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AI-DRIVEN FINTECH AND FINANCIAL INCLUSION: OPPORTUNITIES AND CHALLENGES

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ABSTRACT

The goal of financial inclusion which provides affordable and responsible financial services to all people remains an important global development target because 1.4 billion adults worldwide do not have access to banking services (Demirgüç-Kunt et al., 2022). The conventional FinTech developments have increased digital payment systems but artificial intelligence (AI) delivers a revolutionary advancement through its ability to provide different credit evaluation methods and bespoke customer support and talking banking services and automated danger assessment systems. The research presents a thorough examination of artificial intelligence-based FinTech systems which create both advantages and difficulties for achieving financial access through their application. The research shows that artificial intelligence technology can help organizations in low- and middle-income countries reduce operational expenses while solving problems related to information access and reaching people who have been excluded from financial services. The study identifies major threats which include algorithmic bias that maintains existing discriminatory patterns and hidden processes of "black box" systems that reduce accountability and security breaches of personal information and system deficiencies and the situation where financial inclusion leads to exploitative pricing practices. The responsible AI framework which we present for implementation in Kenya India Mexico and Nigeria is based on four key principles which include fairness and explainability and privacy and human oversight. The paper concludes with actionable policy recommendations for central banks and FinTech firms and international development organizations which aim to use artificial intelligence while preventing the creation of digital and algorithmic disparities.

Keywords: *artificial intelligence, FinTech, financial inclusion, algorithmic bias, data privacy, responsible AI, digital divide*

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1. Introduction

The United Nations Sustainable Development Goals (SDGs) which include SDG 1 (no poverty) and SDG 8 (decent work and economic growth) depend on financial inclusion which delivers affordable financial services to all social groups (World Bank 2022). The Global Findex Database 2021 showed that 1.4 billion adults still lack banking services although the world has made progress for several decades with more than half of these unbanked people located in Sub-Saharan Africa and South Asia and Latin America (Demirgüç-Kunt et al. 2022). The high fixed costs and absence of formal credit histories and distance requirements and risk aversion activities create barriers that prevent traditional financial institutions from serving low-income customers.

The first wave of FinTech encompasses mobile money platforms such as M-Pesa (Kenya) together with digital wallets and peer-to-peer lending services which successfully increased account ownership yet failed to improve customer access to credit and insurance and advanced savings products (Jack & Suri 2011). The second wave of artificial intelligence (AI) consists of machine learning (ML) and natural language processing (NLP) and computer vision which become intelligent systems that enable automated underwriting and personalized advice while achieving almost zero operational costs (Buchak et al. 2021).

The application of artificial intelligence to financial inclusion does not produce an easy solution that works according to techno-solutionist principles. Scholars and practitioners have raised concerns that AI models trained on biased historical data may systematically exclude marginalized groups under the guise of objectivity (Noble 2018 O'Neil 2016). The data which enables inclusion through call logs and location and social media activity creates new privacy threats that affect people who belong to vulnerable groups (Zuboff 2019).

This paper addresses the following research questions: (1) What are the primary opportunities offered by AI-driven FinTech for advancing financial inclusion? (2) What are the major challenges and risks associated with these technologies? (3) How can policymakers and practitioners mitigate these risks while preserving the benefits? The research paper establishes a responsible AI framework which fits the financial inclusion context through its review of academic literature and industry reports and case studies.

2. Literature Review

Financial Inclusion: Definitions and Determinants

Financial inclusion is a multidimensional construct which includes three elements of access and usage and quality and welfare (Klapper et al., 2016).Three traditional barriers exist which include lenders inability to assess creditworthiness because of information asymmetry and the existence of high transaction costs and the presence of financial illiteracy and distrust as behavioral obstacles (Karlan et al., 2014).The research shows that people need more than account ownership to achieve complete inclusion because they also need access to credit and insurance which alternative data and AI technology work to provide (Daud & Ahmad, 2023).

FinTech's First Wave: Digital Payments and Mobile Money

The mobile money service M-Pesa which operates in Kenya achieved two goals through its payment and savings services because it helped 194000 people escape poverty (Suri & Jack 2016). The system failed to increase credit and insurance services because users did not possess official credit records. AI-based solutions are currently set to address the existing credit shortage problem (IFC 2026).

The Role of AI in Financial Services

AI includes machine learning and natural language processing along with other algorithms which learn from data to create predictions and make decisions (Russell & Norvig, 2021). The use of AI for alternative credit scoring has increased in low- and middle-income countries (LMICs) because the technology uses digital footprints which include mobile usage and call logs and behavioral data to forecast repayment (Björkegren & Grissen, 2020). Systematic reviews confirm that AI can increase access to financial services. Singh et al. (2025) identified key themes including AI for customer service, adoption, regulation, and explainability. The study by Alsmadi et al. (2025) showed that AI has potential for transformative change but needs development priorities and ethical safeguards. The study by Bahlool et al. (2026) discovered that organizations handle performance and fairness and explainability as separate issues, which creates a major problem.

The evidence from studies demonstrates that artificial intelligence produces beneficial results. In Nigeria, artificial intelligence technology enabled banks to grant more loans to borrowers who defaulted at lower rates

Vol. 12 Issue 2S (May, 2026)
ISSN: 2208-2190 Pages- 49-58
DOI: https://doi.org/10.69980/gchmn975
although the country experienced different levels of regional infrastructure development (Ibrahim et al., 2025). The operational performance of institutions in Pakistan improved through the use of artificial intelligence technologies (Ahmed et al., 2024). The World Bank surveyed 27 authorities from emerging markets which showed that most authorities expect artificial intelligence to create net positive results yet only a few organizations established board-level plans and sufficient monitoring abilities (Boeddu et al., 2025).
The study of alternative credit scoring methods shows that mobile usage characteristics will improve system performance for classifying users (Chen et al., 2025) while alternative data sources provide unique informational value that traditional data sources fail to disclose (Baidoo & Mazzotta, 2025). The IFC (2026) report states that AI-based scoring systems now provide underserved borrowers in emerging markets with increased financial access because women perform equally well or better than men in these systems.
The literature presents multiple significant hazards which researchers have documented throughout their studies. Studies from Indonesia (Gonzales et al., 2025) and gender-focused research (Smith, 2025) show that algorithmic bias limits access to people who lack online presence and it creates disparities between genders. The research study evaluated bias in loan approvals through its assessment of explainable AI and federated learning and human-in-the-loop frameworks (Meraliyev, 2025).
The current infrastructure system operates as the main obstacle which needs to be overcome. Johnson (2025) discovered that AI adoption faces three main obstacles which include restricted digital skills and inconsistent internet access and expensive implementation costs. The OECD (2025) reported that global AI investments reached USD 100 billion while Africa experienced only a few transactions and the region still struggles with digital literacy and cyber security issues.
The literature demonstrates that AI provides significant potential for financial inclusion yet it requires particular elements which include equitable systems and clear explanations and protection of private information and enhanced infrastructure development, which the paper resolves through its implementation of a responsible AI framework.

3. Opportunities: How AI Can Drive Financial Inclusion

1. Alternative Credit Scoring and Psychometric Assessment

The conventional credit bureaus depend on three requirements which include verified job positions and asset security and documented repayment history which are difficult to obtain for people without bank accounts. AI models exploit digital footprints through mobile phone usage which includes call frequency and top-up patterns and contact information and through smartphone metadata which includes battery level and accelerometer data and through social media activity and through psychometric tests (Berg et al. 2020). A recent study which compared different credit scoring systems discovered that Upstart's AI-based system approved 44.28% more applicants when compared to traditional methods which resulted in 28.8% of its loans being given to borrowers with low and moderate incomes (Munjuluri 2025). In Kenya, empirical research at Faulu Microfinance Bank demonstrated that psychometric credit scoring models significantly predict financial inclusion, accounting for 70.7% of its variance ($\beta = 0.834$, $p = 0.002$), while behavioral credit scoring explains 69.2% of the variance ($\beta = 0.593$, $p = 0.000$) (Njeru, 2025).
Tala uses more than 10000 data points from a users smartphone to create a credit score which takes only minutes to develop. The company has provided loans to more than 7.5 million customers worldwide who represent 63% of first-time digital borrowers while 84% of borrowers have experienced better life quality (Munjuluri, 2025). Tala has provided Sh300 billion in mobile loans to Kenyan residents during the last ten years, with 46% of borrowers using the funds for business purposes and 33% of borrowers using personal loans to cover school fees (Tala, 2024). Branch International implements AI technology to study how users interact with their applications and make payments, which leads to a 50% decrease in default rates when compared to traditional rule-based systems (Branch, 2022). Kaleidofin serves 7.55 million customers who are 98% women, which results in 20-30% higher approval rates when compared to standard bureaus, while their portfolio-at-risk PAR 90 percentage stays below 2% (Munjuluri, 2025).
The OECD's Africa Capital Markets Report 2025 confirms that AI is accelerating financial inclusion across the continent, particularly using mobile money channels and platforms that have enabled access to financial services for previously underserved populations (OECD, 2025). The World Economic Forum states that Brazilian and Mexican companies use Nubank and Konfío AI-based credit scoring systems which evaluate alternative data sources such as utility bill payments and business cash flow to provide banking services to millions of customers who previously lacked access to banking (World Economic Forum, 2025).

Vol. 12 Issue 2S (May, 2026)
ISSN: 2208-2190 Pages- 49-58
DOI: https://doi.org/10.69980/gchmn975

2. Cost Reduction through Automation and Conversational AI

The expenses required to assist low-income customers through manual underwriting processes and branch network operations and call center services exceed the financial gains from small loan transactions. The implementation of AI technology leads to significant decreases in operational expenses. Natural language processing (NLP) chatbots such as Kasisto's KAI and Google's Dialogflow enable organizations to handle customer account requests and loan application processing and complaint resolution through their multilingual system at minimal operational expense. Voice-based artificial intelligence systems such as Google's Duplex and local language speech recognition technology provide low-literacy users with the ability to communicate without needing to read or write (Aker, 2017).

Jio Payments Bank introduced a voice-based AI assistant that functions in Hindi Tamil and Telugu for rural users to check balances transfer money and pay bills through basic voice commands. User participation among illiterate women increased by 300% during the first year (NITI Aayog, 2021). Indian businesses show strong demand for advanced voicebot technology because the conversational AI sector continues to grow at an annual rate exceeding 30% and leading firms like HDFC Bank and Reliance Jio and Flipkart use voicebots as part of their customer support systems (Callin, 2025). The multilingual voicebot of the State Bank of India manages more than 100000 customer interactions each day across 11 different Indian languages (Callin, 2025). The OECD (2025) reports that African financial institutions increasingly adopt artificial intelligence for customer service purposes while using mobile money services to provide affordable financial solutions to large customer bases.

3. Personalized Financial Literacy and Nudging

People must use financial services effectively after they gain access to those services. AI algorithms use transaction history data to find distress patterns which include multiple overdrafts and delayed utility bill payments. The system sends personalized nudges through automated text messages or voice prompts which guide users to save money and alert them about their high-interest debt. A field experiment involved 39000 users testing a personal finance app to demonstrate how AI-generated email reminders helped users decrease their overdraft charges. Users who received Negatively framed messages which showed them how to prevent overdraft fees managed to decrease their overdraft rates by 9% during the next week. The study found that AI-based tailored communication needs to be designed to allow people to use it because it shows positive effects on financial behavior. The World Economic Forum (2025) notes that AI-powered financial coaching now goes beyond simple budget trackers; by analyzing spending habits and cash flow, these systems identify savings opportunities, pre-emptively warn of potential shortfalls, and offer tailored strategies to build emergency funds. Zenka uses machine learning technology to classify users into different risk groups while the digital lender Zenka sends customized reminders to its customers. Users who receive AI-generated savings tips save 22% more over six months (Zenka, 2022).

4. Micro-Insurance and Parametric Payouts

The poor population makes the most inefficient use of insurance services which serve as their only financial resource. The traditional process for underwriting requires excessive expenses and results in delayed claim handling. AI technology creates parametric insurance systems which activate payouts through automatic data collection from sensors and satellites that include rainfall measurement systems which activate crop insurance payments when precipitation drops below a specific level. The process eliminates the need for fraud investigations while it also decreases operational spending.

The Insurance Development Forum 2025 shows how parametric agricultural insurance models use satellite data together with mobile platforms to provide coverage for microinsurance markets in developing nations which encounter climate change challenges. In Senegal the National Agriculture Insurance Company CNAAS developed a multi-risk index insurance product which uses rainfall measurements together with yield data and river flow information to create automatic coverage that protects 35000 farmers in its current pilot testing phase UNDP 2025. In Nepal an AI solution uses muzzle print matching to replace traditional ear tagging in livestock insurance while farmers use a mobile app to photograph their animal noses which then triggers instant payout for death claims UNDP 2025.

In Ethiopia the agricultural InsurTech Pula uses satellite data and machine learning models to forecast drought risk which enables automatic compensation payments to smallholder farmers. Pula 2023 reports that

Vol. 12 Issue 2S (May, 2026)
ISSN: 2208-2190 Pages- 49-58
DOI: https://doi.org/10.69980/gchmn975
more than 1.5 million farmers received coverage which decreased average claim processing time from 45 days to 24 hours. The public-private partnerships in Argentina Mexico Nepal Senegal and Vietnam provide customized agricultural insurance solutions which combine satellite data with mobile platforms and artificial intelligence to improve farmer access to insurance products UNDP 2025.

4. Challenges and Risks

1. Algorithmic Bias and Digital Redlining

The data used to train AI models defines their level of bias. The historical lending data demonstrates systemic discrimination through its representation of racial redlining in the US and caste-based exclusion in India. A model which learns from historical loan data will identify specific postal codes and genders and ethnic groups as high-risk categories because those groups lacked chances to establish creditworthiness. The model results in continuous exclusion of people according to Barocas and Selbst 2016. Evidence: A study of an AI credit scoring system in Mexico found that applicants from predominantly indigenous municipalities received scores 30% lower than comparable applicants from non-indigenous areas, even after controlling for income and education López and Rodríguez 2021. The model had learned a proxy for systemic poverty, not individual creditworthiness.

2. The Black Box Problem and Lack of Explainability

The ability of deep learning models to make accurate predictions stands at a high level yet their results remain difficult to comprehend. A bank provides a loan rejection explanation to its applicants which includes reasons such as insufficient income. A loan rejection system based on neural networks uses hidden reasons that exist within its complex non-linear system. This situation violates the explanation rights which European Union General Data Protection Regulation (GDPR) and new artificial intelligence regulations provide to individuals (Wachter et al., 2017). The absence of transparent information in a system creates trust issues for vulnerable groups while removing their ability to challenge decisions. An applicant denied by an AI cannot fix the problem because they do not know what triggered the rejection.

3. Data Privacy and Surveillance Capitalism

The data collection methods that support AI-based inclusion use call logs and contact lists and location data and browsing history as their main sources while containing sensitive information. Users from low-income backgrounds face difficulties in understanding complex consent agreements while FinTech applications collect excessive data which exceeds their actual requirements. The data can be sold to external parties or utilized for targeted advertising purposes or it may become exposed during security breaches. A data breach exposes a person who experiences poverty to blackmail and phishing attacks which can result in their complete financial collapse according to Zuboff 2019. The 2020 data breach at Carbon which operates as a popular AI lending platform in Nigeria exposed personal data of more than 1 million users including government identification documents and their complete contact information. The breach resulted in an increase of scam phone calls which specifically targeted borrowers according to Ogunlesi 2021.

4. Infrastructure Gaps and Digital Literacy

AI systems need three basic resources which include internet access and electricity power and cloud computing services. In rural Sub-Saharan Africa, only 25% of the population has access to 4G coverage, and electricity is intermittent (GSMA, 2022). Voice-based AI can partially overcome literacy barriers, but even voice systems require a stable network and minimal digital literacy (e.g., knowing how to trigger the assistant). AI models which have been trained on urban user data will demonstrate poor performance when applied to rural environments, which exhibit different usage patterns (see "domain shift" in ML).

5. The Inclusion-Exploitation Paradox

The main problem with this challenge exists in the economic sphere becauseAI-powered lenders need to charge high interest rates which create financial difficulties for low-income customers in order to maintain their lending operations. The alternative scoring models categorize new users as "high risk" which causes their annual percentage rates (APRs) to exceed 100% (e.g., 5% interest on a 30-day loan translates to 60% APR). Users who borrow repeatedly at these rates will become trapped in a debt cycle which defeats the purpose of inclusion (Schicks, 2013).

Vol. 12 Issue 2S (May, 2026)
ISSN: 2208-2190 Pages- 49-58
DOI: https://doi.org/10.69980/gchmn975

Example: In India, several AI-based instant loan apps (e.g., EarlySalary, MoneyTap) charge APRs between 36% and 200%. The regulators have found that users who borrow money to pay back their existing loans will default on their debts which leads to intense collection efforts (Reserve Bank of India, 2022).

6. Case Studies: Comparative Analysis

Region	FinTech	AI Application	Inclusion Outcome	Challenges Identified
Kenya	Tala	Alternative credit scoring (call logs, SMS patterns)	Over 5 million users, 70% first-time borrowers	High APR (up to 180%); privacy complaints
India	Jio Payments Bank	Voice-based NLP assistant (multi-lingual)	8 million rural users, 40% previously unbanked	Digital literacy gap; connectivity issues
Mexico	Konfío	ML credit scoring for SMEs	70% of loans to first-time borrowers	Model bias against informal sector workers
Nigeria	Carbon	Behavioral data scoring + automated collection	1.5 million loans disbursed	Data breach (2020); aggressive AI collection

Sources: Compiled from Tala (2023), NITI Aayog (2021), López & Rodríguez (2021), Ogunlesi (2021).

7. Discussion: A Responsible AI Framework for Financial Inclusion

Research shows that AI-based financial technology exhibits both beneficial and harmful effects. The Responsible AI for Financial Inclusion (RAIFI) framework which we developed will help organizations achieve their advantages while minimizing their adverse impacts through its four core principles of fairness, explainability, privacy protection, and human monitoring.

Pillar 1: Fairness Audits and Bias Mitigation

AI credit models need to complete statistical tests which assess their impact on protected characteristics that include gender and ethnicity and geographical location before they can enter operation and then again during their annual evaluations. The study requires researchers to present demographic parity metrics which show equal approval rates across different groups and equalized odds metrics which display matching rates of false positives and false negatives (Hardt et al. 2016). The Reserve Bank of India and the Central Bank of Kenya should establish fairness audits as essential requirements for license acquisition by financial institutions. FinTech companies do not need to review their algorithms for potential discriminatory effects on historically marginalized groups because no regulatory requirements exist to enforce such reviews.

Pillar 2: Explainability and User Rights

The AI system needs to deliver a counterfactual explanation after any negative outcome which includes both loan rejections and increased loan rates. The user will get this message: "Your loan was denied because your average mobile airtime top-up is below 100 KES per week. If you increase top-ups to 150 KES for six weeks, you may qualify." This method provides users with specific steps needed to achieve their desired results according to Wachter and his colleagues from 2018. Regulatory authorities need to establish "right to explanation" as a legal obligation which carries enforcement penalties for organizations that fail to meet this requirement. Explainability exists as both a technical requirement and an essential consumer protection right in today's world which uses algorithmic systems for making decisions.

Pillar 3: Data Minimization and Privacy by Design

Financial technology companies should gather data which relates directly to their credit risk assessment and service delivery operations. Organizations need to process information in a way that allows users to select specific permissions instead of providing their full approval or complete denial. Data storage operations should implement encryption methods and breach notification procedures to safeguard at-risk users from potential threats. The FinTech licensing process needs to include international standards such as ISO 27701

Vol. 12 Issue 2S (May, 2026)
ISSN: 2208-2190 Pages- 49-58
DOI: https://doi.org/10.69980/gchmn975

which establishes privacy management requirements. Privacy by design protects low income users from surveillance capitalism because it prevents data collection from becoming a method of monitoring their activities.

Pillar 4: Human- in- the- Loop for Edge Cases
AI needs to process common decisions through automatic systems, but all cases involving first-time borrowers and customers from underrepresented groups must receive evaluation by skilled human professionals. The hybrid system stops complete algorithmic discrimination which prevents whole groups from accessing services because of missing data and system bias. FinTech companies need to track their ratio between AI automated decisions and human evaluated decisions which they must share with regulatory authorities. Human monitoring functions as a backup system which prevents automatic rejection of uncommon situations that require special treatment from the automated system.

Infrastructure Prerequisites
The success of any artificial intelligence implementation depends on establishing essential digital infrastructure systems. Governments and development banks should invest in rural 4G and LTE coverage along with community Wi Fi hotspots. The target population needs access to low cost smartphones which include subsidized data plans to use AI financial services. Public digital literacy programs need to focus on women and seniors because these programs help people develop skills needed to use conversational AI and understand credit decisions and protect personal data. The most advanced artificial intelligence model will not be available to its essential users because these fundamental investments remain unimplemented.

8. Policy Recommendations

We provide targeted recommendations for three stakeholder groups which include central banks and financial regulators and FinTech firms and international development organizations based on the RAIFI framework.

For Central Banks and Financial Regulators
Central banks and financial regulators need to establish mandatory AI model validation guidelines which require testing for bias and provide requirements for system explainability. The guidelines need to establish mandatory requirements which define the statistical tests that organizations must use to assess disparate impact and the minimum explainability standards they must meet for adverse actions. The absence of binding guidelines permits businesses to practice algorithmic discrimination without facing any consequences.
Regulators should create sandbox testing programs which enable testing of AI inclusion products through live consumer testing under their regulatory oversight. Sandboxes enable innovators to test new business models while regulators use these tests to discover potential dangers before products enter the market. The programs require consumer consent, which must be verified by independent observers and which establish specific conditions for program termination.
The third essential recommendation requires interest rate limits on AI scored micro loans to stop predatory pricing practices. A maximum annual percentage rate of 50% for loans under $200 establishes a financial framework that allows lenders to achieve profitability while shielding low income borrowers from debt traps. The absence of such limits permits technology which was created to enhance inclusion to function as a tool for resource extraction.

For FinTech Firms
FinTech companies need to implement responsible AI guidelines and create annual reports which show their approval rates based on different demographic categories that include gender and geographic location and income level and ethnic or caste background when applicable. The reports must provide information about the typical interest rates different groups receive and the number of times humans override automated decisions. Organizations achieve transparent operations which enable accountable practices while establishing trust relationships with their customers and regulatory bodies.
Organizations need to create privacy dashboards which enable users to track their collected data and its current usage and its future storage duration. Users must be able to request deletion of their data without penalty or loss of service access. The dashboards need to create interfaces which low literacy users can understand through visual icons and voice control systems which will be used in suitable cases.

Vol. 12 Issue 2S (May, 2026)
ISSN: 2208-2190 Pages- 49-58
DOI: https://doi.org/10.69980/gchmn975

FinTech organizations need to allocate resources towards developing voice artificial intelligence systems in local languages to enable users who face literacy challenges to access their services. Text based interfaces exclude millions of potential users who cannot read or who struggle with digital text. The development of speech recognition and synthesis technology for under resourced languages such as Swahili and Hindi and Yoruba and Quechua represents both a technical challenge and a necessary step towards creating accessible AI systems in financial services.

For International Development Organizations (World Bank, IFC, UNDP)

International development organizations should finance independent studies about AI bias in financial markets of low and middle income countries. Existing bias research primarily examines high income countries while algorithmic discrimination risks remain higher in low and middle income countries because their regulatory systems are underdeveloped and their data protection frameworks are not fully established. Dedicated funding streams for rigorous, longitudinal studies are urgently needed.

Development organizations should create a worldwide certification system that evaluates responsible AI applications in inclusive finance which would function similarly to the Smart Campaign's Client Protection Principles. Such a standard would provide a clear benchmark for FinTech firms, a procurement tool for governments, and a signal of trust for consumers. The organization would offer three certification levels which include bronze, silver, and gold certifications based on the extent of fairness evaluations and explainability elements and privacy protection mechanisms.

A third recommendation is to support open source explainable AI (XAI) toolkits tailored to microfinance contexts. Many existing XAI libraries (e.g., LIME, SHAP) require advanced computing power and specialized knowledge which most LMIC microfinance institutions lack. Open source toolkits built for smaller datasets and lower computational requirements and designed for specific applications would provide widespread access to responsible AI solutions.

9. Future Research Directions

The existing literature has multiple gaps which still need to be addressed. First, researchers must conduct longitudinal studies which assess how AI-scored borrowers achieve financial progress or experience debt traps. Second, researchers need to investigate how users perform adversarial attacks against alternative credit scoring methods through various digital footprint manipulation techniques. Third, researchers should conduct cross-country comparative studies to determine which regulatory methods between the EU's AI Act and India's DPDP Act achieve the best balance between innovation and protection.

10. Conclusion

The financial technology sector which uses artificial intelligence has the potential to bring banking services to all people who currently lack access to banking services. The technology enables AI to reach the most remote customers who banks have neglected for decades because it lowers transaction expenses and creates credit scores based on online behavior and provides tailored financial guidance and insurance claim processing. The study presents case studies from Kenya and India and Mexico and Nigeria and Ethiopia to show how artificial intelligence has enabled first-time borrowers to obtain micro-loans and rural farmers to obtain parametric crop insurance and illiterate users to perform banking transactions through voice assistants. The potential will succeed only if designers create the system while they maintain active monitoring of system functions. The research presented in this paper demonstrates that organizations need to conduct fairness audits and create systems which explain their operations and implement privacy protections and maintain human control over their AI systems. Algorithmic bias has been shown to exclude indigenous communities in Mexico and reproduce gendered disparities in lending across multiple countries. The "black box" problem prevents users from accessing the information which they need to understand their negative outcomes and fight against those outcomes. The data collection practices which conduct excessive data gathering create situations where at-risk groups face both privacy violations and financial exploitation. The exclusion-exploitation paradox occurs when users become trapped in debt cycles because of elevated interest rates that AI-based scoring systems assign to their loans which creates a situation that defeats the objectives of financial inclusion which should promote social welfare.

The Responsible AI for Financial Inclusion (RAIFI) framework which this paper presents provides organizations with a workable implementation method. Its four pillars—fairness audits, counterfactual

Vol. 12 Issue 2S (May, 2026)
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explainability, data minimization with privacy by design, and human in the loop oversight—are not theoretical ideals but actionable requirements. Central banks need to create obligatory standards which validate models and construct regulatory testing environments. FinTech companies need to share complete information about their customer approval rates based on different demographic groups while developing voice AI technology which supports all local languages. International development organizations should finance unbiased research while establishing global standards for certification.

The path forward is not to abandon AI, but to embed it within a responsible framework that prioritizes the welfare of the financially excluded. The capacity of technology to create inclusion or exclusion depends on the systems which control its operations through their established rules and their provided incentives and their monitoring procedures. Organizations need to establish ethical and regulatory frameworks which will progress as generative AI and federated learning and on-device models continue to evolve. Digital financial access must not create a new algorithmic divide according to the joint efforts of policymakers and technologists and civil society members.

The ultimate measure of success is not how many users are onboarded, nor how much data is collected, nor even how many loans are disbursed. AI based FinTech solutions establish their success by examining their ability to improve living standards for people who currently live in poverty while they create pathways for economic growth that reach historically marginalized populations. Organizations need to establish a dedication to fairness and transparency and human dignity maintenance throughout their entire design process and all operational activities and regulatory procedures in order to achieve their objectives.

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