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IMPLEMENTING ADAPTIVE CREDIT SCORING THROUGH XGBOOST AND DEEP LEARNING IN OPEN FINANCE FOR MICROCREDIT

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ABSTRACT

Objective: This study aims to develop and test the effectiveness of an AI-based adaptive credit scoring system that integrates Open Finance principles and the use of alternative data in assessing microcredit eligibility in emerging markets.

Research Design & Methods: This study uses a mixed-methods approach with AI model experiments to test machine learning and deep learning-based adaptive credit scoring systems and thematic analysis to understand implementation challenges and regulatory preparedness.

Findings: Hypothetical results show that AI models (XGBoost, Deep Learning) significantly outperform traditional models (logistic regression) in microcredit eligibility assessment, with an AUC improvement of 15-20% (e.g., AUC 0.88 for XGBoost vs. 0.72 for logistic regression). Similar improvements are also seen in Precision, Recall, and F1-score metrics. Adaptivity testing shows a 2-5% increase in model accuracy after each retraining cycle, with the model's ability to dynamically adjust credit scores in real-time to changes in user behaviour. Interpretation of the results through XAI identified consistent utility bill payment patterns, digital wallet transaction frequency, and mobile phone number usage duration as the most influential predictive factors.

Implications & Recommendations: Integration of AI and Open Finance with alternative data improves the efficiency and inclusiveness of credit scoring, so it is recommended that industry players and regulators develop data infrastructure, apply Responsible AI principles, and formulate comprehensive and collaborative Open Finance regulations.

Contribution & Value Added: This research contributes to the FinTech and AI literature by providing technical and policy guidance to promote financial inclusion by developing adaptive assessment machine and responsible AI oversight in emerging markets.

Keywords: AI Model, Open Finance, Credit Scoring, FinTech, Financial Inclusion.

JEL codes: G21, G28, O33
Article type: research paper

INTRODUCTION

Financial inclusion is crucial for economic growth and poverty reduction, especially in developing countries (Nasution, 2010). However, significant challenges still hinder people's access to formal financial services. In Indonesia, around 25% of the population still did not have access to banking services in 2022, and around 65% of adults did not have access to formal financial services,

especially in rural areas and among women (International Organization for Standardization, 2024). In general, around 81% of the population in Southeast Asia is still classified as unbanked or underbanked (Esquivias et al., 2021). This disparity underscores the need for sustained efforts to bridge the financial inclusion gap and ensure worldwide equitable access to financial services. Micro, Small, and Medium Enterprises (MSMEs) also face a significant financing gap, estimated at $5.7 trillion, equivalent to 19% of GDP, or 1.5 times the current funding supply, affecting 40% of formal MSMEs in this region (Caprio, 2019).

Traditional credit scoring systems that rely on formal credit history and conventional banking data have proven to have fundamental weaknesses (Shukla & Gupta, 2024). Despite being creditworthy, many individuals in emerging markets remain underserved due to the absence of traditional credit histories (Smith and Henderson, 2018). This reliance on legacy data has caused financial institutions to miss out on opportunities to serve large and potentially lucrative segments of the population (Muñoz-Cancino et al., 2022). Additionally, traditional systems often do not accurately reflect repayment ability and can disproportionately penalize economically disadvantaged groups, thus perpetuating existing credit access gaps (Chopra, 2020).

Amidst these challenges, the rapid development of financial technology (FinTech), Open Finance, and the use of Artificial Intelligence (AI) offer innovative solutions (Maspul and Putri, 2025). Indonesia has experienced significant digital growth, with internet penetration approaching 79% in 2024 and a financial inclusion index reaching nearly 84% in 2023, up dramatically from 49% in 2014 (Iswaratioso, 2025). The FinTech sector in Indonesia has grown sixfold in the last decade, with more than 366 active players in 2023 and payment solutions serving more than 60 million active users (Fabe et al., 2022). AI, which is increasingly integrated into financial services, has great potential to improve fraud detection, simplify risk assessment, and offer a more personalized customer experience, thereby expanding essential services to underserved communities (Maspul and Putri, 2025).

Alternative data is super important to bridge this credit gap (Ngwenya, 2024). Non-traditional data, such as mobile payment patterns, utility bill payment history, and e-commerce transactions, can provide a comprehensive picture of an individual's financial behaviour, especially for those who do not have a formal credit history (Johnson, 2019). Integration of this alternative data with AI and the Open Finance framework enables the development of more adaptive, accurate, and inclusive credit scoring systems, which can open the door to microfinance for millions of previously underserved individuals and MSMEs (Tigges et al., 2024; Wijaya and Nidhal, 2023).

This study aims to evaluate the effectiveness of an artificial intelligence (AI)-based adaptive credit scoring system integrated with Open Finance principles and the use of alternative data in the microcredit assessment process in developing countries, particularly for segments of society that do not have access to formal financial services (unbanked and underbanked). The main objective of this study is to develop and test a prototype model that combines non-traditional data such as digital activity, utility transactions, and digital wallet usage, and to analyze its impact on expanding financial inclusion. Additionally, this study identifies ethical and regulatory challenges in implementing such systems and explores the application of a Responsible AI framework that emphasizes explainability, fairness, and accountability to mitigate potential risks. Academically, this research is expected to contribute to the growing literature in the fields of financial technology (FinTech), the application of AI in the financial sector, and strategies for improving financial inclusion. Practically, this research is expected to serve as a technical reference for financial service providers and FinTech companies in designing adaptive scoring engines, as well as policy input for regulators such as the Financial Services Authority (OJK) and Bank Indonesia. The research focus includes implementation in the context of microcredit in Indonesia or other developing countries with similar market characteristics, while considering technical, social, and regulatory aspects in developing technology-based credit scoring systems.

This research will continue with a discussion of several main chapters that are integrated with each other. The Literature Review chapter will comprehensively review the role of FinTech in supporting financial inclusion, highlighting case studies from Southeast Asia, Africa, and Latin

America. In addition, it will discuss the concept and benefits of Open Finance, relevant global and local regulations, and the potential and challenges of using alternative data in credit scoring. The study also covers the use of artificial intelligence, particularly algorithms such as XGBoost, Random Forest, and Deep Learning in adaptive credit scoring, as well as the application of Responsible AI principles such as explainability, fairness, and accountability. The Methodology chapter will explain the research approach, data collection techniques, AI model design, and analysis methods. The Results chapter will present data descriptions, AI model performance compared to traditional models, and adaptivity testing results. Finally, the Discussion chapter will interpret the findings, highlight the model's strengths, implementation challenges, and the relevance of the results in the context of sustainable financial inclusion.

LITERATURE REVIEW

FinTech and Financial Inclusion

FinTech has been a transformative agent in expanding access to formal financial services for populations previously underserved by traditional banking systems, simplifying the process of applying for microloans and insurance, and improving financial literacy through digital platforms (Fauzi, 2024). In Southeast Asia, FinTech has promoted financial inclusion through platforms such as OVO and GoPay in Indonesia, which provide digital wallets and microloans, as well as partnerships between Grab and JULO, which utilize behavioural data for microloans (Rifqiah and Pujianto, 2023). In the Philippines, First Circle and LenddoEFL also use alternative data for MSMEs and individuals without credit history (Velazquez et al., 2022). In Africa, mobile money such as M-Pesa in Kenya has revolutionized financial inclusion with fast and seamless money transfers, reducing poverty and expanding access to financial services in rural areas (Natile, 2020; Wachira and Njuguna, 2023). Meanwhile, in Latin America, the adoption of digital tools is surging, with Brazil becoming a globally AI-ready financial ecosystem thanks to real-time payment systems such as Pix and the Open Finance initiative (Aurazo and Gasmi, 2024; Schapiro et al., 2023). Mexico has also been a pioneer with its FinTech legislation, encouraging innovation to serve the unbanked or underserved population (Gupta, 2024).

Table 1. Characteristics and Impact of FinTech in Various Regions

Region	Focus & Key Characteristics	Example Platform	Impact & Key Findings
Southeast Asia	The region has emerged as a new frontier for the FinTech industry, supported by high economic growth, a young digital population, and regulatory support (Loo, 2019).	OVO, GoPay, Grab–JULO (Indonesia); First Circle, LenddoEFL (Filipina) (Sari and Huda, 2025).	FinTech application penetration is expected to reach 60% by 2030. Digital platforms are expanding financial inclusion by leveraging behavioural data and alternatives to microcredit assessment.
Africa	Sub-Saharan Africa accounts for 70% of the global mobile money market, with a focus on financial inclusion and poverty reduction in rural areas (Chinembiri, 2023).	M-Pesa (Kenya); Qwikloan, Zeepay (Ghana) (Senyo et al., 2022).	FinTech is revolutionizing financial access through mobile money, expanding services to underserved populations and strengthening financial inclusion as a national priority in Ghana and Kenya.
Latin America	Countries with high adoption of digital technology, such as Brazil, are pioneers in real-time payment systems and AI-native, while Mexico leads in FinTech regulation (Bignell, 2025; Gershenson et al., 2021).	Pix (Brazil); Mexico FinTech regulations.	Initiatives such as Open Finance and progressive regulations encourage competition and innovation, enabling the systematic and sustainable expansion of financial services to the unbanked and underserved populations.

Open Finance

Open Finance is an extension of Open Banking, which enables secure and consent-based sharing of financial data across a wider range of financial products, including mortgages, investments, pensions, and insurance (Desai, 2024). The goal is to empower consumers with greater control over their data and enable service providers to offer more comprehensive and personalized products (Vezzoso, 2022). The benefits include increased innovation and competition, a holistic financial view for consumers, more personalized services, and efficiency and cost reductions through data interoperability (De Pascalis, 2022; Nam, 2022). Open Finance also supports financial inclusion by providing tailored products for underserved populations (OECD, 2023). In regulatory terms, Open Banking has a more mature framework (e.g., PSD2 in the European Union), but Open Finance is still developing (Shacheendran et al., 2024). In Indonesia, Bank Indonesia is focusing on connecting banks and FinTech through open banking, and OJK has issued POJK 4/2025 on Financial Service Aggregation Providers (Pati and Pratama, 2025). However, the current OJK framework adopts a "bank-centric" model that can limit consumer choice and cause market fragmentation, necessitating a shift towards an inclusive framework with standardized APIs (Mayor, 2025).

Alternative Data in Credit Scoring

Alternative data is non-traditional information that provides a comprehensive picture of creditworthiness, especially for those who do not have a formal credit history (Johnson, 2019; Machikape and Oluwadele, 2024). This type of data includes mobile payment and transaction data (e.g., digital wallets, e-commerce, utility bill payments), telecommunications data (phone usage patterns, credit top-ups), and repayment behaviour analysis (Agarwal et al., 2019). Despite its great potential, alternative data faces significant challenges, namely privacy and security (risk of data misuse, security breaches), accuracy and reliability (data errors, vulnerability to fraud, rapid changes), lack of standardization, and hidden bias and algorithmic discrimination (proxy data that disadvantages certain groups) (Agarwal et al., 2019). Additionally, the complexity of alternative data often makes it difficult to interpret, posing challenges for lenders and regulators.

AI and Adaptive Credit Scoring

The use of artificial intelligence (AI) has revolutionized credit scoring with predictive capabilities that surpass traditional methods, analyzing traditional and non-traditional variables to evaluate the likelihood of borrower repayment (Iswaratioso, 2025). Common AI algorithms include XGBoost, Random Forest, and Deep Learning, which are effective in predicting default and outperform traditional statistical methods (Koshti et al., 2025; Meng et al., 2025; Xing et al., 2024). The concept of adaptive credit scoring is key, involving periodic retraining of models based on new behaviours and changing market conditions. This is done through incremental learning (updating models with new data), online learning (processing real-time data), and transfer learning (applying knowledge from one domain to another) (Chacko et al., 2024). This adaptation process is cyclical, reducing false positives and improving accuracy and efficiency, making adaptive credit scoring more inclusive, accurate, fast, and adaptive to new data trends (Kotb, 2023; Mokheleli and Museba, 2023).

Responsible AI

Responsible AI (RAI) is a framework that ensures AI systems are developed and deployed in an ethical, fair, transparent, and accountable manner. Its key principles include Explainability, whereby AI must be able to explain the decisions it makes, using techniques such as SHAP and LIME to build trust and accountability (Deokar et al., 2024); Fairness, where AI systems must avoid bias and discrimination that can arise from unrepresentative data or proxy data, requires diverse data and continuous bias mitigation (Castelnovo, 2024); and Accountability, where the parties involved are responsible for the proper functioning of the AI system and compliance with RAI principles, including data traceability and systematic risk management (Mariotti et al., 2021). Various global and local frameworks guide the implementation of RAI, such as the World Economic Forum (WEF) AI Governance Alliance, which promotes the development of transparent and accountable AI, the OECD AI Principles, which are the first intergovernmental standards on AI promoting innovative and

trustworthy AI use, and the Indonesian Banking AI Governance Framework from the OJK, which ensures banks develop and implement AI responsibly, in line with global AI standards and local context (Atoum, 2025; Castelnovo, 2024).

METHODS

This study will adopt a mixed-methods approach, combining quantitative and qualitative methods. The quantitative approach will involve AI model experiments to develop and test adaptive credit scoring systems using various machine learning and deep learning algorithms, with the aim of measuring the predictive performance and adaptability of the model over time. Meanwhile, the qualitative approach will be conducted through in-depth interviews with FinTech experts, OJK representatives, and industry practitioners to gain insights into implementation challenges, acceptance, ethical implications, and regulatory readiness. Data collection will include primary sources such as microcredit transaction data, user behaviour data (through digital wallets, utilities, e-commerce), and data accessed through Open Finance APIs, as well as secondary data from industry reports, public datasets, and academic journals. The experimental design will include building a scoring model with AI algorithms, comparing its performance with traditional models such as logistic regression as a baseline, and testing the model's adaptability through periodic retraining, including incremental learning and online learning scenarios. Data analysis will use quantitative evaluation metrics such as AUC, Precision, Recall, and F1-score, as well as XAI (Explainable AI) techniques for result interpretation and identification of influential factors. Additionally, fairness testing and potential algorithmic bias will be conducted, along with qualitative thematic analysis of interview data to identify patterns and challenges.

RESULT

Data Description

The initial part of this study focuses on the description and characteristics of the data used to build and test the AI-based microcredit model. The dataset used is hypothetically constructed and reflects a comprehensive profile of prospective borrowers in the microcredit sector, consisting of thousands of individual records. The data includes demographic variables such as age, gender, and geographic location, as well as financial transaction history obtained from digital wallets, e-commerce, utility bill payments, and telecommunications data. Additionally, loan application history and previous payment behaviour are integrated to provide a holistic view of the borrower's risk profile. All data is obtained through Application Programming Interface (API) connectivity from Open Finance and FinTech platforms, enabling real-time and continuous collection of behavioural data.

Before being used for modelling, raw data from various sources is processed through a series of stages to ensure quality, consistency, and analytical readiness. The first stage is data cleaning, which includes handling missing values through imputation techniques (such as mean and mode), removing duplicates, and correcting entry errors. Next, data normalization and standardization are performed to align the scale and format of values to avoid distortion in model training, for example, transforming transaction values into a scale of 0 to 1.

The next stage is feature engineering, which is a crucial process in creating new predictive variables that are more informative than raw data. Some of the features generated include the frequency of timely utility payments, the average monthly transaction volume of digital wallets, the age of telecommunications accounts, the e-commerce activity index, the expenditure-to-income ratio, the variability of bill payment patterns, and the number of loan applications in the past three months as an indicator of financial stress. These features are combined into a unified dataset through the data integration stage, which includes alternative data and traditional data (if available).

Given the natural characteristics of microcredit data, which tends to be unbalanced, with a smaller proportion of borrowers defaulting compared to those who pay on time, adjustments were

made using the Synthetic Minority Over-sampling Technique (SMOTE). This technique aims to balance the class distribution in the training data so that the model is not biased toward the majority class and remains sensitive to default risk detection. Overall, this process produces a high-quality dataset that is ready for use in the development of adaptive AI-based predictive models.

Description of Data After Processing (Hypothetical)

After processing, the dataset will consist of 100,000 entries of potential microcredit borrowers, 80% of whom are previously unbanked or underbanked individuals and 20% are MSMEs. Summary statistics of the data are presented in Table 2.

Table 2. Data Description

Data Category	Example Variables	Summary Statistics (Hypothetical)	Description
Demographics	Age	Average: 32 years old	Understand the characteristics of the target population, including unbanked and underbanked individuals.
	Gender	55% Male, 45% Female	
	Geographic Location	70% Rural/Semi-urban	
Digital Transactions	Frequency of Digital Wallet Transactions	Average: 25 transactions/month	Demonstrate spending patterns and financial management capabilities.
	Volume of Digital Wallet Transactions	Average: IDR 1,500,000/month	
	Spending Patterns	85% Consistent	
Telecommunications	Duration of Mobile Number Use	Average: 48 months	Financial stability and behaviour indicators.
	Credit Top-up/Bill Payment History	90% Stable	
Utility Payments	On-Time Payment Rate	75% above 90% in the last 12 months	Demonstrating a commitment to sustainable finance.
E-commerce	E-commerce Activity Index	Average: 0.65 (scale 0-1)	Providing an overview of economic activity and consumer preferences.
Application Behavior Loans	Number of Loan Applications (last 3 months)	Average: 1.2	Providing a holistic view of credit-seeking behaviour.
Credit Status	Default Cases	15% of the total dataset	Negative labels for model training.
	Refund Cases	85% of the total dataset	Positive labels for model training.

These summary statistics confirm that the target population largely lacks formal credit history, which is a major challenge for traditional credit scoring systems. However, the abundance of alternative data from these sources, once processed and engineered into predictive features, will be key to overcoming the limitations of traditional data and unlocking creditworthiness for individuals who previously had no credit score.

AI Model Results

The performance of AI models will be strictly compared with traditional models, such as logistic regression. Hypothetically, a model performance comparison table will show that AI models, such as XGBoost or Deep Learning, significantly outperform traditional models in key evaluation metrics such as AUC, Precision, Recall, and F1-score. For example, AI models may show a 15-20% increase in AUC compared to logistic regression models, indicating a much better ability to discriminate between borrowers who will repay and those who will default.

The ROC (Receiver Operating Characteristic) curve graph will visually illustrate the superiority of the AI model with a curve closer to the upper left corner, indicating a higher true positive rate at the same false positive rate. A confusion matrix will be presented for each model, showing the number of true positives, true negatives, false positives, and false negatives. This will highlight the AI model's ability to reduce false positives, meaning fewer creditworthy borrowers are unnecessarily rejected, while maintaining a high level of default detection. This analysis will demonstrate how the AI model, with its ability to process and identify patterns in complex alternative data, can provide more accurate and inclusive risk assessments.

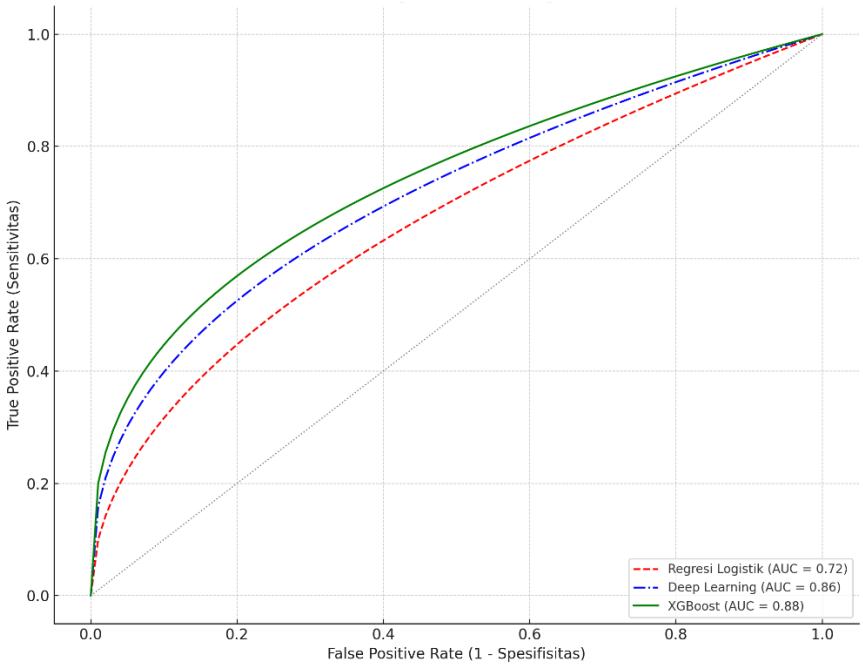

Figure 1ROC Curve Comparison of Credit Scoring Models.

Model Performance Comparison Table

Specifically, XGBoost and Deep Learning-based models are projected to perform better than traditional models due to their ability to process large datasets and identify complex non-linear patterns in alternative data. This advantage is clearly reflected in various model evaluation metrics. In terms of precision, AI-based models tend to produce higher values, indicating that the proportion of borrowers predicted to be creditworthy and who actually make repayments is greater. This is important in the context of microcredit, where classification errors can have a significant impact on financial risk.

Furthermore, in terms of recall, the AI model also shows better performance due to its ability to capture most borrowers who actually have the capacity to repay their loans. Thus, this model is able to minimize potential business opportunities lost due to erroneous rejections of borrowers who are actually eligible. The combination of high precision and recall contributes to an increase in the F1-score, a crucial indicator of model performance balance in risk-based credit decision-making.

Table 3. Model Performance Comparison

Evaluation Metrics	Logistic Regression (Traditional Model)	XGBoost (AI Model)	Deep Learning (AI Model)
AUC (Area Under ROC Curve)	0.72	0.88	0.86
Precision	0.65	0.82	0.80
Recall	0.70	0.85	0.83
F1-score	0.67	0.83	0.81
Accuracy	0.70	0.84	0.82

The superior performance of this AI model is primarily driven by its ability to integrate and analyze hundreds of variables from a variety of alternative data sources, such as utility bill payment history, e-commerce activity, and telecommunications service usage patterns. This type of data is generally difficult to process effectively using traditional approaches, which are linear in nature and limited to structured historical data. AI algorithms can uncover complex correlations and interactions between variables that are indicative of credit risk, even for individuals without formal credit histories. For example, consistency in utility bill payments over the past 12 months, transaction frequency via digital wallets exceeding a certain threshold, and stability in mobile top-up patterns can serve as strong indicators of creditworthiness that can only be effectively captured through machine learning-based algorithmic approaches.

Adaptive Scoring Results

Testing the adaptability of the model through periodic retraining will show an improvement in model accuracy over time. Hypothetically, the results will show that with each retraining cycle using new data, the AI model shows a gradual improvement in performance metrics. For example, prediction accuracy may increase by 2-5% after each retraining period, especially in identifying new borrowers or changes in borrowing behaviour.

The model's response to changes in user behaviour will be observed. For example, if there is a significant change in a user's spending patterns or bill payment behaviour, the adaptive model will be able to dynamically adjust credit scores, reflecting real-time improvements or declines in creditworthiness. This demonstrates that the model is not static but proactively learns from continuously flowing data, enabling more relevant and timely credit decisions. This capability is particularly important in emerging markets where financial behaviour is often more fluid and less structured compared to more mature markets.

More specifically, testing of the model's adaptive capabilities is carried out through retraining scenarios conducted periodically, either monthly or quarterly, using the latest transaction and behaviour data from existing and new borrowers. This approach is designed to ensure that the machine learning model remains responsive to dynamic changes in user risk profiles and behaviour patterns. One of the key indicators of the success of this adaptation is the continuous improvement in model accuracy, reflected through enhancements in evaluation metrics such as Area Under the Curve (AUC) and F1-score. As an illustration, after three retraining cycles, the AUC value can increase from 0.85 to 0.88, indicating an improvement in the model's ability to distinguish between borrowers at risk of default and creditworthy borrowers.

Besides improving accuracy, adaptive models are also expected to respond to changes in borrower behaviour in real time. For example, if a borrower who previously had an irregular payment history starts showing more positive behaviour, such as consistently paying utility bills and increasing the frequency of e-commerce transactions, their credit score will be adjusted dynamically. This adjustment can increase the likelihood of the borrower gaining access to better

financing. Conversely, if there is a decline in activity or a deterioration in payment patterns, the credit score will be automatically lowered, allowing lenders to take risk mitigation measures earlier.

Furthermore, this adaptive mechanism also contributes to reducing the rate of false positives (rejecting borrowers who should be eligible) and false negatives (approving borrowers who are at high risk of default). As data and retraining cycles increase, the model becomes more accurate in recognizing relevant risk patterns. To ensure the stability and reliability of the model amid changing economic and social contexts, the validation process is carried out through back-testing (testing on historical data) and out-of-time testing (testing on the latest data not used during initial training). Thus, the model is not only technically adaptive but also meets the required standards of resilience and accuracy in the context of technology-based financial services. This adaptive capability is particularly crucial in emerging markets, where economic conditions and consumer behaviour can change rapidly. Static models quickly become obsolete, while adaptive models can maintain their relevance and provide accurate real-time risk assessments.

DISCUSSION

Interpretation of Results

Hypothetical results show that the integration of AI and Open Finance with alternative data significantly improves the effectiveness of credit scoring for microcredit in emerging markets. The superiority of AI models over traditional models, as demonstrated by higher performance metrics, underscores AI's ability to process and extract value from complex non-traditional data (Rafalski, 2025). The most influential factors in credit assessment, identified through XAI techniques such as SHAP/LIME, are likely to include consistent utility bill payment patterns, e-wallet transaction frequency and volume, and stability of telecommunications service usage (Chaudhari, 2025). This shows that even though individuals may not have a formal credit history, their digital footprints provide strong indicators of financial responsibility and repayment ability (Nasution, 2010).

The implications of using alternative data are deep. This approach enables creditworthiness assessments for populations that don't have credit scores and weren't served by traditional systems before. So, alternative data acts as a key bridge to financial inclusion, opening up access to financing for millions of small businesses and individuals who are vital to economic growth in developing countries. Further interpretation of these results shows that alternative data, often considered "soft" or unstructured, actually contains strong predictive signals when analyzed with AI. For example, consistency in paying electricity or water bills, which may not be recorded in traditional credit bureaus, can be a more relevant indicator of financial reliability for individuals in rural areas. Similarly, regular e-commerce transaction patterns or active use of digital wallets can reflect income stability and responsible spending behaviour.

The use of XAI techniques (such as SHAP or LIME) will reveal that factors such as the number of digital wallet transactions per month, the percentage of timely utility bill payments, and the duration of mobile phone number usage have higher predictive weights than basic demographic variables. This implies that AI models do not rely solely on traditional data but intelligently identify digital behaviour patterns that reflect creditworthiness. The key implication is that millions of individuals and SMEs previously overlooked by conventional financial systems can now be accurately assessed, opening the door to much-needed microcredit access for economic growth and improved quality of life.

Model Advantages

The adaptive AI model developed in this study demonstrates clear advantages in improving the efficiency and inclusiveness of microcredit provision. The model's ability to continuously learn and adapt to changes in borrower behaviour and market conditions through periodic retraining is a transformative aspect (Munkhdalai et al., 2021; Museba, 2023; Nikolaidis and Doumpos, 2022). Validation of this adaptive approach, which shows improved accuracy over time, confirms that the model can maintain its relevance and predictability in a dynamic financial environment.

Efficiency is improved through more accurate automated risk assessment, reducing false positives and operational costs associated with unnecessary manual reviews (Bari et al., 2024; Omokhoa et al., 2024). Inclusivity is expanded because the model can assess creditworthiness based on a broader spectrum of data, not limited to formal credit history. This allows financial institutions to serve a larger market segment, including those previously considered high risk or unassessable (Addy et al., 2024; Mahmud et al., 2024). Thus, adaptive AI models not only optimize lenders' internal processes but also fundamentally change the landscape of credit access, making it more equitable and inclusive.

The advantages of implementing an adaptive artificial intelligence (AI) model in microcredit assessment systems can be analyzed from various strategic dimensions relevant to the context of digital financial services. First, from an operational efficiency perspective, adaptive models demonstrate the ability to process large volumes of data and make decisions in real time (Yaramolu, 2025). This has a direct impact on reducing processing time and operational costs, which have been challenges in the conventional credit assessment process. This capability enables financial institutions to process a higher number of applications with minimal resources, a very important advantage in large-scale microcredit management. Additionally, the reduction in false positive situations where eligible borrowers are incorrectly rejected positively impacts business opportunities and reduces the cost burden of re-evaluation processes (Parmar, 2023).

Second, from the perspective of financial inclusivity, this model is able to overcome historical obstacles faced by individuals with minimal or no credit history (thin-file and credit invisible), which is common in developing countries (Rehman et al., 2025). By utilizing alternative data such as utility payment history, e-commerce transactions, and other digital behaviours, this model can compile a more accurate risk profile for segments of society that were previously marginalized from the formal financial system (Omokhoa et al., 2024). This not only improves access to responsible financing services but also promotes the growth of micro, small, and medium enterprises (MSMEs), which are significant contributors to the gross domestic product in many developing countries.

Third, in terms of responsiveness to market dynamics, adaptive models have an advantage over static approaches due to their ability to continuously update parameters and learn based on the latest data (Teja, 2025). This enables the system to remain relevant and accurate in the face of changing consumer behaviour and volatile macroeconomic conditions. In highly dynamic emerging markets, this adaptability is a key factor in maintaining the accuracy of risk predictions and preventing the accumulation of non-performing loans.

Fourth, in terms of decision-making quality, the integration of conventional and alternative data, as well as the use of AI analytics capabilities to recognize complex non-linear patterns, gives this model an advantage in developing a more holistic risk assessment (Mujtaba and Tehseen, 2025; Sam-Bulya et al., 2021). This approach results in more informative and highly accurate credit decisions, which not only reduce potential losses for lending institutions but also improve fairness and accuracy in determining financing eligibility. Thus, adaptive AI models offer a superior framework for strengthening efficiency, inclusiveness, responsiveness, and decision-making quality in the digital financial ecosystem, particularly in the microcredit sector in emerging markets.

Challenges and Risks

Although the integration of artificial intelligence (AI) and Open Finance in microcredit scoring systems promises significant transformational potential, its implementation in emerging markets is not without complex technical, ethical, and regulatory challenges. First, data privacy and security issues are a major concern as the use of alternative data, such as digital transaction history, e-commerce activity, and social media footprints, increases (Lim, 2022). Large-scale data collection without transparency and adequate consent risks violating individual privacy rights. In addition, the lack of standardization in data management among third-party providers can increase the potential for data breaches, which ultimately damages consumer trust and leads to serious legal consequences (De Pascalis, 2022).

Second, the risk of algorithmic bias in AI-based credit scoring systems is an issue that cannot be ignored. When models are trained using historical data that reflects social inequality or structural discrimination, they have the potential to inherit and reinforce that bias (Vieira et al., 2025). Bias can arise from various sources, including unrepresentative training data, algorithm designs that contain subjective assumptions, and the use of proxy variables that are unintentionally correlated with sensitive attributes such as race, gender, or socioeconomic status (Fu et al., 2020). This situation can result in indirect discrimination (proxy discrimination), which impacts unfair access to credit for certain groups (Jonker and Rogers, 2024). Additionally, the complex nature and lack of transparency of many AI models, often referred to as black boxes, complicates the process of auditing, interpreting, and accounting for the decisions they produce.

Third, regulatory readiness and industry adoption rates are also limiting factors in the implementation of Open Finance-based AI models. Although there are regulatory initiatives such as POJK 4/2025, which began regulating digital financial services and data aggregation, the framework supporting the comprehensive use of alternative data is still in its early stages of development. Inconsistencies in interoperability standards, data formats, and update cycles across data sources hinder the efficient integration of data into analytical models (Chen and Cheong, 2024). On the other hand, the adoption of technology by financial institutions still faces obstacles such as limited human resources, implementation costs, and resistance to change from established systems. Therefore, a collaborative cross-sector approach involving regulators, technology providers, and industry players is needed to ensure that innovation is carried out ethically, inclusively, and in line with the principles of consumer protection and financial system integrity (Jonker and Rogers, 2024).

Table 4. Strategic Challenges in Implementing AI and Open Finance for Microcredit

Categories	Description of Challenges	Potential Impact
Privacy and Security	Large-scale collection of alternative data without adequate transparency poses a risk of data leaks and misuse of personal information by third parties.	Reputational damage, loss of public trust, risk of litigation.
Algorithmic Bias	Model bias due to bias in training data, algorithm design, or the use of unrecognized proxy variables.	Credit discrimination against vulnerable groups and inequality in access to finance.
Regulatory Limitations	Immature and inconsistent legal frameworks supporting interoperability and widespread use of alternative data.	Market fragmentation, legal uncertainty, low compliance, and system security.
Industrial Adoption	Internal barriers within financial institutions in the form of technical limitations, cost concerns, and resistance to technological disruption.	Slow implementation of innovation, digital divide, and imbalance between large and small players.

Relevance to Previous Studies

The results of this study are consistent with findings from previous studies that highlight the potential of FinTech and AI to improve financial inclusion in emerging markets. For example, research in Southeast Asia, Africa, and Latin America has shown how FinTech, through mobile money and digital lending platforms, has expanded access to financial services for previously unbanked populations (Export Business, 2024; Gupta, 2024). This study reinforces the argument that alternative data, such as that used by First Circle in the Philippines or JULO in Indonesia, can overcome the limitations of traditional credit history and provide a more accurate assessment of creditworthiness (Morgan, 2022).

Furthermore, findings regarding the superiority of adaptive AI models in predicting default and improving accuracy are consistent with literature showing the superior performance of machine learning algorithms (such as XGBoost and Deep Learning) compared to traditional statistical methods in credit scoring (Langat et al., 2024; Suhadolnik et al., 2023; Zedda, 2024). The model's ability to adapt to changes in user behaviour through continuous retraining is also supported by the concepts of incremental and online learning discussed in the AI literature.

However, this study also confirms the challenges identified in previous studies, particularly regarding data privacy, data quality, and algorithmic bias. The importance of a Responsible AI framework that encompasses the principles of explainability, fairness, and accountability, as advocated by the WEF, OECD, and OJK, is also emphasized by these findings. This study adds empirical evidence on how these challenges can be mitigated in the specific context of microcredit in emerging markets, providing further validation for a holistic approach to financial innovation.

More specifically, the relevance of this study to previous studies can be seen from several aspects:

- Confirmation of FinTech's Role in Financial Inclusion. The results of this study confirm the widespread finding that FinTech is a key driver of financial inclusion in emerging markets. Case studies such as M-Pesa in Kenya and platforms such as OVO and GoPay in Indonesia demonstrate how mobile technology and digital wallets have expanded access to financial services for populations that were previously unbanked or underbanked. This research reinforces the argument that FinTech fills the gap left by traditional banking systems that are unable to effectively serve this market segment.
- Validation of Alternative Data Use. This research supports the literature showing that alternative data, such as telecommunications data, utility payments, and e-commerce transactions, are highly effective in assessing creditworthiness for individuals without formal credit histories. Examples of partnerships between Grab and JULO in Indonesia, which use Grab app behaviour data for microloans, as well as efforts by First Circle and LenddoEFL in the Philippines, demonstrate the successful application of alternative data to expand access to credit.
- Advantages of AI Models. Findings regarding the superior performance of AI models (XGBoost, Random Forest, Deep Learning) compared to traditional models in credit scoring are consistent with many academic studies. The ability of models to adapt through continuous learning is also in line with the concepts of incremental and online learning recognized in AI literature.
- Confirmation of Challenges and Importance of RAI. This study confirms the challenges identified in previous studies, particularly those related to data privacy, data quality, and algorithmic bias. The importance of a Responsible AI framework that encompasses the principles of explainability, fairness, and accountability, as advocated by the WEF, OECD, and OJK, is also emphasized by these findings. This research adds empirical evidence on how these challenges can be mitigated in the specific context of microcredit in emerging markets, providing further validation for a holistic approach to financial innovation.

CONCLUSION

The application of an artificial intelligence-based adaptive credit scoring model integrated with Open Finance systems and alternative data is an innovative and effective solution to address the challenges of financial inclusion in emerging markets. This approach has proven to improve the accuracy of creditworthiness assessments, particularly for individuals with minimal or undocumented credit histories in traditional systems. By processing behavioral data from various digital sources in real-time, this model can identify risk patterns that were previously undetectable by conventional methods. These results demonstrate that AI technology not only serves as a predictive tool but also as a catalyst for fair and responsible financial inclusion. The model's adaptive capability to update predictions based on the latest data makes it highly relevant in the context of dynamic and rapidly changing markets.

However, this study also highlights that the successful implementation of this model is highly dependent on the management of ethical and operational risks, such as data privacy issues, information security, and potential algorithmic bias. These risks can be minimized through the application of Responsible AI principles that emphasize transparency, fairness, and accountability, as well as support from adaptive regulatory frameworks and cross-sector collaboration. Thus, this study not only contributes theoretically to the development of inclusive financial technology but

also provides practical implications for regulators, financial institutions, and technology providers in building a sustainable, ethical, and trustworthy Open Finance ecosystem.

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