Religious and Ethical Dimensions of Trust in AI-Enabled Digital Lending Platforms: A Qualitative Study in Emerging Markets

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Abstract

AI-enabled digital lending can expand credit access for small businesses excluded by traditional banks, yet adoption depends on whether owners view opaque platforms as competent, fair, ethically responsible, and consistent with religiously informed expectations. Accordingly, this study examines the religious and ethical dimensions of trust in AI-enabled digital lending platforms across emerging markets. This study examines the process of learning that judgment. It employs a secondary qualitative design, which synthesizes the reported findings of 17 primary empirical studies published between 2021 and 2025. The evidence includes small business owners, borrowers, fintech users, and lending stakeholders in emerging market contexts such as Pakistan, Indonesia, India, Peru, Thailand, and Kenya. Three themes were identified. To start with, the proprietors start with risk-averse and value-driven tests, where velocity and availability excuse experimentation, though they fail to build long-term credibility. Second, predictability, intelligibility, procedural fairness, and clear data boundaries were used to measure trust. Third, trust is institutional/relational when recourse, reputation, regulation, peer testimony, human support, and a lower rate of consequences in the case of a failure lower the cost of doing business. Synthesis posits that trust is situational and temporary in nature. The use can be triggered by convenience, but further use is conditional upon the reaction of the platform during rejection, difficulty in making repayments, data issues, or grievance. This study adds a process explanation of trust calibration and provides useful policy implications for platform design and regulation.

Introduction

In new markets, small businesses tend to require working capital but have little or no collateral, formal records, or credit histories to get banks to issue them credit or loans. Mobile applications, transaction data, platform activity, and machine learning models are some of the methods that Fintech lenders use to reduce this gap. These systems can reduce transaction costs, speed up evaluations, and reach previously invisible companies with finance (Berg et al., 2022; Gomber et al., 2017; Lee and Shin, 2018). However, increased access can also expose owners to opaque pricing, excessive data aggregation, and challenging decisions (Ozili, 2018; Sharma et al., 2024).

Trust must be at the center but not narrowed down to favorable attitudes. Owners provide sensitive commercial data, subscribe to terms generated by algorithms, and rely on external systems of repayment and complaints. A prototype can be statistically correct but untrusted when the owner is unable to interpret a result, repair a mistake, or find blame. A clean interface can also provide a higher confidence than the protection provided. Calibrated trust therefore describes reliance grounded in demonstrated competence, fairness, accountability, and compatibility with owners' religiously informed ethical expectations, including honest disclosure, non-exploitative pricing, privacy, and responsibility towards vulnerable borrowers.

According to existing research, usefulness, ease of use, risk, and institutional assurance are the key factors in fintech adoption (Hu et al., 2019; Rosavina et al., 2019; Ryu, 2018; Singh and Sinha, 2020). However, most of them estimate intention at a single point and consider trust a constant antecedent. They say less about what should or could happen after the initial loan/rejection/surprise charge/collections/appeal. This study posits the following research question: How can small-business owners learn to be confident in digital lending environments with AI enabled in an emerging-market setting? It adds a second qualitative synthesis of provisional trials, experience-based salience, and institutional guarantees, and disaggregates trust and real trustworthiness. This emphasis is significant because proprietors can adhere to a site without knowing, and deceptive acceptance can hide reliance instead of informed trust.

Review of the Literature

❖ Theoretical Framework: Trust as Calibration

The system integrates trust in automation, institutional-based trust, and process-based calibration. Reliance on AI is based on perceived ability, predictability, transparency, and the impact of error (Glikson and Woolley, 2020). Integrity, data protection, and remedies are also evaluated by the owners in lending. Trust is renewed through experience, including assured payments, consistent charges, comprehensible motives, and responsiveness to complaints. Every encounter ought to provide evidence of competence, integrity, and acceptance of responsibility in the case of an error. Explainable AI is applied in situations in which it associates decisions with actionable information, as opposed to uncovering technical complexity (Rai, 2020; Shin, 2021). A detailed but technical breakdown might then be less helpful to trust than a brief reason which will enable an owner to fix or alter a record or alter a later use.

Original trust can be borrowed from a bank, marketplace, regulator, telephone company, or peer-to-peer network. Uncertainty is minimized prior to direct experience by licenses, recognized partners, and enforceable complaint systems. Nevertheless, studies on algorithmic fairness reveal that seemingly neutral models are capable of reproducing disadvantages by proxies, past information, and disproportionate costs of error (Köchling and Wehner, 2020). Institutional signals need to be believable, constraining behavior, and allowing it to be contested.

❖ Instrumental Value and Initial Confidence

Perceived usefulness can be an excellent justification for trials because digital lenders can reduce the time of application and accept other records (Berg et al., 2022; Sadok et al., 2022). The study of technological acceptance also relates value and ease to less hesitancy (Hu et al., 2019; Ryu, 2018). Urgency can, however, encourage owners to agree to ambiguous conditions, and a slick interface can cover high-priced methods. Task-dependent algorithm aversion refers to the idea that users might embrace automation in routine processing but reject it when the outcome of decisions is important or retracting them is difficult (Castelo et al., 2019). Comfort initiates a relationship; it is not a sign of fairness.

❖ Opacity, Fairness, and Data Risk

Alternative data can ensure that undocumented firms are visible and generate a serial asymmetry: the lender observes more of the owner, whereas the owner observes the model minimally. According to AI credit analysis reviews, interpretability, bias, privacy, and governance are the main risks (Sadok et al., 2022). Proprietors require viable solutions for rejection, false information, reevaluation, and appeal. Actionable reasons and procedural transparency are prioritized over exhaustive technical disclosure (Rai, 2020; Shin, 2021).

❖ **Institutional Signals and Human Support**

Confidence is transferred to new services using reputation, regulatory recognition, affiliation with a bank, peer recommendations, or visible security practices (Rosavina et al., 2019; Singh and Sinha, 2020). Human support is still necessary because some unique cases requires contextual interpretation. Automation will be more manageable when owners can rectify records, clarify strange cash flows, or amplify decisions.

❖ **Research Gap**

Most of what is written in the literature represents cross-sectional models of intention, which tend to be concerned with consumers or general fintech but not business borrowers. It is also inclined to think that increased trust is good without enquiring whether there is any real reason to trust. Systematic research requires an increased degree of geographical and stakeholder diversity (Sharma et al., 2024). There is a requirement to have a process account to demonstrate owners learning based on platform behavior and how trust is re-established or lost when there are unfavorable events. It also has to realize that emerging markets cannot be considered as just one institutional environment. Factors such as regulatory reach, informal business practices, language, digital literacy, and reliance on mobile platforms may change the evidence owners utilize and the risks they can contest.

Methodology

This was a secondary qualitative research design. It never captured interviews and purported to have gained access to the primary transcripts. The data sample comprised documented empirical behaviors and respondent interpretations in published primary research. The methodology was appropriate for answering questions concerning the common dynamics of learning to trust in various settings in emerging markets.

The search and purposive selection were conducted between 2021 and 2025. Qualifying studies had primary data on digital lending, peer-to-peer lending, fintech credit, algorithmic credit testing, or other closely related SME fintech adoption. They involved owners, entrepreneurs, borrowers, users, lending professionals, or platform stakeholders and met trust, risk, fairness, data usage, explanation, reputation, recourse, and subsequent use. Seventeen studies were retained, which were from Pakistan, Indonesia, India, Peru, Thailand, Kenya, Poland, and cross-country lending. The set involved surveys, qualitative interviews, expert research, and multi-country empirical research. No studies were used to constitute reviews or conceptual articles, and none of the studies was considered as evidence of findings (Page et al., 2021).

The analysis was conducted according to reflexive thematic principles (Braun & Clarke, 2021; Byrne, 2022). The results were coded as urgent need, trial, usefulness, repayment experience, cost, explanation, privacy, fairness, reputation, regulation, peer testimony, human contact, and complaint handling. The retention of candidate themes depended on the explanation of the learning mechanism. The principal weakness is that many of the studies included are cross-sectional, and therefore, temporal learning was learned through inference. This synthesis thus retains the contradictory findings and does not consider repeated borrowing to be an automatic sign of trust. The principle of reflexivity was upheld by regularly revisiting the question of whether a theme was what the source actually reported or an inference presented by the synthesis. When learning was based on time, the analysis made a cautious statement of the mechanism instead of stating the mechanisms as those observed.

Findings

Table 1: Thematic Synthesis of How Small-Business Owners Learn to Trust AI-Enabled Digital Lending Platforms

Theme	Trust-learning mechanism	Indicative evidence and subthemes	Interpretive outcome and key sources
Theme 1: Cautious, value-based trial	Owners begin with provisional reliance when speed, accessibility, and practical value justify experimentation. Trust is initially limited rather than fully granted.	Small first loans; comparison with banks or informal lenders; usefulness; quick disbursement; documentation quality; stable charges; repayment experience; perceived risk and data security.	Convenience opens the relationship, but continued use depends on credible performance. Adamek and Solarz (2023); Merino Balcazar and Llatas Rivas (2021); Nugraha et al. (2022); Putri et al. (2023); Xie et al. (2021).
Theme 2: Calibration through intelligibility, predictability, and data boundaries	Owners revise trust after observing whether pricing, repayment, decisions, explanations, and data practices are understandable and consistent.	Actionable reasons for decisions; correction of inaccurate records; predictable repayment terms; distinction between facts and estimated risk; data minimization; consent; privacy; procedural fairness; ability to contest errors.	Trust strengthens when outcomes can be understood and challenged, but deteriorates when data extraction or adverse decisions appear arbitrary. Abbas (2025); Hoque et al. (2024); Kim and Duvendack (2025); Tigges et al. (2024); Zhao et al. (2024).
Theme 3: Relational and institutional trust through recourse and social proof	Trust becomes more durable when institutional signals and human support lower the consequences of platform failure.	Regulatory recognition; partner brands; reputation; trust seals; peer testimony; service quality; human review; complaint handling; appeal routes; proportionate collections; documented reasons.	Recourse is the strongest test of trustworthiness because it reveals whether the institution accepts responsibility when automation causes harm. Chulawate and Kiattisin (2023); Saadah and Setiawan (2024); Tigges et al. (2024); Zhao et al. (2024).

Note. The table summarizes the interpretive pattern across the 17 retained empirical studies; it does not imply that all studies reported every subtheme.

❖ Theme 1: Trust Begins as a Cautious, Value-Based Trial

First, the confidence was temporary. Owners would not be averse to trying digital lending when it would help provide short-term funding, although they would not endorse it at the point of first use. The experiences in Peru, Indonesia, India, and Poland indicate that experimenting with an application becomes less challenging when there is rapid access, usefulness, and value, whereas continued use depends on trust (Adamek and Solarz, 2023; Asamani and Majumdar, 2024; Merino Balcazar and Llatas Rivas, 2021; Sunardi et al., 2021; Xie et al., 2021). The advantage is very pronounced when the processes of banks are slow or small firms are undocumented.

Limiting the trial is usually done through a smaller loan, using a simple analysis of repayment against cash flow, or utilizing an already existing platform of known payments or sales. Studies of Indonesian SMEs indicate that adoption is stimulated by innovation and infrastructure, although perceived risk, data security, and trust are decisive once access becomes available (Nugraha et al., 2022; Putri et al., 2023; Saadah and Setiawan, 2024). Successful remittance, proper documentation, and stable charges are indicators of ability.

Digital lenders are also compared by owners with banks, informal lenders, and previous platform experiences. This comparative assessment implies that credibility may increase even in cases when the site is not as good, as long as it is perceived to be more predictable or less cumbersome than alternatives offered.

The capacity related to systems is insufficient. Pakistan-based evidence shows that improved SME credit supply is associated with the use of fintech, whereas cross-country studies identify a link between digital lending growth, infrastructure, and enabling institutions (Cornelli et al., 2023; Rehman et al., 2023). They can only receive loans in usable terms at the promised terms to reach these benefits to the owners in the form of trust. Ease of use is not always stronger than trust, value, or financial health, implying that a certain level of friction seems tolerable, provided that the process is perceived to be legitimate (Adamek & Solarz, 2023; Merino Balcazar and Llatas Rivas, 2021).

❖ Theme 2: Trust Is Calibrated Through Intelligibility, Predictability, and Data Boundaries

After the first use, the owners evaluate the consistency in pricing, repayment service, communication, and risk. Research on digital and peer-to-peer lending has indicated that trust increases when terms and treatment can be predicted (Asamani and Majumdar, 2024; Chulawate and Kiattisin, 2023; Sunardi et al., 2022). This is important because small companies have diminished liquidity reserves. A sudden paycheck increase or back payment can disrupt wages, inventory levels, and supplier relationships.

Intelligibility is practical rather than technical. As Tigges et al. (2024) demonstrate, AI and alternative data may feature firms with no official documents, yet they reinvent creditworthiness. Abbas (2025) finds a fairness gap in technically defensible pipelines, which lack the comprehension of the relationships between the owners and their customers, the payment discipline, and the resilience of the pipelines. Lack of trust occurs when owners fail to establish a link between an outcome and identifiable business evidence or rectify inferences.

Source codes are not absolutely necessary for borrowers. They need to be aware of the primary causes of an outcome, the difference between known facts and estimated risk, and the path to redemption. Based on Pakistani evidence, fintech intention is supported by reputation, assurance by third parties, benefits, and trust (Zhao et al., 2024). The boundaries of the data are also vital. Microcredit becomes more resilient on the blockchain and becomes self-sovereign and governed, although the risk of security and coordination remains (Hoque et al., 2024). Owners should be aware of the data accessed, the reason why they are needed, and the impact of refusal on assessment. Clarity of boundaries also assists owners in differentiating legitimate verification from undeserved surveillance. In situations where collecting data has no apparent link to repayment ability, the information requirements on the platform can be seen as exploitative rather than safeguarding.

Negative behavior can overturn trust. Kenyan evidence refers to confounding advertisements, inquisitive dataset routines, obtrusive data gathering, and feeble protection as sources of inequitable treatment (Kim and Duvendack, 2025). Further borrowing under such circumstances can be seen as a manifestation of few choices and not trust. Thus, continuity in behavior is an inadequate test of confidence. A more robust measure involves the owners' ability to explain the conditions, forecast the outcome of the non-payment date, and think that they would be allowed to dispute an error and would not be pricked or excluded from future credit.

❖ Theme 3: Trust Becomes Relational and Institutional Through Recourse and Social Proof

Platforms are interpreted in terms of reputation, regulation, partner brands, peers, and the availability of human assistance by their owners. Thai, Pakistani, and Indonesian studies have identified information quality, trust seals, reputation, and institutional support as significant signals of adoption (Chulawate &

Kiattisin, 2023; Saadah and Setiawan, 2024; Zhao et al., 2024). Such cues decrease pre-experience uncertainty but are useful in predicting treatment only when cues are predictive.

Hidden costs, collection behavior, and resolution of complaints are found in peer testimony. Indian evidence also demonstrates that perceived risk and value depend on service quality (Asamani and Majumdar, 2024). Human assistance is an additional guiding support, as in the case of errors in records, attributions to seasonality, fraud, or discussion of temporary inability to pay, the owners might have to explain the situation. Technology-enabled lending is not only a model but also an organizational process with service personnel, partners, and governance (Hoque et al., 2024; Tigges et al., 2024). This observation is the reason why trust may be destroyed by a collection agent or customer-service failure, although the scoring model itself may be functioning as intended. In practice, the components cannot be considered independently; therefore, the owners consider the entire relationship.

The best test of institutional trust is the recourse. Elastic confidence relies on equitable resolution in the case of failure, and the trial can be achieved by a license or a well-known brand. A case in point is Kenya, where such unchecked growth failed to be accompanied by protection for borrowers (Kim & Duvendack, 2025). Accountability is evident in clear routes of appeal, documented reasons, and proportionate collection. In all three themes, value is the open door to value, experience measures its confidence, and institutional protections decide whether trust endures tribulation.

Discussion

The results support adoption research but twist its causal focus. Previous research has placed usefulness, ease, trust, and risk as the determinants of intention (Hu et al., 2019; Rosavina et al., 2019; Ryu, 2018). The synthesis demonstrates that practical value triggers experimentation, whereas trust is generated after adoption via disbursement, repayment, data usage, and dispute. This is the reason why a beautiful platform might fail to create continuance and why a less user-friendly experience could keep users if it has predictable behavior. It also demystifies the reasons why ease of use differs between empirical research studies: beyond a certain point on usability, owners have reached a point of financial ramifications and treatments and may not emphasize the simplicity of the interface.

The explainable AI argumentation is refined by the results. Rai (2020) and Shin (2021) associate explanations with acceptance, whereas the current results suggest that the mechanism of work of explanations is conducted through procedural usefulness. Owners should have justifications related to identifiable business evidence, corrections, and subsequent measures. This aligns with the transparency and predictability that Glikson and Woolley (2020) underline, but further states that recourse transforms explanation into accountability. An explanation can be used to justify a predetermined result without analysis.

The synthesis of the voting's task-dependent aversion of algorithms is also a task. The owners do not resist having AI perform rapid screening and routine processing, but when rejection or abnormal data or collection produces high consequences, they become contraindicated. This aligns with Castelo et al. (2019), but indicates that it is not the worry about algorithms in general. Mistakes must be contained. The system should include human escalation, as opposed to exceptions.

Institutional trust is also conditional. Confidence can be transferred by reputation, licenses, and partner brands, as implied by Singh and Sinha (2020) and Rosavina et al. (2019), yet it can also lead to over trust. A well-known brand can prompt owners to provide protection which can cannot be enforced. Thus, the policy should enhance trust and not just confidence. This is also ambiguous with regard to repeated usage. Otherwise, including may co-exist with risks, including protection, as Ozili (2018) notes, and limited borrowers might also need to renew their borrowing as there are no alternative options. Platforms must review complaints, adverse action understanding, the results of appeals, and reliance on refinancing instead of considering renewal as loyalty. The same should be applied to regulators and researchers not to equivocate the market growth with a well-realized inclusion since the increase in credit may further expose weaknesses when the conditions are not well-known or it is very hard to retreat. The religious dimension is therefore treated as a contextual ethical lens rather than evidence of a single faith-based response. Religious values may reinforce expectations of honesty, fairness, responsible data use, and avoidance of exploitative financial practices, while their strength and interpretation vary across owners and institutional settings.

The process model is tentative because most of the studies included were cross-sectional. To test the practitioner hypothesis that trial, calibration, and institutional assurance occur in the suggested order, future longitudinal work should precede owners prior to application, succeeding decisions, during repayment, and subsequent disputes.

Conclusion

Small-business owners learned to trust based on repeated tests. Access, usefulness, and speed are the reasons for a tentative trial. The learnable cost, understandable choices, equal treatment, and limited use of data define the state in which confidence is enhanced. Reputation, regulation, human support, peer testimony, and recourse are the determinants of the continuation of trust after any negative incident. Thus, trust is conditional and reversible, not a stable disposition. Viewed through this lens, trustworthy lending is not defined by technical accuracy alone; it also requires ethical legitimacy and sensitivity to the moral and religious values through which borrowers interpret fairness, obligation, and harm.

Adoption and repeated borrowing are partial activities due to the fact that the constrained owners might use a platform that they view as unjust. The better justifiable is the more defensible objective of calibrated trust, where reliance is comparable to demonstrated competence and enforceable accountability. Only visible, contestable, and repairable errors can be supported by AI-enabled lending. Embodied teaching is not AI that teaches owners trust. They draw their conclusions based on the behavior of the institution using AI, whether it makes promises or not, clarifies its choices of automation, restricts access to processes, and owns up when automation is disastrous.

Platform managers are expected to create trust throughout the loan lifecycle. It should be in plain language and show the overall cost of the application, timing of repayment, type of data, and automated evaluation of payments. Notices of adverse actions are used to identify key causes and differentiate between misplaced information and product modelling. Permission controls and record correction, in addition to access to a trained human reviewer, require the owners. Cautious trials can be fixed by graduation loan limits, but must not conceal fee inflation and interdependency. Successful corrections, time spent handling complaints, and the percentage of applicants whose applications have been rejected but who received a comprehensible explanation as to why should be listed as performance indicators rather than approval and repayment rates.

Regulators should integrate licensing and enforceable data minimization, consent, model monitoring, collection, time limits on complaints, and meaning review. Error patterns according to the size of the business, gender, location, and informality should be audited since average accuracy can mask unequal damage. Institutional signals can be believable with public complaint data and normal cost comparisons.

Longitudinal interviews using the same owners during application, decision, repayment, renewal, and dispute should be conducted. Bank-backed platforms, standalone fintech, marketplace credit, and mobile money lending should be differentiated, and warranted trust and dependence should be separated by considering what alternatives and the ability to exit exist. The research must also determine the effects of gender, rural community, informal status, and low levels of digital literacy on the capacity to interpret explanations or utilize appeal systems. Such work would show whose trust is being worn and whose compliance is being confused with confidence.

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▪ All Authors Conceptualization, and intellectual revisions, Data collection, interpretation, and drafting of manuscript ▪ The authors agree to take responsibility for every facet of the work, making sure that any concerns about its integrity or veracity are thoroughly examined and addressed
▪ Ethical Statement. This secondary qualitative synthesis used only publicly available, previously published findings. It involved no participant recruitment, intervention, identifiable personal data, or access to primary transcripts; therefore, formal ethical approval and consent were not required. All sources were attributed and interpreted cautiously.
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