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Article

Constructing Financial Trust in AI-Enabled Digital Credit Information Systems: A Grounded Theory of SME Adoption Under Algorithmic Opacity

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Abstract: AI-based digitall credit information systems made possible by AI offer quicker and expanded finance to small and medium enterprises (SMEs), but the rationale behind their scoring is typically unknown to the applicants. This study posits the question of how financial trust is created when SMEs are required to approve consequential credit decisions that they cannot view the algorithm behind the decision. A secondary qualitative synthesis was designed based on grounded theory utilising a purposely segregated evidence structure. The literature review and methodology were sensitised using 20 studies published between 2016 and 2023, and a corpus of 15 different primary empirical studies between 2021 and 2024 was formed. Constant comparison, focused coding, memo writing, and theoretical integration yielded three themes: evidentiary legibility, procedural agency and contestability, and ecosystem-embedded assurance. Bounded authorisation under managed opacity is the core category that describes adoption as a temporary choice to trust a digital lender when controlled evidence limits the observance of a lack of transparency by knowledgeable evidence and conditions of practical appeal as well as responsible institutional frameworks. The analysis questions the premise that more technical disclosure is necessarily a generation of trust. Foodless endowments may form a misleading promise of security, and cursory consent may hide stigmatizing information procedures or feeble lines of remediation. Trust is thus tuned based on the system performance, control by the applicant, lender behavior and the business value realized. The research adds an information-systems explanation of SME digital credit adoption, which connects explicable artificial intelligence, financial technology, and governance. Here it also outlines design and policy priorities; reason codes associated with corrective action, human review of disputed decisions, data provenance controls, similar pricing, and on-going accountability of post-loan.
Keywords: algorithmic opacity, digital credit, explainable artificial intelligence, financial trust, information systems, SME adoption

1. Introduction

Insider financial institutions are digitally converting transaction histories, platform usage, device information, and other digital traces into quick lending models. These systems can also lower the costs of search and processing and increase access to finance for SMEs that have no traditional collateral or audited histories [1,2]. Efficiency alone does not account for the adoption. The study of FinTech indicates that perceived benefits are in conflict with legal uncertainty, operational risk, loss of control [3], and security and data-handling practices, which influence customers' perceptions of whether a provider is trustworthy [4]. In credit, these considerations are consequential because a poor score may limit working capital without indicating the information or conclusion involved in the judgment.

Predictive improvement does not resolve whether the decision is fair, intelligible, or contestable; however, predictive improvement can be achieved with alternative data and machine learning, establishing some risk beyond traditional scores [5,6]. An SME might receive a quicker offer but still cannot comprehend the price change, rectify a wrong data path, or even recognise actual individualisation and concealed discrimination. In this context, trust in finance is not just an easy belief in technology. This means a readiness to delegate business information, take a judgment with a machine, and make a repayment commitment when asymmetric knowledge is present.

This study provides a developed description of such willingness based on secondary evidence. This poses the question: How can SMEs build ample trust to implement AI-enabled digital credit information systems under algorithmic opacity? This study makes a three-fold contribution. First, it redefines the notion of trust as temporary authorisation rather than fixed faith. Second, it distinguishes between explanatory transparency and practical recourse, revealing that explanatory statements out of the agency can vindicate, as opposed to diminishing opacities. Third, it finds adoption in the lender, data intermediary, regulatory, and business-result ecosystems. The derived model will serve information systems research and digital lending design and governance purposes.

2. Literature Review

A. Digital credit infrastructures and SME finance

Lending through FinTech re-structures credit in the form of an information-processing service. It is done through platforms that bring together data capture, scoring, pricing, contracting, and monitoring of repayment, and sometimes with less physical interaction compared to bank lending. This architecture can overcome thin credit files, although it ends up concentrating power in the hands of organisations that manage data access and model design. Empirical evidence indicates that alternative data have the potential to differentiate risks and price some borrowers more efficiently [5,6]. However, there is an uneven distribution of efficiency. Borrowers can be faster, and lenders have a better idea of model constraints, feature utilization as well as portfolio incentives. SME finance reviews reveal the presence of access benefits and privacy, cybersecurity, regulation, and exclusion issues [15,16]. The issue of whether digital credit has created value is central; however, the question is whether SMEs can consider the value of such a commitment prior to acquiring a binding obligation.

B. Trust, explanation, and calibrated reliance

The literature on human trust in AI demonstrates that reliability, transparency, the type of task, and the manner in which a system is faced influence reliance [7]. However, not all transparency is good. Research on interfaces reveals that further information about the processes can only enhance trust to a certain level and might reveal the complexity that users are not able to assess [8]. Additional research on algorithm aversion demonstrates that humans can reject a faulty model once they have been shown the error; however, restricted chances to edit an output can reintroduce utilisation [9]. Other experiments have detected the appraisal of an algorithm [10] and situational aversion [11], implying that trust is not a fixed preference towards human or machine judgment. Explainability reinforces perceived causality and acceptance [12], but a plausible explanation boosts confidence with no change in decision quality. In the case of digital credit, this difference can be critical because the opaque score presented through persuasive interfaces can seem comprehensible, whereas data errors and negative decisions can be virtually unappealing.

C. Fairness, data governance, and institutional assurance

Legal and organizational decisions have credit algorithms in them. Discrimination in FinTech lending suggests that technology can minimise certain interpersonal differences and leave or transfer unequal results through pricing and proxies of data [13]. Machine learning can also alter the groups of underserved individuals, as gains in prediction are not socially neutral [14]. Therefore, trust is not solely based on model accuracy. It is also founded on security, limitation of purpose, uniform treatment, an explainable logic of adverse actions, and plausible accountability in the case of harm [4,13]. SMEs are especially susceptible to institutional assurance since they might have limited bargaining power and might incur immediate liquidity costs if an application is not possible to be fulfilled or not.

D. Theoretical framework

Three sensitising concepts were incorporated into the research. The former is calibrated trust: the use of appropriate reliance is proportional to proven ability and riskiness [7,8], rather than to a generic hope of AI. The second is perceived value vulnerability: adoption is conceivable when speed, access, and flexibility superiority to the anticipated privacy, price, and dependency outlays prevail [3,15]. The third is procedural legitimacy: users do not only evaluate the results but also the ability to get, correct, and review decisions [9,12-14]. These concepts are not addressed as facts to be verified. They tilt the focus on the conditions where an SME permits a system to operate despite the remaining opaque conditions. The developing grounded theory can then alter, relate, or deny these sensitising concepts.

E. Research gap

Current streams are still discontinuous. The adoption intention or credit access is usually in SME FinTech research, whereas XAI research usually involves experiment-based tasks unrelated to long-term credit-debt interactions. Fair-lending studies establish aggregate results but disclose less about the notion that applicants make trust judgments. Subsequently, the literature fails to explain the combination of technical explanation, applicant agency, institutional safeguards, and realised business value over time. It also tends to consider the problem of (or lack of) transparency as a shortcoming addressed by disclosure, ignoring the notion that SMEs can have a rational reason to develop a partially opaque system when there are limits to transparency. This requires a process theory that describes how trust is gathered, tried, and updated prior to and following adoption.

3. Methods

A grounded theory-informed secondary qualitative design was employed. It is said to be informed and not a classical grounded theory because the research examined published empirical reports and reported findings, as opposed to creating data at the participant level by conducting interviews. Grounded theory, however, offers an appropriate logic of procedure in the form of iterative coding, constant comparison, memo writing, and integration around a central category [17]. Qualitative transparency criteria were used to report decisions, specifically, transparency regarding the choice of evidence, interpretation by the researcher, and transferability limitations [18].

A systematic search was performed between 2021 and July 2026, which involved the combination of SME, small business, digital lending, FinTech credit, AI credit scoring, algorithmic opacity, explainability, trust, fairness, adoption, and contestability. The searches included Scopus, Web of Science, ABI/INFORM, ScienceDirect, ACM Digital Library, and Google Scholar and were performed with the assistance of backward and forward citation checking. The results pool comprised 15 primary empirical research papers published since 2021. Qualified studies were those that described original quantitative, qualitative, mixed-method, experimental, or administrative data evidence on SME digital finance or user dependence on consequential AI. The corpus of findings did not include reviews, commentaries, duplicate reports, or studies whose methods or results were unavailable.

The analysis was performed in four steps. First, the actions and conditions involved in the result statements were coded on a line-by-line basis, such as seeking a reason, correcting data, comparing prices, accepting speed, and looking at the reputation of providers. Second, the lending and explainability studies focused on comparing codes. Third, the negative cases explored in memos involved cases with greater explanation-confidence but not accuracy or greater access with uncertain fairness. Fourth, a conditional process model was used to relate the categories. Theoretical sufficiency was not considered through the allegation of saturation of the participants but rather through the proportions of the categories and the reappearance of that mechanism in heterogeneous situations. This difference is relevant because saturation guidance is best applicable to primary qualitative samples [19]. The visibility of interpretation and the desire not to present codes as a resultant discovery were enabled by reflexive thematic principles [20]. To enhance analytical separation, a citation ledger was maintained, whereby no contextual literature review research was coded into the findings code set. More than one disciplinary or national setting had to support each focal category. The evidence that contradicted the majority interpretation was stored in memos. Such measures minimise but do not remove partisan synthesis and researcher bias confirmation. No enlisted human subjects or confidential documents were used in this study. This research has limitations, namely publication bias, contextual heterogeneity, and reliance on reported findings of authors. The progression from initial action and condition codes to focused categories and the core category is summarised in Table 1.

Table 1. Thematic coding pathway from initial codes to grounded categories

Representative initial codes	**Focused category**	**Integrated theme and theoretical meaning**
Seeking a reason; checking the assessment period; identifying the data source; assessing relevance; recognising uncertainty	Decision-useful evidence	Evidentiary legibility: the SME can construct a testable business account of the decision without requiring source-code disclosure.
Correcting transaction data; submitting contextual evidence; comparing total	Reversible procedural control	Procedural agency and contestability: uncertainty becomes bounded when

cost; requesting human review; pausing or withdrawing an application		reliance can be challenged, corrected, reviewed, or exited.
Evaluating lender reputation; checking data stewardship; comparing contract terms; observing servicing; assessing post-loan value	Institutional and realised assurance	Ecosystem-embedded assurance: trust becomes durable when responsible governance and realised business outcomes reinforce initial reliance.
Provisional acceptance; monitored use; reassessment after performance; withdrawal following unresolved harm	Bounded authorisation	Core category: controlled opacity is accepted temporarily while evidence, recourse, and accountability remain credible.

Note: The codes are representative analytical labels developed through constant comparison of the 15 primary empirical studies.

4. Findings

A. Theme 1: From black-box accuracy to evidentiary legibility

The first theme reveals that SMEs do not need extensive access to the source code; instead, they need evidence that links the choice to an intelligible business account. Financial adviser experiments revealed that explanations can enhance adoption, but the effect varies based on the perception by users that the explanations are relevant and decision-useful [21]. A study of social transparency through interviews also found that individuals want to know who utilised the system, in what context, and what the effects of the system were, rather than a more technical account of what the models did or did not do [22]. Thus, legibility is a relational aspect. One of the reasons like fluctuating cash flow can be said to be credible when the applicant can determine when the actual time frame is under consideration, the consequences of the lending and the evidence which may change the evaluation.

The danger of decorative explanations was also found in the synthesis. Cognitive forcing experiments have shown that users are over-reliant on AI unless the interface asks them to think independently [23]. Comparative studies have found that explanations do not always enhance human-AI decision-making and may increase dependency on flawed recommendations [24]. To this end, trust is not built by maximising the number of explanations. It emerges when there is evidence that is testable, modest concerning the lack of evidence, and associated with a meaningful decision. The appropriate shift is between clouded authority and obvious legibility. A platform adds temporary confidence when the SME can develop a working causal explanation of the outcome and is conscious of the one that is not yet known.

B. Theme 2: Procedural agency converts uncertainty into bounded reliance

The second theme relates to actions that an applicant can take when the system is incorrect, incomplete, or commercially inappropriate. There is some administrative evidence on the FinTech borrowing population that digital lenders might treat creditworthy borrowers differently than traditional lenders; however, the rapid screening of borrowers can also imply selective borrower profiles instead of eliminating information asymmetry [25]. In crisis scenarios, owners of small businesses are motivated by perceived usefulness and access to FinTech borrowing in cases where traditional channels are limited [26]. Massive lending experiments also show that nonbank and FinTech lenders grow in areas where they squeeze banks or where banks do not process credit flexibly [27-29]. These advantages generate an incentive to put with opaqueness, yet they do not solely generate trust.

The limits were accepted in the uncertainty, which was capped by the agency across the evidence. Applicable mechanisms entailed the possibility of fixing transaction information, filing situational files, comparing overall costs, suspending an application, seeking human consultation, and obtaining a rationale for adverse rulings. The meaning of agency altered due to the construction of a meaning of opacity, since the unknowable model was no longer seen as an unquestionable authority. Speed without recourse, on the other hand, creates dependency: the SME can obtain capital very quickly but is still vulnerable to mysterious pricing, redundancy of data retrieval, or robotic rejection. This classification thus differentiates between access and authorisation. Adoption occurs when the enterprise has a sufficient level of procedural control to manage reliance as something reversible and subject to review versus giving up the platform.

C. Theme 3: Trust becomes durable through ecosystem-embedded assurance

The third theme is how to achieve lasting adoption with only an acceptable interface. Manufacturing SMEs survey evidence attributes FinTech usage to credit supply, although its usage is conditionalized by organizational capability and banking relationships in the environment [30]. Other studies on the adoption of digital lending also determine that usefulness, ease, compatibility, perceived risk, and trust are not independent but complementary factors [31]. International evidence indicates that digital lending increases because of the presence of enabling technology, unfulfilled credit demand, and institutional circumstances [32]. Finntech applications in small food businesses are related to openness and business innovation, which echo the value of credit technology when it facilitates a more operating model [33]. Indian data also indicate that adoption indicates platform characteristics and readiness among borrowers [34]. Data on loan applications also show that FinTech credit has the potential to generate real impacts by making viable SMEs financially more flexible [35].

The results of these studies led to the category of ecosystem-embedded assurance. Trust was long-lasting as four types of assurances came together: reliable data stewardship, recognisable lender responsibility, equal and comparable terms and conditions in contracts, and business value achieved post-disbursement. However, an effective loan was not the end. The handling of repayment, reuse of data, recovery of services, and the impact of financing on operations were fed back to the later trust. The central theme that connects all others is the limited authority of controlled invisibility. SMEs provide the system with a provisional passage in situations where the legibility of the evidence provided is apparent, recourse to action is feasible, and misuse is limited by institutions. Then, through experience, trust is written afresh. Opacity is controlled instead of being abolished and is conditional depending on the onwards performance of the entire credit information ecosystem. Table 2 consolidates the conditional process through which trust is initiated, tested, reinforced, or withdrawn.

Table 2. Conditional process model of trust construction and breakdown

Analytical stage	**Enabling conditions**	**Breakdown indicators**	**Trust outcome**
Application assessment	Relevant reason codes, identifiable data provenance, uncertainty cues, and understandable cost implications	Generic explanations, hidden data sources, unexplained pricing, or confidence unsupported by decision quality	Initial bounded confidence or scepticism
Decision challenge	Correction routes, contextual evidence, substantive human review, and the ability to pause or withdraw	Repeated automated responses, no correction mechanism, ceremonial review, or costly appeal	Procedural authorisation or dependency
Credit use and servicing	Comparable terms, secure and limited data reuse, responsive servicing, and transparent repayment handling	Unexpected fees, secondary data reuse without clear limits, weak remedies, or inconsistent treatment	Reinforced or weakened reliance
Post-loan reassessment	Realised liquidity or operational benefits, fair recovery practices, accountable lender conduct, and feasible switching	Business harm, unresolved disputes, reputational damage, or inability to exit without disproportionate cost	Durable trust, recalibration, or exit

Note: Trust is treated as a revisable process. The same stage can strengthen or weaken authorisation depending on whether safeguards are credible in practice.

5. Discussion

The results confirm and add to the literature review on FinTech adoption. The logic of benefit and risk [3] by Ryu is valid because there is a trade-off between speed and access and privacy, price, and dependency of SMEs. The contemporary model goes further to demonstrate how risks are not weighed as perceptions. Correction, review, comparison, and exit are actively bounded to them. Equally, security-based trust [4] is required but not complete, as safe data processing cannot justify an unjustifiable or unattractive credit decision. Table 1 makes this analytical contribution explicit by showing that the categories were developed from recurring actions and conditions rather than imposed directly from the sensitising literature.

This theory of evidentiary legibility aligns with the desirable consistency of AI trust to reliability and transparency [7] and studies that demonstrate the potential of explainability to augment acceptance [12]. However, this goes against a simple disclosure prescription. Prior results in this area indicated that additional information was not necessarily beneficial to trust [8], and the main results indicated that explanations might lead to over-reliance [23,24]. The design goal of interest is tuned knowledge and not peak visibility. This also filters algorithm aversion and appreciation results [9-11]. The choice in SME credit is neither a unilateral forecasting task nor a preference. It has liquidity, privacy, and contractual implications, and such restricted amendments and recourse are important because they maintain applicant agency.

The ecosystem assurance theme correlates with reviews that find regulatory and infrastructural circumstances surrounding SME FinTech [15,16], but introduces a time mechanism. The post-adoption process involves service rebuilding, data reuse, and realised financial flexibilities to rebuild trust. This assists in relating access evidence [25-35] to issues of fairness in the literature review. Bartlett et al. [13] and Fuster et al. [14] demonstrate that prediction can redistribute and not erases inequality. The grounded model describes why even with constraining institutional controls and business requirements, an SME might still embark on limited authorisation, which can be rationalised when its exposures are restricted by the existence of institutional and business requirements. However, such is the severe caution of this model. Practical needs can result in compliance similar to trust. Therefore, researchers and providers must differentiate voluntary and informed dependence from adoption attributable to credit shortages.

Another theoretical implication is the distinction between trust calibration and market discipline. Under competitive accounts, an SME may take revenge and deal with an opaque lender by switching lenders. The findings imply that this mechanism is weak where repetitive applications are harmful to credit profiles, where platforms employ similar data brokers, or where liquidity crises reduce the set of feasible options. In such circumstances, obvious adoption might indicate restrained consent and not trust. The core category thus involves a threshold test: reliance is only financially trustworthy when the enterprise can deny, challenge, or quit without unwarranted damage. This test also demystifies the fact that institutional assurance cannot be presented on an explanation screen. When the lender is unable to determine the data source, the automated result is restated by a human reviewer, or the terms of the contract allow the broad use of secondary data between clear reason codes, which is of limited value. However, in contrast, a partly opaque model may encourage a suitable defense of reliance in cases where such error is constrained by the effect of independent audits and corrective obligations that are enforceable and reflective pricing. This emphasises the switching of the theoretical focus of the black box to its ruling frontier. The breakdown indicators in Table 2 also demonstrate that apparent adoption can coexist with constrained consent when correction, review, or exit is costly.

The secondary design is unable to determine whether all SMEs adhere to the suggested sequence, and whether the corpus is a mixture of countries, types of platforms, and methods. It is based on theoretical integration, as opposed to prevalence estimates. Further primary research should measure how transitions occur among the three themes and explore the unsuccessful construction of trust, particularly between rejected, data-poor, or digitally marginal businesses.

6. Conclusion & Implications

This study theorises SME confidence in AI-powered digital credit as constrained authorisation through controlled non-transparency. The latter is achievable when an enterprise can comprehend the evidentiary basis of a choice, exercise purposeful procedural agency, and depend on responsible ecosystem plans. A technical explanation is insufficient and can lead to an illusion of security. Trust is tentative, model-revisable, shared, and spread among the model, interface, lender, data partners, and regulatory environment. This theory thus changes the focus of the issue of whether SMEs trust AI to how certain controls render dependence justifiable, despite the unknown.

For system designers, explanations must include decision-specific reason codes, data provenance, uncertainty indications, and corrective actions. Interfaces should provide review channels and friction on high-stakes spots instead of only streamlining the process of immediate completion. As applied to lenders, trust metrics must span conversion and repayment to challenge decisions, remedy time, pricing understanding, data reuse grievance, and after-loan business results.

To regulators, explainability mandates must be accompanied by contestability, audit trails, similar total-cost disclosure, and enforceable responsibility among lenders and third-party data providers. Human review is supposed to be substantive and not just ceremonial. For researchers, the model provides propositions of a testable process: evidentiary legibility must increase adoption only when recourse is credible, and initial access benefits must generate lasting trust only when servicing and data management ensure institutional assurance. These propositions should be tested under both regulatory and cultural conditions, which requires primary longitudinal studies of SME applicants, including rejected applicants.

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