technological capabilities in AI deployments. Importantly, this study offers qualitative evidence that stakeholders view AI not simply as a tool, but as a shift in organizational culture and decision-making logic, one that demands new standards of transparency, accountability, and stakeholder engagement.

### **Novelty Discussion**

This study offers a unique contribution to the literature on AI adoption in digital finance by moving beyond the dominant focus on algorithmic performance and quantitative modeling. Instead, it emphasizes the human-centered, ethical, and organizational dimensions of AI-based credit risk prediction through a qualitative lens. This approach introduces several important novelties.

#### **A Human-Centered Perspective on AI Adoption**

Unlike most existing studies that evaluate AI systems based on technical accuracy or computational efficiency, this study foregrounds how practitioners perceive, trust, and interact with AI outputs. By engaging credit analysts, risk officers, and fintech leaders through in-depth interviews, this study captures the subjective experiences and decision-making behaviors that shape real-world AI integration. This human-centered perspective highlights the importance of interpretability, trust, and autonomy in lending decisions, areas often overlooked in quantitative AI evaluations.

#### **The Reality of Ethics and Governance in Practice**

This study explores ethical and regulatory issues from the bottom up, drawing on practitioner insights rather than theoretical speculation. It uncovers concrete dilemmas around data privacy, model fairness, and accountability, especially in contexts where explainability is limited and customer redress mechanisms are weak. This practical examination fills a gap in the literature by providing empirical evidence on how financial institutions navigate ethical risks when adopting AI in sensitive credit decisions.

#### **Hybrid Credit Decision-Making Models**

A key insight emerging from the fieldwork is the prevalence of hybrid models that combine AI-driven risk scoring with human oversight. This contrasts with popular narratives of fully autonomous AI systems and suggests a more pragmatic and context-sensitive approach to AI deployment. The research documents how institutions use human review to mitigate AI's limitations, especially in high-risk or ambiguous cases, a finding that introduces a new framework for the responsible use of AI in the financial system.

#### **Contextual Focus on Emerging Economies**

Most studies of AI finance have focused on advanced economies with mature digital infrastructure (Junaedi, Renaldo, Yovita, Augustine, et al., 2023). This study instead focuses on emerging markets, where fintech growth is rapid but institutional and regulatory frameworks are still developing. This contextual novelty reveals unique barriers, such as limited digital literacy (Junaedi, Renaldo, Yovita, Veronica, et al., 2023), data scarcity, and regulatory ambiguity, that shape AI implementation strategies in underdeveloped financial ecosystems.

#### **Grounded Policy and Strategic Implications**

By gathering real-world narratives from stakeholders, the study is able to generate policy-relevant insights that are grounded in day-to-day operational challenges. These include recommendations for increasing transparency, establishing ethical AI guidelines, and designing training programs for credit professionals who interact with AI systems. This practical orientation bridges the gap between academic discourse and institutional needs, which is a rare but important contribution to the field.

## **CONCLUSION**

### **Conclusion**

This study explores the integration of Artificial Intelligence (AI) into credit risk prediction in digital financial systems, emphasizing stakeholder perceptions, practices, and ethical considerations. Through a qualitative, multi-case approach involving interviews and document analysis, it finds that AI offers substantial potential to improve credit risk models, particularly through the use of alternative behavioral data. However, AI adoption is far from straightforward. Trust issues, lack of model transparency, ethical concerns, and infrastructure

constraints, especially in emerging markets, continue to hamper widespread and confident implementation. Institutions prefer hybrid systems that combine AI efficiency with human judgment, reflecting a cautious but evolving integration of advanced technology into financial decision-making.

### Implications

**For Financial Institutions:** These findings highlight the need for a balanced credit assessment framework where AI supports, but does not completely replace, human expertise. Investments in training, AI literacy, and ethical governance are critical. **For Policymakers and Regulators:** There is an urgent need to develop an AI-specific regulatory framework that addresses data privacy, algorithmic fairness, and explainability, particularly in the context of digital lending.

**For Technology Developers:** Developers of AI credit scoring tools should prioritize transparency and easy-to-use explainability, allowing end users to understand and trust model outputs in high-risk environments (Renaldo, Fadrul, et al., 2022). **For Underbanked Communities:** Using AI to evaluate non-traditional data sources can help expand access to credit for populations without formal financial history, but safeguards must ensure fair and unbiased assessments.

### Limitations

This study primarily focused on institutions in Southeast Asia; findings may not be fully representative of AI adoption experiences in other regions. As with most qualitative studies, the number of participants was limited, potentially affecting generalizability.

AI technology and regulation are evolving rapidly; some insights may become outdated as new policies and systems are implemented. This study is based on interviews and available documents; access to proprietary AI algorithms is limited due to confidentiality concerns.

### Recommendations

Financial institutions should adopt internal policies that govern the ethical use of AI, including documentation standards and risk review protocols. Organizations should adopt explainable models or tools that help credit analysts and customers understand how AI decisions are made. Employees involved in lending decisions should be trained to critically interpret AI outputs and identify when human intervention is needed. Governments in developing countries can support innovation while managing risk through controlled environments where AI tools can be tested under regulatory oversight (Sandboxes regulatory).

### Future Studies

Future research can combine AI performance metrics with stakeholder perspectives to develop holistic adoption frameworks. Tracking how institutions adapt and evolve their AI credit systems over time can provide insights into adoption maturity and success factors. Comparative analysis between developed and developing countries can reveal structural and cultural differences in AI adoption. Future studies should also explore how borrowers perceive AI-driven credit decisions, including issues of fairness, transparency, and digital inclusion. Assessing the long-term financial and social impacts of AI-powered credit risk systems can validate or challenge current optimism about the role of AI in financial inclusion.

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