

A Comprehensive Conceptual Study of Artificial Intelligence, Fintech Adoption and Digital Financial Inclusion: Mechanisms, Trust and Governance

***Dr. Swati Siddharth Sultania**

Abstract

Artificial intelligence and fintech are widely expected to widen access to finance, yet adoption does not always translate into inclusion. This conceptual paper asks why. It integrates 22 peer-reviewed studies published between 2019 and 2025 to build a model in which AI-enabled credit assessment, digital channels and automated services affect inclusion through three mechanisms: reduced information asymmetry, adoption and layered trust, and fairness safeguards. Literacy and the enabling environment moderate these links. Six propositions are derived, each tied to supporting evidence and a boundary condition. The central argument is that technology creates the possibility of inclusion but literacy, trust, fairness and governance determine whether it is realised. The paper closes with a research agenda for emerging economies such as India.

Keywords: artificial intelligence; fintech; digital financial inclusion; trust; algorithmic fairness; financial literacy

I. INTRODUCTION

A paradox runs through the recent history of digital finance. Mobile payments, digital wallets and AI-based decision tools have reached millions of people who were poorly served by branches, and yet studies repeatedly find that adopting a fintech service does not guarantee that a household or firm becomes financially included in any meaningful sense. A recent survey in Qatar, for example, found that fintech adoption had no significant relationship with inclusion (Al-Sharshani et al., 2025). The paradox suggests that the question for research is not whether technology matters but through what mechanisms and under what conditions it matters.

Three developments sharpen the question. First, AI and machine learning have changed credit assessment by allowing lenders to use alternative data for borrowers with little or no credit history. Second, digital payment systems and, in some countries, central bank digital currency pilots have altered how people hold and move money. Third, regulators and scholars have become concerned that automated decisions may reproduce bias, that users may distrust or misunderstand them and that digital services may carry new risks.

The literature that addresses these developments is fragmented. Studies of credit models seldom measure inclusion, studies of adoption seldom examine fairness, and studies of inclusion seldom

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model the technology. A conceptual integration is therefore valuable. It can specify the causal logic, state the conditions under which it holds and give empirical researchers a set of testable claims.

The contribution differs from existing reviews in the corpus. Those reviews are organised by technology, such as machine learning for credit scoring, or by risk, such as the risks of fintech for inclusion. This paper is organised by mechanism and condition, which allows it to explain when the same technology produces different results.

The paper has three aims. It identifies the mechanisms through which AI and fintech may widen inclusion. It specifies the conditions that moderate those mechanisms. And it derives propositions that future studies can test. The argument is that technology is necessary but not sufficient: inclusion emerges when capability, trust, fairness, literacy and governance work together.

The remainder of the paper reviews the relevant literature, explains the theory-building approach, presents the conceptual model and propositions, and concludes with implications and a research agenda.

II. REVIEW OF LITERATURE

2.1 AI, information and credit

The first mechanism concerns information. Mhlana (2021) argues, in a review of secondary sources, that AI and machine learning strongly affect credit risk assessment when lenders use alternative data, which helps address information asymmetry, adverse selection and moral hazard and lets lenders extend credit to the underbanked. Kumar et al. (2021) reviewed 25 studies on digital credit scoring in rural finance and report that machine learning models can outperform standard econometric approaches when given expanded feature sets, although hybrid models may suit best. Hayashi (2022) reviewed deep learning methods for credit scoring and reports that recent classifiers often exceed ensemble and rule-based methods in accuracy, while rule extraction can make them more explainable. Suhadolnik et al. (2023) compared ten classifiers on more than one million loans and found that boosting ensembles, especially XGBoost, outperformed logistic regression, although the best test accuracy was about 65 per cent. Better models are therefore available, but their performance varies.

2.2 Fairness and algorithmic risk

Better prediction is not the same as fair prediction. Kumar et al. (2021) flag algorithmic discrimination and the need for regulation. Vieira et al. (2025) screened 414 articles and analysed 34 on bias in credit decisions, finding that preprocessing is the dominant mitigation approach, gender and race are the most studied attributes, and some methods achieve fairness gains above 30 per cent with minimal accuracy loss. They also report that only about a quarter of papers use multiple fairness metrics and that none used causal inference to detect proxy discrimination. Kpatcha (2025) shows that a post-processing threshold adjustment can improve fairness substantially with minimal impact on predictive reliability for logistic regression, random forests and XGBoost. Fairness can therefore be

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engineered, but evidence of it working in live lending is limited.

2.3 Adoption, trust and the user

A second body of work explains why users adopt or resist. Noreen et al. (2023) surveyed 799 respondents in five Asian countries and found that awareness, attitude, subjective norms, perceived usefulness and AI knowledge were positively linked to intention to adopt AI in banking, while perceived risk was negatively linked. Sabir et al. (2023) found that perceived ease of use, usefulness and convenience shaped attitudes towards robo-advisors, moderated by technology readiness. Gupta et al. (2023) surveyed 517 respondents during India's 2022 CBDC pilot and found that performance expectancy and hedonic motivation positively shaped intention, perceived risk reduced it, and prior experience with the Unified Payments Interface weakened some paths. Jena (2025) studied 433 rural residents in four Indian states and found that attitude, perceived behavioural control and ease of use positively influenced adoption intention, perceived insecurity reduced it, and adoption intention in turn influenced financial inclusion.

Trust is more than a single attitude. Cheng et al. (2019) interviewed 27 investors and surveyed 230 to show that trust in a robo-advisor depends on trust in the vendor and trust in the technology, and that supervisory control, meaning human oversight, strengthens trust in technologies. Amnas et al. (2024) surveyed 608 fintech users in India and found that trust, service quality and perceived security encouraged use, that digital financial literacy mediated the link between fintech and inclusion, and that perceived regulatory support strengthened it.

2.4 Literacy, regulation and the enabling environment

Literacy and governance form the third group. Mei et al. (2024) found, for 435 bank customers in China, that technological literacy strengthened the link between green performance expectancy and emotion, which in turn raised AI device use. Mishra et al. (2024) surveyed 385 women in two Indian states and found that digital financial literacy and financial accessibility, among other factors, predicted financial decision-making, explaining about 71 per cent of its variance. Evidence on channels and regulation is more varied. Ebong and George (2021) show that in Uganda branch and ATM expansion slowed while mobile money grew, and they argue for stronger regulation of digital financial service risks. Vilcanqui Velazquez et al. (2022) compared four fintech platforms and found that basic mobile money transfer platforms showed no link to savings or credit card provision, while a platform with a microfinance partnership did. Pushp et al. (2023) found that financial inclusion supported sustainable development in Indian states but that the association weakened where internet subscribers were many. Vijayagopal et al. (2024) conclude from a comparison of the United States, the United Kingdom and India that digital infrastructure, financial inclusion, literacy and collaboration among regulators and firms need improvement. Mandić et al. (2025) reviewed 398 papers and identify data privacy, regulation and financial literacy as central risks to inclusion.

2.5 Digital money and institutional performance

Digital money is a further frontier. Nández Alonso et al. (2020) compare official positions on central bank digital currency and conclude that large-scale adoption seems distant and that pilot tests are needed to understand economic effects and public acceptance. Hamdouni (2025) reports that AI-enabled fintech use in ten Saudi banks was associated with better performance, sustainability and stability, which suggests that institutions may also benefit when they adopt such tools.

2.6 Points of agreement and disagreement

The studies agree on four points. Alternative data and machine learning can improve credit assessment. Bias in automated decisions is a real concern that can be reduced. Perceived usefulness, ease of use and trust matter for adoption, and perceived risk deters it. Literacy and regulation condition the benefits of digital finance. They disagree or are silent on three points. Reported accuracy gains vary with the data and the method. Evidence that adoption leads to inclusion is mixed, with positive results in rural India and null results in Qatar. And few studies follow users or borrowers over time, so the persistence of effects is unknown.

III. METHODOLOGY

The paper follows a conceptual theory-building approach, which is suited to a problem in which empirical studies exist but have not been integrated into a causal account. It does not test hypotheses with primary data. Instead it uses an integrative synthesis in five steps: framing the problem, assembling a bounded corpus, extracting constructs, mapping mechanisms and conditions, and deriving propositions with boundary conditions.

The corpus comprises 22 peer-reviewed articles published between 2019 and 2025 in open-access journals of one publisher: the Journal of Risk and Financial Management, Sustainability, the International Journal of Financial Studies, Risks, Economies, Electronics and Mathematics. Articles were selected through topic searches on AI in credit and banking, fintech adoption, trust, digital financial inclusion, financial literacy and digital money. Studies were retained if they were peer reviewed, reported evidence or a structured review, and addressed at least one construct in the model. The bibliographic record and abstract of each article were read, and findings were coded to constructs. Null and contrary findings were retained as boundary conditions and not discarded.

The theory-building logic is abductive. Observed regularities, such as high adoption without matching inclusion, were treated as puzzles, and constructs were then selected that could explain them. Each mechanism was specified as a causal sentence of the form technology, mechanism, outcome, and each moderator as a condition that strengthens or weakens a link. Rival explanations were considered, including measurement error in inclusion outcomes and self-selection of adopters. To strengthen the credibility of the propositions, each was required to be supported by at least two independent studies and to carry a stated boundary condition. The approach has limits. The corpus is purposive and drawn from one publisher, extraction relied on abstracts, and the propositions are conceptual and

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have not been tested. Table 1 defines the constructs that organise the synthesis.

Table 1. Constructs and supporting studies

Construct	Definition	Supporting studies
AI-enabled credit assessment	Use of machine learning and alternative data to score borrowers	Mhlanga (2021); Kumar et al. (2021); Hayashi (2022); Suhadolnik et al. (2023)
Algorithmic fairness	Absence of systematic disadvantage across groups in model outcomes	Vieira et al. (2025); Kpatcha (2025)
Adoption intention	Willingness to use digital or AI-based services	Noreen et al. (2023); Sabir et al. (2023); Gupta et al. (2023); Jena (2025)
Trust and perceived risk	Confidence in vendor and technology; perceived insecurity	Cheng et al. (2019); Amnas et al. (2024)
Literacy	Financial, digital and technological knowledge	Amnas et al. (2024); Mishra et al. (2024); Mei et al. (2024)
Enabling environment	Regulation, infrastructure and channel design	Ebong & George (2021); Vijayagopal et al. (2024); Mandić et al. (2025)
Digital financial inclusion	Access to and productive use of formal services through digital channels	Al-Sharshani et al. (2025); Pushp et al. (2023); Vilcanqui Velazquez et al. (2022)

IV. RESULTS: THE CONCEPTUAL MODEL AND PROPOSITIONS

4.1 The model

Figure 1 presents the model. Three technological capabilities, namely AI-enabled credit assessment, digital channels and payments, and automated advice, operate through three mechanisms. The first is reduced information asymmetry, which affects access to credit. The second is adoption and layered trust, which affects usage and welfare. The third is a set of fairness safeguards, which affects how benefits and risks are distributed. Two sets of moderators condition these links: literacy and the enabling environment.

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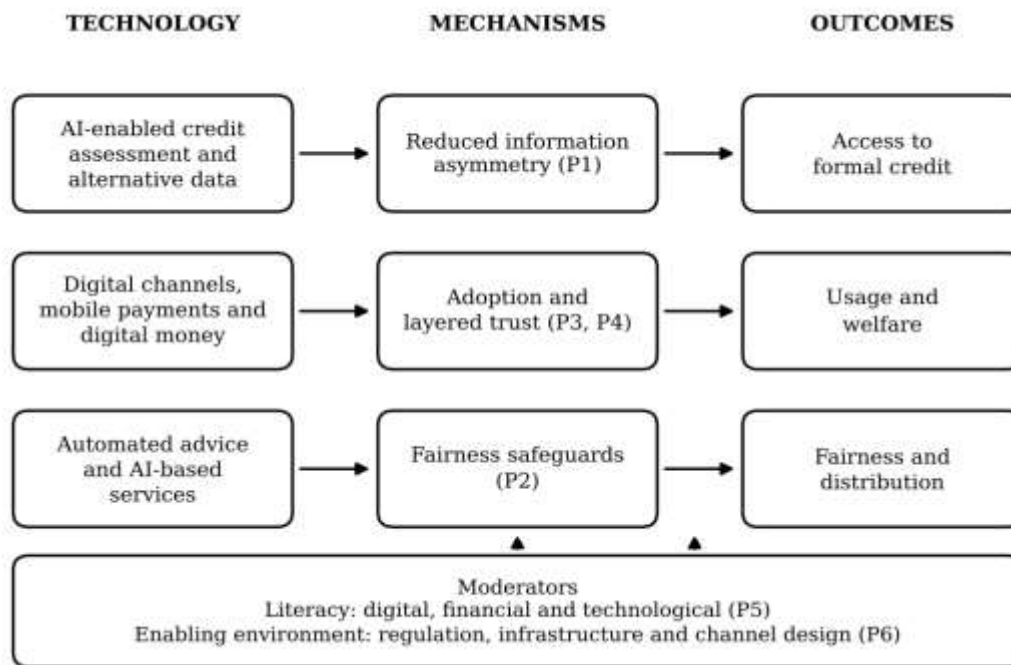


Figure 1. Conceptual model of AI, fintech and digital financial inclusion

4.2 Propositions

Proposition 1 (information). AI-based credit assessment using alternative data reduces information asymmetry and widens access to credit for thin-file and underbanked borrowers. The reviews of credit risk assessment and rural digital scoring agree on this mechanism, and the comparative classifier evidence shows that gains depend on the method. The boundary condition is data quality, since the best accuracy in one large test was modest.

Proposition 2 (fairness). The inclusion gain from algorithmic credit decisions is conditional on fairness safeguards, which can improve fairness at small cost to accuracy. The systematic review of bias mitigation and the threshold-adjustment study support this, and earlier reviews warn of discrimination. The boundary condition is that most evidence comes from offline experiments and that causal tests for proxy discrimination are absent.

Proposition 3 (adoption). Adoption of AI-enabled and digital services rises with perceived usefulness, ease of use, a favourable attitude and trust, and falls with perceived risk or insecurity. Surveys of banking customers, robo-advisor users, CBDC pilot users and rural residents agree. The boundary

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condition is that the evidence is cross-sectional and self-reported.

Proposition 4 (layered trust). Trust has a vendor layer and a technology layer, and it is strengthened by human oversight and perceived regulatory support. The robo-advisor and Indian fintech studies support this. The boundary condition is that the evidence comes from specific user groups.

Proposition 5 (literacy). Digital financial literacy converts adoption into inclusion, and technological literacy strengthens favourable responses to AI services. The Indian fintech and women's decision-making studies and the Chinese banking study support this. The boundary condition is that literacy is usually measured by self-report.

Proposition 6 (enabling environment). Adoption alone does not ensure inclusion; infrastructure, regulation and channel design determine whether adoption becomes productive use. The Qatari null result, the Ugandan channel evidence, the platform comparison and the Indian state-level evidence support this. The boundary condition is that findings are context specific, and the Indian evidence suggests that more internet access may not strengthen the inclusion–development link on its own.

Table 2 summarises the propositions.

Table 2. Propositions, evidence and boundary conditions

Proposition	Principal evidence	Boundary condition
P1 Information	Mhlanga (2021); Kumar et al. (2021); Hayashi (2022); Suhadolnik et al. (2023)	Data quality; modest accuracy in some tests
P2 Fairness	Vieira et al. (2025); Kpatcha (2025); Kumar et al. (2021)	Offline experiments; few causal tests
P3 Adoption	Noreen et al. (2023); Sabir et al. (2023); Gupta et al. (2023); Jena (2025)	Cross-sectional, self-reported surveys
P4 Layered trust	Cheng et al. (2019); Amnas et al. (2024)	Specific user groups
P5 Literacy	Amnas et al. (2024); Mishra et al. (2024); Mei et al. (2024)	Self-reported literacy
P6 Environment	Al-Sharshani et al. (2025); Ebong & George (2021); Vilcanqui Velazquez et al. (2022); Pushp et al. (2023)	Context specific

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4.3 Reading the model against the paradox

The model explains the opening paradox. Adoption is one stage in a chain. Where credit models are accurate and fair, users trust the service, they have the literacy to use it productively and the environment supports it, adoption becomes inclusion. Where any link is weak, adoption can be high while inclusion is not. The Qatari null result and the weak link between basic mobile money transfers and savings or credit are consistent with a break in the chain after adoption, while the rural Indian evidence shows that adoption intention can feed inclusion where attitudes and perceived control are favourable.

4.4 Relevance for India and other emerging economies

Several of the supporting studies are Indian, which allows the model to be read against a context where digital payments are widespread and inequalities in access and literacy persist. The evidence indicates that rural adoption depends on attitude, perceived control and perceived security, that trust and regulatory support strengthen the link between fintech and inclusion, that digital financial literacy matters for women's decision-making and that experience with an existing payment system can change how people respond to a new form of digital money. It also indicates that more connectivity does not automatically strengthen the link between inclusion and development. The implication is that policy in such settings should combine infrastructure with literacy, consumer protection and fairness oversight, and that research should measure each element rather than treat adoption as the outcome.

4.5 Alternative explanations and limits of the model

Three alternative explanations deserve attention. Measurement may explain null results, since inclusion is measured in different ways across studies and a survey scale may miss productive use. Self-selection may inflate adoption effects, because users who adopt AI services may already be more literate or trusting. And reverse causality is possible, since financial inclusion may itself raise confidence in digital services. The model does not rule these out. It also leaves out supply-side incentives of lenders and platforms, competition and macroeconomic conditions, which may affect inclusion independently. These limits do not weaken the propositions as testable claims, but they indicate the controls and designs that tests should include.

V. CONCLUSION AND FUTURE RESEARCH

This paper integrated 22 studies published between 2019 and 2025 into a model of how AI and fintech relate to digital financial inclusion. It argues that technology creates the possibility of inclusion through reduced information asymmetry, adoption and trust, and fairness safeguards, but that literacy and the enabling environment determine whether the possibility is realised. The theoretical contribution is to connect three literatures, on credit models, adoption and inclusion, that are usually separate, and to state boundary conditions for each link.

The practical implications follow from the model. Lenders should build fairness checks into AI credit

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models and report more than one fairness metric. Fintech providers should design for layered trust, with visible human oversight and transparent data practices. Regulators should treat regulatory support, infrastructure and consumer protection as part of the inclusion strategy and not as separate agendas. Educators and policymakers should treat digital and financial literacy as a condition of inclusion and not an optional extra. Investors and bank managers can note that AI-enabled fintech was associated with stronger performance in one banking system, but that the evidence is limited.

Future research can use the Theory–Context–Characteristics–Methods structure shown in Table 3.

Table 3. Research agenda

Dimension	Gap	Direction
Theory	Few integrated models link AI mechanisms to inclusion outcomes	Test the model with mediation and moderation; combine adoption theories with information economics
Context	Evidence concentrated in single countries; limited field data from India	Multi-state Indian studies, including rural areas and women borrowers
Characteristics	Fairness, trust and literacy rarely modelled together	Model them as simultaneous mediators and moderators
Methods	Mostly cross-sectional surveys; few causal or longitudinal designs	Field experiments, panels and mixed methods with configurational analysis

Taken together, the paper suggests that research and policy on AI in finance should move from asking whether technology includes people to asking for whom, through which mechanism and under what governance. Further work should also extend the corpus beyond one publisher, appraise full texts and test whether the propositions hold in live lending and payments data.

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