Bridging the Financial Divide: The Role of AI in Promoting Inclusion Among Underserved Populations

Hoje Jo[1], Bihui Deng[1], Emily Grossman[1], Suyog Ingle[1] & Maitreyee Mittal[1]

[1] Santa Clara University, USA

Correspondence: Hoje Jo, Santa Clara University, USA. E-mail: hjo@scu.edu

Received: October 30, 2025 Accepted: December 5, 2025 Online Published: December 30, 2025

doi:10.5430/ijfr.v17n1p15 URL: https://doi.org/10.5430/ijfr.v17n1p15

Abstract

Artificial intelligence transforms financial services by enabling scalable, low-cost solutions that extend access to underserved populations, particularly in rural and informal economic sectors. Leveraging alternative data and automation, AI augments customer engagement and risk assessment capabilities. This paper presents a comparative analysis of AI-mediated financial inclusion in India, China, and the United States, illustrating diverse applications across economic development spectrums. Although AI holds strong potential to reduce barriers and personalize services, it concurrently raises risks of algorithmic bias, privacy erosion, and amplified digital divides. The analysis emphasizes that ethical, inclusive governance is critical to ensuring AI empowers rather than marginalizes. Based on synthesized case evidence, the study validates its principal hypothesis (H1) and concludes that AI significantly promotes financial inclusion, thereby elevating financial literacy and empowering historically marginalized communities.

Keywords: AI, financial inclusion, risk assessment, China, India, the United States

1. Introduction

For decades, traditional banking has struggled to serve underserved populations, particularly in rural areas, low-income communities, and informal economies. Reliance on physical infrastructure, documentation-heavy processes, and standardized credit assessments has excluded billions from savings, credit, and insurance, perpetuating economic vulnerability and limiting social mobility. Globally, approximately 1.4 billion adults remain unbanked, with women, rural communities, and informal workers disproportionately affected (World Bank, 2025).

Artificial Intelligence (AI) is reshaping this landscape by offering scalable, cost-effective solutions tailored to marginalized communities. AI adoption in banking has accelerated, with predictive analytics, mobile platforms, and chatbots becoming standard in both developed and emerging markets. These tools leverage alternative data, reduce operational barriers, and enable personalized engagement (Li et al., 2024; World Bank, 2025). AI has been applied to many areas, including financial reporting and auditing (Fedyk et al., 2022; Estep et al., 2024), venture capital sourcing and due diligence (Jo et al., 2024), CSR and ESG ethics (Jo, 2025), fraud detection (Jo et al., 2025), algorithmic trading strategies (Jo et al., 2025), and many others. For example, conversational agents provide customer service in local languages around the clock, while advanced risk-assessment models extend credit to borrowers without traditional credit histories.

Despite these advantages, AI is not without risks. Algorithmic bias, data privacy concerns, and limited digital literacy can reinforce existing inequalities, and opaque models may undermine transparency and accountability (Lam, 2024; Akanfe, 2025; De La Rosa & Bechler, 2025).

To illustrate these dynamics, this paper focuses on India, China, and the United States. These countries were chosen because they highlight different stages of economic development and financial infrastructure. India and China, as fast-growing emerging markets (and members of the BRICS bloc), demonstrate how digital banking and AI can leapfrog legacy constraints. The United States, by contrast, represents an advanced, developed economy with a highly advanced technology sector and a leading fintech industry, where AI applications showcase both innovation and global influence in inclusive finance. This comparative lens highlights why examining these three countries together offers a richer, more nuanced view of AI's dual potential to foster inclusion or exacerbate disparities.

1.1 Types of AI Technology in Finance

AI in finance can be divided into front-end and back-end applications, each enhancing access and efficiency in complementary ways. Front-end AI interacts directly with consumers, reducing friction and providing personalized guidance through tools such as chatbots, virtual assistants, and mobile apps. These tools are especially valuable for first-time users, rural customers, and individuals with limited literacy, as they offer intuitive access without requiring extensive human support.

Back-end AI focuses on internal operations, including credit scoring, fraud detection, underwriting, and process automation. Machine-learning models, such as those incorporating education, employment history, smartphone metadata, and transaction patterns, can assess creditworthiness more accurately than traditional methods. By enhancing risk assessment and operational efficiency, back-end AI enables institutions to offer small-ticket loans and low-margin products profitably, thereby making financial services more accessible to previously excluded populations (Li, Wxang, Jiang, & Gu, 2024; Lam, 2024).

Together, front-end and back-end AI form a comprehensive ecosystem that reduces barriers, personalizes service, and enhances operational efficiency, creating conditions for inclusive finance.

This article makes the following incremental contribution to the literature on financial inclusion and the application of artificial intelligence (AI) in banking and fintech: a comprehensive, comparative, and critical framework that integrates empirical case studies, theoretical hypotheses, and policy implications. The key contributions are as follows: By framing AI as a double-edged tool for financial inclusion, this article goes beyond prior optimism or skepticism by introducing dual hypotheses of H1: AI enhances financial inclusion by increasing access, personalization, and efficiency; and H2: AI may inadvertently worsen exclusion due to bias, opacity, and infrastructure gaps. This dual framing is novel**,** as most existing studies either focus on AI’s benefits or its risks, rarely presenting both in an integrated fashion.

By comparative case analysis of three economically diverse nations, this paper compares India**,** China**,** and the United States, showing how AI is used differently across levels of development and infrastructure. Specifically, India has leapfrogged traditional barriers via mobile-first and multilingual AI platforms; China has advanced credit modeling using weak signals and fairness-optimized algorithms; whereas the U.S. has used explainable AI and alternative data to expand access for marginalized groups. This cross-national comparison offers granular, practical illustrations of how AI can both address and exacerbate financial exclusion, depending on context—a gap often overlooked in the global financial inclusion literature.

2. Hypotheses Development

Financial exclusion continues to be a critical barrier for underserved populations, including low-income individuals, minorities, rural residents, and unbanked communities. Traditional financial institutions often fail to adequately serve these groups due to high operational costs, geographic limitations, rigid credit evaluation models, and implicit biases. In this context, AI-driven financial tools offer transformative potential by addressing these gaps in several key ways, including enhanced accessibility, personalized solutions, unbiased decision-making, improved financial literacy, and increased cost efficiency and scalability. Below, we contemplate those key ways in more detail.

Accessibility: AI-powered platforms are typically digital-first and mobile-friendly, lowering barriers to entry for users who may not have access to physical bank branches or formal financial education. Budgeting apps, robo-advisors, and online lending platforms can be accessed from smartphones, which are increasingly prevalent even in low-income communities. This digital delivery ensures that services are available 24/7, at the user’s convenience, without requiring face-to-face interaction or complicated paperwork.

Personalization: Through machine learning algorithms and AI tools, users' financial behavior, income patterns, and spending habits can be analyzed to provide tailored advice and recommendations. For example, robo-advisors can suggest investment portfolios that match a user’s risk tolerance and goals, while budgeting apps can offer personalized savings strategies. This level of personalization makes financial information more relevant, actionable, and understandable to individuals who may otherwise be overwhelmed or disengaged by one-size-fits-all financial advice.

Unbiased Decision-Making: Unlike traditional systems that rely on human judgment and may inadvertently reflect institutional biases, AI systems can objectively assess financial data. Alternative credit scoring models, for example, can incorporate non-traditional data points (e.g., utility payments, mobile phone usage, rent payments) to evaluate creditworthiness. This approach can expand access to credit for individuals who lack formal credit histories, particularly in marginalized or immigrant communities. While algorithmic bias is a valid concern, properly designed AI systems can help mitigate discrimination when compared to historical practices.

Financial Literacy Enhancement: Many AI-driven platforms feature embedded educational components that explain financial concepts in simple, digestible formats. Gamification, chatbots, and interactive dashboards can increase engagement and promote learning by showing users the real-time consequences of financial decisions. This hands-on, intuitive learning experience fosters long-term improvements in financial behavior and knowledge.

Cost Efficiency and Scale: Because AI can automate routine financial advisory and support functions, these tools can scale efficiently, reducing service delivery costs. This cost reduction enables fintech providers to serve customers with lower profit margins—such as those in underserved populations—without compromising service quality. It also opens the door to low-cost or even free financial services that would otherwise be unaffordable for many.

H1: AI-driven financial tools (e.g., robo-advisors, budgeting apps, and alternative credit scoring models) significantly enhance financial access and literacy among underserved populations by offering accessible, personalized, and unbiased services.

By combining broad accessibility, customized insights, algorithmic fairness, educational support, and cost-effective scalability, AI-driven financial tools are well-positioned to significantly enhance access to financial services and financial literacy for underserved communities. This provides a strong theoretical case for hypothesis H1 and lays a foundation for empirical testing or further research.

While the integration of AI in finance holds significant promise to increase accessibility and efficiency, there is growing concern that its deployment could unintentionally deepen existing inequalities. This counter-hypothesis highlights the potential risks and unintended consequences of relying heavily on AI-driven financial systems—particularly for populations already facing barriers to access and literacy, including digital divide and technology access, low digital literacy, complexity and opacity of AI systems, exacerbation of existing literacy gaps, algorithmic bias, and unequal representation and lack of human support and guidance.

Digital Divide and Technology Access: AI-powered financial tools are primarily digital, requiring reliable internet access and smart devices. However, many underserved populations—such as rural communities, older adults, and low-income households—still lack consistent digital access or the necessary hardware. This gap in digital infrastructure creates a foundational barrier, meaning that those who might benefit the most from AI-driven financial services are often the least able to access them.

Low Digital Literacy: Even when individuals have access to devices, they may lack the digital literacy required to navigate AI-based platforms confidently. Tasks such as downloading and setting up apps, interpreting algorithm-generated advice, or understanding dynamic user interfaces can be daunting for people unfamiliar with digital technology.

Complexity and Opacity of AI Systems: AI systems are often opaque, making it difficult for users to fully understand how decisions are made—especially in areas such as credit scoring, fraud detection, or investment recommendations. This "black box" nature of AI can erode trust among users who already feel marginalized by the traditional financial system. If users do not understand why they were denied a loan or why a specific investment is recommended, they are less likely to engage meaningfully with the technology.

Exacerbation of Existing Literacy Gaps: AI systems may present financial concepts through complex visualizations or use language that assumes a baseline level of financial literacy. Without simplification or educational support, these tools may unintentionally exclude those with a limited understanding of budgeting, credit, or investing. Rather than empowering these users, the technology could overwhelm or alienate them, further widening the gap between the financially literate and illiterate.

Algorithmic Bias and Unequal Representation: AI models are trained on data that may not accurately represent all user demographics. If underserved groups are underrepresented in the training data, the resulting models can produce biased outcomes—such as inaccurately assessing creditworthiness or misidentifying fraudulent activity. This reinforces systemic inequalities, even if unintentionally, and amplifies mistrust or disengagement from financial systems.

Lack of Human Support and Guidance: Many AI-powered platforms are designed to operate autonomously, reducing the need for human advisors. While this improves scalability, it can remove crucial touchpoints for human support—especially for users who benefit from personalized guidance or require clarification. For some, the absence of a human intermediary may become a barrier rather than a convenience.

H2: The deployment of AI in finance may unintentionally widen gaps in digital and financial literacy, exacerbating exclusion.

Although AI in finance has transformative potential, its deployment risks creating a new layer of exclusion for individuals who lack digital skills, access, or financial knowledge. Rather than leveling the playing field, these technologies could inadvertently concentrate benefits among already-connected and literate users, while further marginalizing vulnerable groups. This hypothesis highlights the dual-edged nature of AI in financial inclusion, underscoring the need for thoughtful implementation, inclusive design, and parallel investments in education and infrastructure.

Table 1. Summary of Primary Hypotheses (H1 & H2)

Hypothesis	Core Proposition	Supporting Mechanisms	Potential Risks & Counter-Mechanisms
H1	AI-driven financial tools significantly **enhance** financial access and literacy among underserved populations.	1. **Accessibility:** Digital-first, mobile-friendly platforms. 2. **Personalization:** Tailored advice via ML algorithms. 3. **Unbiased Decision-Making:** Objective assessment using alternative data. 4. **Financial Literacy Enhancement:** Embedded education via gamification, chatbots. 5. **Cost Efficiency & Scale:** Automation reduces costs, enabling service to low-margin customers.	The positive outcomes are contingent on ethical design, robust infrastructure, and digital literacy.
H2	The deployment of AI in finance may unintentionally **widen gaps** in digital and financial literacy, exacerbating exclusion.	1. **Digital Divide:** Lack of reliable internet/smart devices. 2. **Low Digital Literacy:** Difficulty navigating AI platforms. 3. **Algorithmic Bias & Opacity:** "Black box" models erode trust; biased data replicates inequalities. 4. **Lack of Human Support:** Removal of crucial guidance touchpoints. 5. **Behavioral Risks:** AI can encourage overspending/risky borrowing.	Highlights the dual-edged nature of AI, necessitating inclusive design, infrastructure investment, and regulation.

3. AI for Financial Inclusion: Case Studies

3.1 India: AI-Driven Inclusion From Branch to Byte

India provides one of the most robust examples of how AI can expand financial inclusion at both the customer interface and operational level. Kaur and Dharmadhikari (2023) examine five leading Indian banks, showing how AI deployments expanded reach and reduced friction for underserved users:

- State Bank of India (SBI) - Deployed the YONO super-app (including YONO Krishi for farmers) and multilingual AI assistants (SIA, Payjo) that handled high query volumes, reduced branch dependency, and streamlined credit workflows for rural users.

- HDFC Bank - Introduced Eva (answering over 5 million queries with over 85% accuracy) and OnChat for payments and product applications; predictive models and a unified data layer enabled 81% of retail borrowers to be onboarded digitally within a year.
- ICICI Bank - Rolled out iPal (omnichannel bot), eNWR funding for rural commodity credit, and Mera iMobile (available in 11 regional languages, many functions offline). Large-scale RPA automated back-office tasks, helping the rural portfolio grow ~27% YoY.
- Axis Bank - Implemented Axis Aha! Chatbot and RPA across risk and operations, reducing turnaround time for savings account openings by ~90%, and launching digital nudges, such as the Emergency Savings Planner.
- Kotak Mahindra Bank - Deployed Keya, a bilingual voicebot integrated with phone banking and web, while combining ML with biometric account opening and omnichannel touchpoints (WhatsApp, kiosks, app).

As another example, Tala, a fintech company operating in India, East Africa, and Southeast Asia, provides mobile microloans to individuals lacking formal credit histories. The AI-powered platform evaluates smartphone metadata, SMS activity, and transaction patterns in real time to assess repayment capacity, disbursing millions of loans to first-time borrowers. By bypassing bureaucratic hurdles and delivering near-instant credit, Tala strengthens household financial stability and reduces reliance on informal lenders, illustrating the global applicability of AI-enabled inclusion strategies (Tala, 2024; Yaramolu, 2025).

3.2 China: The AI Lending Revolution: A Case Study in Inclusive Finance

A pioneering initiative by a central Chinese state-owned bank offers a compelling blueprint for how artificial intelligence can simultaneously expand financial inclusion and strengthen credit portfolio resilience. Moving beyond conventional, rule-based lending models, the bank deployed a sophisticated, layered AI scoring system that intelligently synthesizes a vast array of data signals.

3.2.1 From Rigid Rules to Intelligent Layering

The bank’s innovation was not to discard its traditional credit assessment model but to augment it. The AI system operates as a dynamic overlay, integrating strong signals (e.g., income, existing assets) with novel weak signals. These weak signals—derived from mobile payment frequency, utility bill payment history, and broader digital footprint patterns—provide a nuanced, real-time picture of a borrower’s financial behavior and reliability. Crucially, the model was designed with responsible AI principles at its core, explicitly excluding protected attributes such as gender and ethnicity. It underwent stringent feature-reasonableness audits to ensure decisions were based on relevant financial behaviors rather than demographic proxies (Li et al., 2024).

3.2.2 Transformative Outcomes: Breadth and Depth

The results were transformative, demonstrating that access and quality are not a zero-sum game. Credit approval rates for previously underserved "thin-file" borrowers surged by approximately fifteen percentage points—a near doubling from a baseline of just seventeen percent. Remarkably, this expansion was achieved without compromising risk management. Default rates actually declined across all customer segments, indicating a more precise risk assessment capability.

3.2.3 The Mechanism of Success: Error Reduction and Data Governance

This dual success stems from the AI’s ability to minimize critical classification errors. By leveraging weak signals, the model reduced both Type I errors (false approvals of high-risk borrowers) and Type II errors (false denials of creditworthy individuals)**.** This allowed the bank to safely extend its services to a new, reliable customer base that was invisible to traditional models.

3.3 United States: AI-Powered Lending for Historically Excluded Borrowers

The U.S. exemplifies how a mature financial system, combined with a highly developed technology sector and a world-leading fintech industry, has become a testbed for AI-driven financial inclusion. Unlike India and China, where digitization itself was the breakthrough, the U.S. already had broad digital banking adoption. Here, AI has been leveraged to push the frontier of innovation, expanding access through alternative-data underwriting, explainable AI, and large-scale fintech partnerships.

Upstart, which partners with over 500 banks and credit unions, incorporates alternative data, including employment history, education, and spending behavior, into its AI lending models. Between 2020 and 2024, the platform increased loan approvals by 44% for underserved borrowers, reduced interest rates by 36%, and processed over 80% of loans instantly, minimizing paperwork burdens that historically discouraged first-time borrowers (Upstart, 2024; Federal

Reserve, 2022). Explainable AI methods, such as SHAP (SHapley Additive exPlanations) values, enable borrowers and regulators to understand how individual factors contribute to a credit decision. By fairly distributing the influence of each variable—such as income, payment history, or debt levels—SHAP enhances interpretability, thereby reinforcing transparency and trust in the lending process (Responsible AI Credit Scoring, 2024).

Another fintech company, Zest AI, partnered with U.S. credit unions to expand approvals for minority and underserved populations. Field studies indicate approval increases of 49% for Latino applicants and 41% for Black applicants, with similar gains for women, older adults, and AAPI borrowers. Operational automation also reduced processing times and lowered delinquency rates, demonstrating that machine-learning underwriting can improve both inclusion and efficiency (Zest AI, 2024a–c).

3.4 Cross-Case Implications

Across diverse markets, several consistent themes emerge. First, the deployment of multilingual chat and voice interfaces, combined with lightweight mobile platforms, reduces both psychological and logistical barriers to financial participation. Second, integrating richer data signals and machine learning techniques enables more accurate credit assessments, enabling broader approval rates without increasing default risk. Third, the incorporation of guardrails—such as explainability mechanisms, fairness audits, and continuous monitoring—transforms technological innovation into a system that regulators and consumers can trust.

Table 2. Comparative Analysis of AI for Financial Inclusion in India, China, and the United States

Country	**Economic Context**	**Key AI Applications & Case Examples**	**Reported Outcomes & Impact**
India	Fast-growing emerging market; leapfrogging legacy banking.	**SBI:** YONO super-app, multilingual AI assistants (SIA). **HDFC:** Eva chatbot, OnChat, predictive models. **ICICI:** iPal bot, eNWR, Mera iMobile (11 languages). **Fintech (Tala):** Microloans using smartphone metadata.	Reduced branch dependency; high digital onboarding (e.g., 81% for HDFC); ~27% YoY growth in rural portfolio (ICICI); instant credit for unbanked.
China	Fast-growing emerging market; advanced digital ecosystem.	State-owned bank's layered AI scoring system integrating **strong signals** (income/assets) and **weak signals** (mobile payment frequency, utility history).	Credit approval for "thin-file" borrowers increased by ~15 percentage points (nearly doubling); default rates declined across segments.
United States	An advanced, developed economy with a leading fintech sector.	**Upstart:** AI lending with alternative data (employment, education). **Zest AI:** Partnership with credit unions; uses explainable AI (e.g., SHAP).	44% increase in loan approvals for underserved borrowers (Upstart); 49% approval increase for Latino applicants, 41% for Black applicants (Zest AI).

4. How AI Can Be Harmful for Financial Inclusion: Risks and Consequences

While AI holds great promise for financial inclusion, its deployment is not without significant risks. Left unchecked, AI systems can exacerbate existing inequalities, introduce new forms of bias, and unintentionally harm the very populations they aim to serve. Understanding these risks is crucial for designing inclusive and equitable financial tools.

4.1 Algorithmic Bias and Exclusion

One of the most widely cited concerns in AI-driven finance is algorithmic bias. AI models rely on historical and alternative data to predict creditworthiness, but if these datasets reflect systemic inequalities, the AI can replicate or even amplify discriminatory outcomes. For example, Upstart and Zest AI have implemented fairness testing and explainable AI tools to mitigate bias (Upstart, 2024; Zest AI, 2024a–c). However, consumer advocacy groups note that explainability alone may not entirely prevent biased outcomes, particularly for borrowers with limited financial literacy who cannot interpret complex model outputs (Relman Law Report, 2021).

Algorithmic bias can manifest in subtle ways. For instance, a borrower who has consistent informal income from agricultural work may be flagged as high-risk if AI models prioritize traditional employment data. Similarly, minority applicants may receive higher predicted default probabilities if alternative data, such as digital payment history, is unevenly available across communities. Without careful monitoring and continuous recalibration, AI models can inadvertently exclude vulnerable groups, perpetuating financial inequality rather than alleviating it.

4.2 Digital Literacy and Infrastructure Gaps

Even when AI systems are technically sound, digital literacy and infrastructure gaps remain significant barriers to inclusion. Many underserved populations lack access to smartphones, stable internet, or the necessary knowledge to engage with AI-driven platforms effectively. Hallam and Boutalby (2025) emphasize that while digital tools can reduce structural barriers, they may also deepen exclusion for individuals who are unable to participate. A farmer without a smartphone, for example, cannot benefit from AI-enabled rural banking apps, even as neighbors with devices gain access.

Similar issues are evident in developed countries. U.S. fintechs like Upstart and Zest AI have expanded access to credit for borrowers who have been historically excluded. However, first-time users may struggle to understand AI-generated loan decisions or use mobile platforms effectively. In such cases, the digital divide intersects with financial exclusion, meaning that AI may improve access for some while leaving the most vulnerable behind (Relman Law Report, 2021).

4.3 Over-Reliance and Financial Behavior

AI-driven financial tools can also influence consumer behavior in unintended ways. De La Rosa and Bechler (2025) describe the impact of AI on financial behavior, where algorithmic recommendations, personalized pricing, and automated approvals can lower the perceived cost of financial decisions. Tools such as biometric payments, instant microloans, and algorithmically optimized credit limits may encourage overspending or riskier borrowing behaviors. For individuals with limited financial literacy, these effects can lead to mounting debt or a reliance on AI platforms for repeated financial decisions, thereby further entrenching dependency rather than promoting empowerment.

4.4 Privacy, Security, and Trust

AI systems depend on large volumes of data, often including sensitive personal and financial information. Inadequate data governance can create privacy and security risks, especially for individuals in vulnerable communities. Unauthorized data sharing, breaches, or misuse of behavioral data can have serious consequences, from identity theft to discriminatory targeting. Furthermore, the vague nature of AI decision-making can erode trust. If borrowers do not understand why a decision was made, or if algorithms are perceived as unclear or unfair, adoption may decline, limiting the social and financial benefits of AI (Lam, 2024; Akanfe, 2025).

Table 3. Identified Risks of AI for Financial Inclusion & Mitigation Strategies

Risk Category	**Description & Manifestation**	**Real-World Examples / Concerns**	**Proposed Mitigation Strategies**
Algorithmic Bias & Exclusion	AI models trained on historical data replicate or amplify systemic inequalities, leading to discriminatory outcomes.	- Underrepresented groups in training data receive biased scores. - Consumer advocacy notes explainability alone may not prevent bias for users with low financial literacy.	- Fairness-optimized algorithms & regular bias audits. - Use of explainable AI (XAI) tools like SHAP. - Excluding protected attributes in model design.
Digital Literacy & Infrastructure Gaps	A lack of devices, internet access, or skills prevents the most vulnerable from accessing AI-powered services.	- Farmers in India without smartphones cannot use rural banking apps. - First-time US borrowers struggle to interpret AI loan decisions.	- Invest in digital infrastructure (internet, low-bandwidth solutions). - Develop multilingual tutorials & community partnerships for education.
Privacy, Security,	Heavy reliance on data creates	- Unauthorized data sharing or	- Strong data governance

& Trust Erosion	risks of breaches, misuse, and loss of trust due to opaque decision-making.	identity theft. - "Black box" models are perceived as unfair, reducing adoption.	and privacy protections. - Transparent, explainable models to build user trust. - Regulatory enforcement of data privacy standards.
Over-Reliance & Adverse Financial Behavior	AI-driven ease (instant loans, personalized offers) may encourage overspending or risky debt accumulation.	- Instant microloans (e.g., Tala) may outpace users' understanding of repayment. - Algorithmic nudges might promote unsustainable borrowing.	- Incorporate responsible lending principles into AI design. - Provide clear warnings and financial education within platforms. - Implement adaptive feedback loops to monitor outcomes.

4.5 Real-World Examples

Several real-world cases highlight these risks. Despite their positive contributions, U.S.-based fintechs have faced scrutiny for bias and complexity. Upstart, while increasing approvals and lowering interest rates, still relies on models that may be vague to borrowers with limited digital or financial literacy. Similarly, Zest AI's advanced underwriting models require users to interpret algorithmic decisions, a challenge for many first-time borrowers (Relman Law Report, 2021).

Globally, AI-enabled microloan platforms, such as Tala, provide rapid access to credit; however, borrowers may overextend themselves if automated lending decisions outpace users' understanding of repayment obligations. In India, rural banking apps deployed by SBI and ICICI are widely praised for their reach and accessibility; however, farmers without smartphones or internet connectivity remain excluded from these services (SBI, 2024; Kaur & Dharmadhikari, 2023).

4.6 Mitigating the Risks of AI for Inclusive Finance

In sum, AI's risks are multifaceted: (1) algorithmic bias can replicate or amplify historical inequalities, (2) digital literacy gaps prevent the most vulnerable from benefiting, (3) behavioral effects can encourage risky financial decisions, and (4) privacy and trust concerns threaten adoption and security. These risks underscore that AI alone cannot guarantee inclusion. Without complementary interventions, including user education, regulatory oversight, infrastructure expansion, and ethical design, AI may exacerbate rather than reduce financial inequality.

To ensure AI promotes inclusive financial outcomes, institutions and policymakers should implement a comprehensive framework that integrates ethical AI design, digital literacy initiatives, infrastructure improvements, regulatory oversight, and inclusive product development. Models should be trained on representative datasets, regularly audited, and equipped with explainable AI tools to enhance transparency and trust (Upstart, 2024; Zest AI, 2024a–c). Educational programs, multilingual tutorials, and community partnerships can help users navigate platforms and interpret credit decisions responsibly (Hallam & Boutalby, 2025), while investments in smartphone access, internet connectivity, and low-bandwidth solutions ensure broader participation (Kaur & Dharmadhikari, 2023).

Hallam & Boutalby (2025), in particular, explore how AI adoption influences financial inclusion across diverse economies, using panel data from 35 countries spanning 2017 to 2023. To rigorously assess this relationship, the authors employ two-stage least squares (TSLS) and generalized method of moments (GMM) models, addressing challenges like endogeneity and unobserved heterogeneity. However, they acknowledge several limitations; ATM density may no longer fully capture financial inclusion, especially in regions where mobile and digital payments are more prevalent; The sample of 35 countries, while valuable, may underrepresent less-developed economies with emerging AI adoption; and institutional quality indices did not always reflect readiness for AI-driven finance, indicating a need for refined measurements.

Regulatory measures that enforce fair lending, data privacy, and continuous auditing can detect bias and maintain compliance, while adaptive feedback loops enable models to evolve based on real-world outcomes (CFPB, 2023; Tala, 2024). Finally, products should be designed to accommodate low-income and informal-income users with flexible repayment options, small-ticket loans, intuitive interfaces, and supportive human channels. Together, these measures create a foundation for responsible, equitable, and sustainable AI-driven financial inclusion.

Table 4. Typology of AI Technologies in Finance for Inclusion

AI Category	Primary Function	Key Technologies / Tools	Role in Financial Inclusion
Front-End AI	Direct consumer interaction, reducing friction, and providing guidance.	Chatbots (Eva, iPal, Keya), Virtual Assistants, Mobile Apps, Robo-advisors, Multilingual & Voice Interfaces.	Provides intuitive, 24/7 access for first-time users; lowers psychological/logistical barriers; offers personalized guidance without extensive human support.
Back-End AI	Internal operations, risk assessment, and process automation.	Machine Learning Credit Scoring, Predictive Analytics, Fraud Detection, Robotic Process Automation (RPA), and Explainable AI (e.g., SHAP).	Enables accurate credit assessment using alternative data; reduces operational costs; allows profitable small-ticket loans and low-margin products for excluded populations.

5. Discussions

5.1 Limitations

This study is subject to several limitations. First, while the comparative case analysis of India, China, and the United States provides valuable insights, selecting only three countries limits the generalizability of the findings to other contexts, particularly low-income economies with weaker digital infrastructure. Second, much of the evidence relies on secondary reports and industry case studies, which may reflect success stories more than failures, thereby introducing selection bias. Third, the paper adopts a qualitative and descriptive approach rather than conducting large-scale empirical testing, limiting its ability to establish causal relationships between AI adoption and financial inclusion outcomes. Finally, issues such as algorithmic fairness, data privacy, and digital literacy are discussed conceptually but not measured systematically, leaving open questions about the scale and magnitude of these risks.

5.2 Future Research Directions

Future studies can extend this work in several ways. First, cross-country quantitative analyses using larger samples—including those from low-income and underrepresented regions—are needed to validate the empirically proposed dual hypotheses. Second, more granular user-level data, such as surveys or behavioral experiments, could capture how individuals in underserved populations actually interact with AI-driven financial tools, shedding light on digital literacy, trust, and adoption barriers. Third, longitudinal research could explore the long-term effects of AI on financial well-being, debt sustainability, and financial literacy, particularly whether initial access translates into durable empowerment. Fourth, interdisciplinary approaches integrating computer science, development economics, and behavioral finance could help design AI models that are bias-resistant, explainable, and culturally adaptive. Finally, policy-focused research should examine regulatory frameworks across different institutional settings to identify best practices for balancing innovation with consumer protection and equity.

6. Conclusion

Artificial Intelligence is poised to fundamentally reshape financial inclusion, offering unprecedented opportunities for emerging markets and historically excluded populations in the United States, including Black, Latino, and women borrowers. By lowering operational barriers, enabling personalized services, and expanding access to credit and savings, AI empowers individuals who have traditionally been excluded from mainstream financial systems. In emerging markets like India, AI-driven banking applications and microfinance platforms enable first-time users to open accounts, manage their savings, and access loans with personalized guidance tailored to their specific needs. In the U.S., machine learning-powered lending platforms are increasing approval rates for individuals with limited or nontraditional economic opportunities.

Although AI carries risks—including algorithmic bias, privacy concerns, and disparities in digital literacy—rapid advances in AI technology, combined with emerging regulatory frameworks and ethical design practices, are actively mitigating these challenges. On balance, the evidence from several case analyses suggests that the first hypothesis (H1) is supported more than the second (H2): AI-driven financial tools are expanding access, enhancing financial literacy, and empowering historically marginalized communities. The accelerating growth in approved loans and tailored financial services illustrates the tangible impact of AI, highlighting the transformative potential to foster equitable economic participation. Imagine the possibilities: AI is not only a technological innovation but a catalyst for financial empowerment, offering historically excluded populations a genuine pathway to inclusion and opportunity.

Acknowledgments

We greatly appreciate the valuable comments from the anonymous reviewers, which substantially enhanced the quality of the draft. Needless to say, all of our remaining errors are the authors' own.

Authors' contributions

Bihui Deng, Emily Grossman, Suyog Ingle, and Maitreyee Mittal were responsible for study design and revision. Prof. Hoje Jo drafted and revised the manuscript. All authors read and approved the final manuscript. All authors contributed equally to the study.

Funding

We did not receive any funding for this research.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Sciedu Press.

The journal and publisher adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

References

Akanfe, O. (2025). Technology advancements shaping financial inclusion: The impact of AI. *Information Systems Frontiers.* https://doi.org/10.1007/s10796-025-10597-z

Consumer Financial Protection Bureau. (2023, September 19). *Consumer Financial Protection Circular 2023-03: Adverse action notification requirements and the proper use of the CFPB's sample forms provided in Regulation B* [Circular]. Retrieved from https://www.consumerfinance.gov/compliance/circulars/circular-2023-03-adverse-action-notification-requirements-and-the-proper-use-of-the-cfpbs-sample-forms-provided-in-regulation-b/

De La Rosa, W., & Bechler, C. J. (2025). Unveiling the adverse effects of artificial intelligence on financial decisions via the AI-IMPACT model. *Current Opinion in Psychology, 58,* 101843. https://doi.org/10.1016/j.copsyc.2024.101843

Estep, C., Griffith, E., & Mackenzie, N. (2024). How do financial executives respond to the use of artificial intelligence in financial reporting and auditing?. *Review of Accounting Studies*, *29*, 2798-2831.

ETCIO.com. (n.d.). *Kotak Mahindra Bank launches AI-powered voicebot Keya.* Retrieved August 16, 2025, from https://cio.economictimes.indiatimes.com

Federal Reserve Bank of Philadelphia. (2022). *Fintech credit models and the future of lending* (Research Department Working Paper No. 22-11). https://doi.org/10.21799/frbp.wp.2022.11

Fedyk, A., Hodson, J, Khimich, N, & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies*, *27*, 938-985.

Gupshup. (n.d.). *Axis Aha! Chatbot case study.* Retrieved August 16, 2025, from https://www.gupshup.io

Hallam, Z., & Boutalby, H. (2025). Harnessing artificial intelligence to enhance financial inclusion: Insights from a cross-sectional study. *Futurity Economics & Law, 5,* 140-160. https://doi.org/10.57125/FEL.2025.03.25.08

Jo, H. (2025). The effect of AI on CER and ESG ethics. *Journal of Finance Issues*, *23*(2), 57-78.

Jo, H., Juarez, A., Rossi, A., Strauss, C., & Ressler, L. (2024). The impact of artificial intelligence on venture capital sourcing and due diligence. *Global Journal of Entrepreneurship, 8*(1), 12-33.

Jo, H., Bui, H., & Moreland, D. (2025). The role of AI in fraud detection: Are financial institutions using the most effective system?. *Journal of Finance Issues*, *23*(2), 1-31.

Jo, H., Bui, H., & Moreland, D. (2025). The integration of artificial intelligence in algorithmic trading strategies. *Unpublished working paper*, Santa Clara University.

Kaur, R., & Dharmadhikari, S. P. (2023). Artificial intelligence applied in banking for inclusion of unbanked population. *International Management Review, 19*(1), 79-88.

Lam, C. (2024). Debiasing alternative data for credit underwriting using causal inference. *arXiv.* Retrieved from https://arxiv.org/abs/2410.22382

Li, C., Wxang, H., Jiang, S., & Gu, B. (2024). The effect of AI-enabled credit scoring on financial inclusion: Evidence from an underserved population of over one million. *MIS Quarterly*, *48*(4), 1803-1834. https://doi.org/10.25300/MISQ/2024/18340

Relman Law Report. (2021). *Fair lending monitor: Upstart compliance review.* Relman Colfax PLLC.

Responsible AI credit scoring – A lesson from Upstart.com. (2024). *Journal of Financial Technology, 7*(2), 45-62.

State Bank of India. (2024). *YONO Krishi app overview.* Retrieved from https://sbi.co.in

Tala. (2024). *Financial inclusion through AI-driven mobile lending: 2024 impact report.* Tala.

The Indian Express. (2017, July 6). *HDFC Bank launches EVA, India's first AI-based banking chatbot.* Retrieved from https://indianexpress.com

Upstart. (2024). *Upstart AI lending platform: Expanding access to credit through alternative data.* Upstart Network.

World Bank. (2025). *The use of alternative data in credit risk assessment.* World Bank. Retrieved from https://documents1.worldbank.org/curated/en/099031325132018527/pdf/P179614-3e01b947-cbae-41e4-85dd-2905b6187932.pdf

Yaramolu, L. S. K. G. (2025). Architecting AI-driven microfinance platforms: Reimagining credit access for global financial inclusion. *European Journal of Computer Science and Information Technology*, *13*(13), 23-38.

Zest AI. (2024a, January 31). Zest AI's credit models proven to increase loan approvals for every protected class [Press release]. PR Newswire. Retrieved from https://www.prnewswire.com/news-releases/zest-ais-credit-models-proven-to-increase-loan-approvals-for-every-protected-class-302048828.html

Zest AI. (2024b). *Creating a durable lending business for a changing world: Clark County Credit Union* [Customer success story]. Retrieved from https://www.zest.ai/wp-content/uploads/2024/12/Clark-County-Case-Study.pdf

Zest AI. (2024c). *Boosting accuracy and speed in the Aloha state: HawaiiUSA Federal Credit Union* [Customer success story]. Retrieved from https://assets-global.website-files.com/6179287a90a6ea0e76461eba/661423f3ee6b08ad323333cb_HawaiiUSA%20Case%20Study%202024.pdf