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Research Article

Perceived Security and Trust as Mechanisms of P2P Adoption Technology: Evidence from Pre-Adopters Using PLS-SEM Approach

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ABSTRACT

Peer-to-peer (P2P) lending can expand working-capital access for micro-entrepreneurs, yet borrowing via digital platforms heightens perceived vulnerability due to sensitive data disclosure and binding repayment obligations. This study examines how perceived security and trust shape adoption intention in a high-stakes fintech context by extending the Technology Acceptance Model (TAM) and testing whether security and trust transmit the effect of perceived usefulness to intention. Using an explanatory cross-sectional design, we collected offline-administered survey data from 204 Indonesian micro-entrepreneurs who had not previously adopted P2P lending to capture pre-adopter perceptions better and reduce digital-selection bias. The model was estimated using PLS-SEM v3. The results indicate that all hypothesized relationships are positive and statistically significant. Perceived usefulness significantly enhances perceived security (β = 0.562) and trust (β = 0.259), while perceived security exerts a strong positive effect on trust (β = 0.517). Intention to use P2P lending is directly influenced by perceived security (β = 0.337), trust (β = 0.213), and perceived usefulness (β = 0.208). Mediation analysis confirms that perceived security (β = 0.189) and trust (β = 0.055) partially mediate the effect of perceived usefulness on intention to use. The model explains 42.4% of the variance in intention to use (R-squared = 0.424) and demonstrates adequate predictive relevance (Q-squared = 0.263). Overall, perceived security emerges as the most influential determinant of adoption intention, underscoring the importance of security-by-design features, transparent governance, and robust consumer-protection frameworks in fostering trust and accelerating P2P lending adoption among micro-entrepreneurs.

KEYWORDS adoption intention • digital financial security • perceived security • reduced inequalities • social protection systems

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1. INTRODUCTION

Financial technology (FinTech) has accelerated the digital transformation of financial intermediation by enabling scalable delivery of payments, savings, investment, insurance, and—critically—credit through platform-based models and data-driven decision systems. In credit markets, peer-to-peer (P2P) lending represents a salient form of "FinTech credit" that reconfigures the traditional lending value chain by digitizing borrower onboarding, screening, matching, disbursement, and repayment monitoring [1]–[3]. By lowering search and transaction costs and expanding the range of information beyond conventional banking records, P2P platforms may expand access to working-capital finance for borrowers who are frequently excluded from formal credit due to limited collateral and thin credit histories [4], [5]. This value proposition is particularly relevant for micro-entrepreneurs, whose business continuity often depends on short-cycle liquidity, rapid inventory turnover, and flexible repayment schedules.

To keep the term "vulnerable micro-entrepreneurs" operational, this study treats micro-entrepreneurs as owners of micro businesses as defined in Indonesia's MSMEs classification (No. 7/2021), i.e., enterprises with business capital up to IDR 1 billion (excluding land/buildings) or annual sales up to IDR 2 billion. Within this population, "vulnerability" refers to limited financial buffers and capability constraints that heighten exposure to loss in digital credit transactions—typically reflected in irregular cash flows, limited collateral and thin credit histories, lower digital/financial literacy, and constrained access to reliable digital devices and connectivity. These conditions imply that risk-mitigating beliefs—especially perceived security and trust—are likely to play an outsized role in micro-entrepreneurs' evaluations of P2P lending adoption.

However, adoption of digital lending cannot be explained by efficiency considerations alone. Compared with lower-stakes FinTech services (e.g., digital payments), borrowing via P2P lending entails heightened perceived vulnerability because it requires disclosure of sensitive identity and business information, acceptance of binding repayment obligations, and reliance on platform governance for pricing, data handling, and collection practices. International policy and supervisory evidence have highlighted consumer risks in digital credit ecosystems, including opaque and complex pricing, over-indebtedness, aggressive or abusive collection behavior, and misuse or excessive collection of personal data [6], [7]. These risks can be amplified in emerging markets where digital and financial literacy are uneven, limiting consumers' capacity to interpret disclosures, evaluate consent terms, and assess platform legitimacy—thereby weakening intention to adopt even when perceived benefits are recognized.

Indonesia represents a salient case within a broader global pattern of P2P lending adoption under conditions of elevated institutional and informational uncertainty. Across many emerging and transitional economies, regulated digital lending platforms coexist with persistent concerns regarding illegal or unlicensed operators, misuse of personal data, opaque pricing, and coercive collection practices—risks that have been documented to spill over into users' perceptions of digital credit markets as a whole, including regulated providers [8], [9]. Empirical and policy-oriented studies from Asia, Africa, and Latin America indicate that the presence of illicit digital lenders can undermine trust in platform-based credit more broadly by blurring the distinction between formal and informal providers in consumers' eyes [2], [10]. As a result, adoption decisions in P2P lending environments are shaped not only by platform-specific attributes but also by systemic perceptions of regulatory effectiveness, market discipline, and consumer vulnerability.

In response to these challenges, financial regulators worldwide have intensified governance, prudential oversight, and consumer protection requirements for P2P lending and other forms of FinTech credit, reflecting a growing consensus that technology-enabled financial inclusion must be balanced with robust safeguards [11], [12]. In Indonesia, the Financial Services Authority (OJK) issued Financial Services Authority Regulation of the Republic of Indonesia Number 40 of 2024 on information Technology–Based Joint Funding Services (POJK 40/2024; promulgated 27 December 2024), which replaces earlier rules and strengthens enforceable standards for (i) personal-data governance (consent-based collection/processing, retention, and breach notification), (ii) platform governance and accountability grounded in good corporate governance principles, and (iii) consumer-protection mechanisms such as transparency and dispute-resolution/complaint-handling provisions in electronic agreements. By codifying these safeguards, POJK 40/2024 can function as an institution-based trust signal and a regulatory source of perceived security, reducing perceived vulnerability when micro-entrepreneurs consider borrowing through digital platforms. Under such conditions of heightened perceived risk, micro-entrepreneurs' intention to adopt P2P lending is best conceptualized as a risk–benefit trade-off rather than a purely efficiency-driven decision: while digital platforms promise instrumental advantages such as speed, convenience, and improved access to working capital [4], [5], these benefits are weighed against the need for credible assurances regarding data security, fair treatment, and institutional reliability. This tension underscores the central role of perceived security and trust in shaping adoption intentions in digital lending markets worldwide, particularly among micro-entrepreneurs, whose heightened financial exposure heightens their sensitivity to potential losses [13]–[15].

Intention-based adoption theories provide a structured lens for modelling this decision-making. The

Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) position behavioral intention as the most proximal antecedent of behavior and emphasize the roles of attitude, subjective norms, and perceived behavioral control in shaping intention [16], [17]. Complementarily, the Technology Acceptance Model (TAM) identifies perceived usefulness as a central determinant of intention, capturing the extent to which a user believes that a technology improves task performance [18]–[20]. Yet in high-stakes financial contexts, such as digital borrowing, TAM's instrumental logic is often insufficient without complementing it with mechanisms that reduce uncertainty. Borrowers must rely on the platform under conditions of information asymmetry and perceived opportunism; thus, trust becomes pivotal. Trust in digital contexts is commonly theorized as confidence in a provider's competence, integrity, and benevolence, and it has been repeatedly linked to adoption of online financial services [13], [21]. Moreover, perceived security—beliefs that a platform safeguards personal and transactional data and provides safe processes—can serve as both a direct driver of intention and an antecedent of trust, as security protections signal organizational capability and responsibility [15], [22]. Finance research further indicates that trust dynamics extend beyond platform-specific evaluations, as trust in traditional finance can shape the propensity to adopt FinTech products, including P2P lending [23].

Despite growing research on FinTech adoption, three gaps remain particularly salient for the Indonesian P2P lending context. First, a substantial share of prior work relies on general consumer samples or digitally active respondents, which may underrepresent micro-entrepreneurs who face heterogeneous capability constraints, limited formalization, and distinct working-capital needs. Second, many studies use online-only surveys, which can introduce under coverage and self-selection bias, thereby overestimating adoption readiness among less digitally connected populations [24], [25]. Third, while perceived security and trust are often modelled as direct predictors, fewer studies explicitly test mediating mechanisms that explain how instrumental beliefs translate into intention in high-uncertainty lending decisions—particularly whether perceived usefulness influences intention indirectly through perceived security and trust, and whether perceived security operates as a trust-building mechanism within a protective belief system.

This study develops and tests an integrated adoption framework that combines TAM with perceived security and trust as risk-mitigating beliefs to explain Indonesian micro-entrepreneurs' intention to use P2P lending apps. Perceived usefulness is modelled as a key exogenous belief that directly and indirectly affects intention via perceived security and trust, with perceived security also specified as an antecedent of trust. Using offline-administered survey data from micro-entrepreneurs who pre-adopted (non-users), the study reduces digital-selection bias and captures early-stage adoption perspectives. The study contributes by (i) extending TAM in a high-stakes digital credit context through dual mediation by perceived security and trust, (ii) leveraging an offline pre-adopter sample, and (iii) offering implications for platform governance and consumer-protection enforcement amid Indonesia's evolving regulatory environment. Building on our prior work [26] that tested perceived security as a single mediator, this paper advances the mechanism by integrating trust and modelling security relationship trust, thereby establishing a dual risk-mitigation pathway from usefulness to intention.

2. LITERATURE REVIEW

2.1. FinTech P2P Lending and Adoption Challenges

Peer-to-peer (P2P) lending platforms—often classified as IT-based collective funding or marketplace lending—reconfigure the lending value chain by digitizing core processes, including onboarding (e-KYC), credit assessment using alternative data, loan matching, disbursement, and repayment monitoring. This form of digital intermediation reduces search and transaction costs. It expands access to finance for micro- and small enterprises that face collateral constraints and limited formal credit histories (thin-file borrowers) [27]–[29]. However, adoption decisions among micro-entrepreneurs are not driven solely by efficiency. Digital credit is a high-stakes financial service that requires the disclosure of sensitive personal and business data and binds borrowers to formal repayment obligations. Consequently, P2P lending involves higher perceived vulnerability and uncertainty than lower-risk FinTech services, such as digital payments or informational applications [2], [30].

Prior research and policy reports identify substantial consumer risks in digital credit ecosystems, including opaque pricing, over-indebtedness, aggressive collection practices, and misuse of personal data [6], [31]. In emerging markets, uneven digital literacy and limited capacity to evaluate complex privacy and security disclosures further weaken informed consent [32], [33]. In Indonesia, public concerns regarding illegal online lending, data breaches, unethical marketing, and fraud have contributed to adverse risk perceptions—even toward licensed platforms—prompting strengthened supervision and consumer protection under OJK Regulation No. 40 of 2024. Accordingly, micro-entrepreneurs' intention to adopt P2P lending reflects a dual evaluation of expected instrumental benefits (e.g., speed, convenience, and access to working capital) and risk-mitigating assurances (e.g., security, institutional credibility, and trust). This supports an integrated adoption framework that combines perceived usefulness

with relational and protective beliefs, particularly trust and perceived security [34]–[36].

2.2. Behavioral Intention: TRA and TPB

The Theory of Reasoned Action (TRA) posits that human behavior is primarily determined by behavioral intention, which is shaped by individuals' attitudes toward the behavior and subjective norms reflecting perceived social approval or pressure from salient referent groups [17], [37], [38]. The Theory of Planned Behavior (TPB) extends TRA by incorporating perceived behavioral control (PBC), defined as individuals' perceptions of their ability to perform a behavior given available resources, knowledge, and opportunities, as well as perceived external constraints [39]. PBC is particularly salient in contexts characterized by uncertainty or resource constraints because it influences intention and may also directly affect behavior when actual control is incomplete [40].

TRA and TPB provide a robust conceptual foundation for examining adoption intention in FinTech P2P lending. First, borrowing decisions on digital lending platforms are deliberate and goal-oriented, involving risk evaluation and forward-looking commitments, which align well with intention-based behavioral models [38], [41]. Second, FinTech studies—particularly in emerging markets—often rely on cross-sectional survey data in which actual usage or repayment behavior may be unobservable, making behavioral intention a theoretically appropriate and empirically reliable proxy for pre-adoption outcomes [42], [43]. Meta-analytic evidence further indicates that intention explains substantial variance in actual behavior across domains, including technology use and financial decision-making [39], [44]. Accordingly, TRA/TPB offer a well-established behavioral framework for modeling micro-entrepreneurs' intention to adopt P2P lending while allowing the integration of complementary constructs—such as perceived usefulness, trust, and security—to capture the risk–benefit trade-offs inherent in FinTech adoption.

2.3. Technology Acceptance Model: Usefulness and Ease of Use as Instrumental Beliefs

The Technology Acceptance Model (TAM) explains technology adoption through two core cognitive beliefs—perceived usefulness (PU) and perceived ease of use (PEOU)—which shape users' attitudes and, in turn, their behavioral intention to use a system [18], [45]. Perceived usefulness refers to the extent to which an individual believes that using a system enhances task performance or goal attainment. In FinTech contexts, this belief typically reflects expectations of faster transactions, improved access to financial resources, greater convenience, and more efficient financial management [46], [47]. For micro-entrepreneurs, PU is particularly salient because financial technologies are evaluated instrumentally based on their capacity to support working-capital needs, reduce administrative burdens, and overcome constraints associated with traditional banking.

Perceived ease of use captures the extent to which a user believes that using a system requires minimal effort, including the perceived simplicity of procedures, interface clarity, and ease of learning [18], [45]. In FinTech lending, PEOU (or perceived effort/complexity) may be especially relevant for micro-entrepreneurs who face constraints in digital literacy, time availability, and administrative capacity; a platform perceived as complex may reduce adoption intention even when its benefits are recognized. Consistent with TAM, PEOU is expected to strengthen PU by enabling users to realize promised benefits more readily and may also exert a direct effect on intention in settings where procedural burden constitutes a salient barrier. Extensive empirical research across digital banking, mobile payments, and FinTech services consistently identifies PU as a strong predictor of adoption intention [48]–[50]. However, FinTech lending differs from many other digital services due to elevated financial, legal, and data-related risks, suggesting that instrumental beliefs alone may not fully explain adoption behavior. Accordingly, prior studies argue that TAM should be extended to include risk-mitigating beliefs—such as trust and perceived security—to capture decision-making in high-uncertainty financial contexts [2] more accurately, [34], [36]. This extension is particularly relevant for P2P lending, where perceived benefits must be weighed against risks related to data disclosure and repayment obligations.

2.4. Trust in FinTech Environments

Trust in digital and online services is commonly defined as the belief that a service provider is competent and reliable and will act in ways that protect users' interests under conditions of uncertainty and vulnerability [21], [51]. In FinTech environments, trust plays a central role by reducing perceived risk and enabling users to engage in transactions involving sensitive personal data and binding financial commitments. Accordingly, a growing body of empirical research identifies trust as a key determinant of adoption intention across FinTech services, including mobile payments, digital banking, and online lending platforms [14], [47], [48], [52].

Importantly, trust in technology-mediated financial services does not emerge in isolation but is shaped by other cognitive evaluations. Prior studies suggest that both functional and protective beliefs influence trust. When users perceive a FinTech platform as highly useful—such as enabling timely access to working capital or improving operational efficiency—they may infer provider competence and institutional reliability, thereby strengthening trust [34], [51]. For micro-entrepreneurs, whose business viability often depends on liquidity and speed, perceived usefulness may therefore indirectly enhance trust by signaling platform capability and effective management. This mechanism positions trust as

both an outcome of prior beliefs and a critical antecedent of behavioral intention in FinTech adoption models.

2.5. Perceived Security as a Risk-Reducing Belief

Perceived security refers to the extent to which users believe that a technology and its underlying infrastructure adequately protect personal and financial information and ensure transaction safety [53], [54]. In FinTech applications, perceived security encompasses confidence in data privacy, secure authentication mechanisms, confidentiality, and safeguards against fraud, cyberattacks, and unauthorized access. Given the data-intensive nature of digital lending platforms, security perceptions are especially salient for users required to disclose sensitive identity, financial, and business information.

Extant research consistently identifies perceived security as a significant predictor of adoption intention across mobile wallets, online banking, and FinTech services [46]. Beyond its direct effect, perceived security also shapes trust. Robust security mechanisms signal provider competence, regulatory compliance, and ethical responsibility, thereby strengthening users' trust in the platform [22], [55]. Accordingly, perceived security functions both as a direct risk-mitigating belief influencing intention and as an antecedent to trust, supporting its inclusion as a core construct in integrated FinTech adoption models.

2.6. Hypothesis Development

This study integrates the Technology Acceptance Model (TAM) with trust and security perspectives to explain micro-entrepreneurs' intention to use P2P lending FinTech applications. The model positions perceived usefulness as a key exogenous construct that influences intention to use both directly and indirectly through trust and perceived security.

2.6.1. Perceived Usefulness

Perceived usefulness represents micro-entrepreneurs' beliefs that P2P lending FinTech applications enhance business operations by facilitating faster access to capital, simplifying lending procedures, and improving financial efficiency. In line with TAM, perceived usefulness is theorized as a fundamental determinant of behavioral intention and as a precursor to more affective and risk-related evaluations in digital financial contexts. As depicted in the model, perceived usefulness is expected to exert a direct effect on intention to use FinTech applications [56]–[58]. This relationship reflects the premise that users are more likely to adopt FinTech services when they perceive tangible performance benefits [47], [48], [50].

Beyond its direct effect, perceived usefulness is hypothesized to shape trust and perceived security. When FinTech platforms are perceived as efficient and beneficial, users may infer that the provider is competent, reliable, and professionally managed, thereby strengthening trust [46], [59]. Similarly, a system that delivers high functional value is often assumed to be technically robust and well designed, which can enhance users' perceptions of security. Prior studies support the proposition that perceived usefulness positively affects perceived security in digital financial services [59], [60].

H1. Perceived usefulness positively influences trust in FinTech applications.
H2. Perceived usefulness positively influences perceived security of FinTech applications.
H3. Perceived usefulness positively influences intention to use FinTech applications.

2.6.2. Trust and Perceived Security as Mediators

In the structural model, trust and perceived security function as central mediating mechanisms that transmit the effect of perceived usefulness to intention to use. Trust reflects users' confidence in the FinTech provider's reliability, integrity, and benevolence. In environments characterized by financial risk and information asymmetry, trust plays a critical role in reducing uncertainty and encouraging adoption. Consistent with prior FinTech research, trust is expected to positively influence intention to use FinTech applications [61], [62].

Perceived security refers to users' beliefs that the FinTech platform adequately protects personal information and financial transactions. As shown in the model, perceived security is expected to affect intention to use directly, reflecting the salience of security considerations in lending-related FinTech decisions [58]. Moreover, perceived security is theorized to enhance trust. When users believe a platform effectively safeguards data and transactions, their confidence in the provider increases, reinforcing trust. This relationship is well supported in the FinTech and online financial services literature [46], [55].

H4. Trust positively influences intention to use FinTech applications.
H5. Perceived security positively influences intention to use FinTech applications.
H6. Perceived security positively influences trust in FinTech applications.

2.6.3. Mediating Effects in the Structural Model

Consistent with the model structure, perceived usefulness is expected to influence intention to use not only directly but also indirectly through trust and perceived security. These mediating pathways reflect the logic that usefulness-based evaluations precede trust formation and security perceptions, which, in turn, drive adoption intention. Specifically, perceived usefulness enhances trust, which, in turn, increases the intention to use FinTech applications. This indirect pathway

underscores trust as a psychological mechanism translating functional benefits into behavioral intention.

Similarly, perceived usefulness is expected to enhance perceived security, thereby strengthening the intention to use. This mediation pathway highlights that usefulness perceptions may contribute to adoption by reinforcing security-related beliefs in FinTech platforms.

H7. Trust mediates the relationship between perceived usefulness and intention to use FinTech applications.
H8. Perceived security mediates the relationship between perceived usefulness and intention to use FinTech applications.

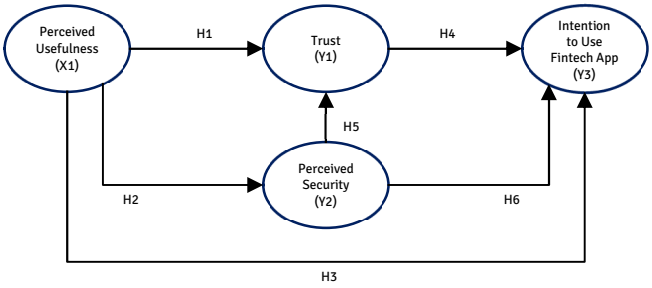

Figure 1. Conceptual framework of P2P lending adoption intention (extended TAM with perceived security and trust).

3. MATERIALS AND METHODS

3.1. Research Design and Conceptual Model

This study employed an explanatory quantitative design, using a cross-sectional survey, to examine the determinants of micro-entrepreneurs' intention to use peer-to-peer (P2P) lending. The conceptual model integrates core Technology Acceptance Model (TAM) logic—perceived usefulness (PU) as a key belief predicting behavioral intention—with trust and perceived security as salient beliefs in digital financial services. TAM's perceived usefulness construct is grounded in Davis's (1989) [18] work. Trust and perceived risk/security variables are widely recognized as critical in online transaction contexts (e.g., e-commerce and e-services), motivating their inclusion in P2P lending adoption research.

3.2. Population, Sampling & Data Collection

Data were collected in Malang City, East Java, Indonesia. The sampling frame was obtained from the Malang City Office of Cooperatives, Industry and Trade, which maintains an official registry of 78,725 micro-entrepreneurs operating in the service, trade, and industry sectors across eight subdistricts. To ensure geographical representativeness, the study used a multistage sampling design, purposively selecting the eight subdistricts to reflect variation in micro-enterprise density (high/medium/low) and in coverage of central versus peripheral areas, while maintaining field accessibility and safety. Within each subdistrict, proportional simple random sampling was performed using randomly generated IDs, ensuring that the selection probability was proportional to the subdistrict's population size.

Trained enumerators administered offline, paper-based questionnaires in Bahasa Indonesia. Of 1,200 eligible owners approached, 864 completed the survey (response rate = 72.0%). Consistent with the study objective of examining intention formation, the final analytic sample was restricted to pre-adopters (micro-entrepreneurs who had not yet adopted fintech P2P lending platforms). After data screening, questionnaires with >10% missing responses were excluded, leaving 204 valid responses for analysis. Offline administration was chosen to reduce selection bias commonly associated with online surveys and to better include micro-entrepreneurs with limited digital access or low exposure to fintech ecosystems, thereby strengthening representativeness and external validity.

3.3. Measures and Instrument Development

All constructs were measured using multi-item reflective scales on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The measurement instrument was adapted from well-established, validated studies to ensure content validity and support hypothesis testing in the context of FinTech adoption.

The study assessed four latent constructs: perceived usefulness, trust, perceived security, and intention to use FinTech applications. Items measuring perceived usefulness were adapted from Chawla and Joshi [46] and Najib and Fahma [47]. Trust was measured using scales adapted from Gefen [51, 63] and Najib and Fahma [47], whereas perceived security items were adapted from Kumar et al. [53]. Measures of intention to use FinTech applications were drawn from prior FinTech and technology-acceptance literature. All items were slightly modified to fit the context of peer-to-peer (P2P) lending among micro-entrepreneurs while preserving their original conceptual meaning.

Table 1. Measurement Items (Survey Instrument)

Construct	Item	Measurement Statement	Sources
Perceived Usefulness (PU)	X1.1	Fintech applications have clear features for micro-entrepreneurs to make online loans.	Davis (1989) [18]; Venkatesh & Davis (2000) [64]

Construct	Item	Measurement Statement	Sources
	X1.2	Fintech applications make it easier for micro-entrepreneurs to get online loans.	Davis (1989) [18]; Chawla and Joshi (2019) [46]
	X1.3	Fintech applications provide micro-entrepreneurs with access to online loans.	Venkatesh et al. (2003) [43]; Najib and Fahma (2020) [47]
	X1.4	Fintech applications make it easier for micro-entrepreneurs to apply for online loans.	Davis (1989) [18]; Venkatesh & Bala (2008) [65]
Trust (TR)	Y1.1	Fintech application services for online loan transactions can be trusted.	McKnight et al. (2002) [21]; Gefen et al. (2003) [51]
	Y1.2	Online loans using fintech applications meet user expectations.	Pavlou (2003) [34]; Gefen (2003) [51], [63]
	Y1.3	Fintech applications can complete online loan transactions accurately in accordance with user requests.	McKnight et al. (2002) [21]; Najib and Fahma (2020) [47]
Perceived Security (PS)	Y2.1	Fintech applications provide users with a sense of security when applying for online loans.	Kim et al. (2008) [15]; Featherman & Pavlou (2003) [13]
	Y2.2	Online lending fintech applications protect user data.	Salisbury et al. (2001) [66]; Kumar et al. (2018) [53]
	Y2.3	Online loan fintech applications can maintain the confidentiality of transaction files.	Flavián & Guinalíu (2006) [67]; Kumar et al. (2018) [53]
	Y2.4	Fintech applications for online loans can provide technical support to resolve technical issues that arise.	Kim et al. (2010) [68]; Kumar et al. (2018) [53]
Intention to Use Fintech Application (ITU)	Y3.1	I have always been interested in using fintech applications for online loans.	Davis (1989) [18]; Venkatesh et al. (2003) [43]
	Y3.2	I plan to use a fintech application to make online loans.	Ajzen (1991) [16]; Venkatesh et al. (2003) [43]
	Y3.3	I am interested in using the online loan fintech application for the first time.	Bhattacherjee (2001) [69]

3.4. Data Analysis Approach

This study employed a quantitative explanatory approach to test the proposed hypotheses using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM was selected because it is well-suited for prediction-oriented and explanatory research, particularly in entrepreneurship and fintech studies that involve complex models, mediation effects, and small-to-moderate sample sizes [70], [71]. Compared to covariance-based SEM, PLS-SEM is more robust to non-normal data distributions, has fewer identification constraints, and allows the simultaneous estimation of reflective and formative constructs.

The hypothesized model was analyzed using SmartPLS 3.0, following established methodological guidelines. Model evaluation was conducted using a two-stage procedure comprising measurement and structural model assessment to ensure the reliability, validity, and explanatory power of the proposed model.

3.5. Model Evaluation and Hypothesis Testing

3.5.1. Measurement Model Evaluation

The reflective measurement model was assessed for reliability and validity. Indicator reliability was evaluated using outer loadings (≥ 0.70). Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR), with thresholds of ≥ 0.70. Convergent validity was assessed using the Average Variance Extracted (AVE), with values ≥ 0.50 indicating adequate validity. Discriminant validity was evaluated using the Heterotrait–Monotrait (HTMT) ratio, which is considered a more sensitive criterion than traditional Fornell–Larcker and cross-loading approaches in variance-based SEM.

3.5.2. Structural Model Evaluation

The structural model was evaluated by examining path coefficients and their statistical significance via bootstrapping. The model's explanatory power was assessed through the coefficient of determination (R^2) for endogenous constructs. At the same time, predictive relevance (Q^2) was evaluated using the Stone–Geisser criterion, where values greater than zero indicate predictive relevance.

3.5.3. Mediation Analysis

Mediation effects were tested by examining the bootstrapped significance of specific indirect effects, such as perceived usefulness → trust → intention to use and perceived security → trust → intention to use. This procedure follows recommended practices for mediation

analysis in PLS-SEM and enables a robust assessment of indirect relationships within the proposed model.

4. RESULTS

4.1. Respondent Profile

The sample was dominated by women (64.71%), reflecting women's strong participation in microenterprise ownership. Respondents were largely active in the trade sector (75.49%), followed by services (15.20%) and industry (9.31%). The most frequent age group was 36–41 years (19.61%). Most respondents held a high school education (70.10%).

Table 2. Demographic Characteristics (n = 204)

Demographic	Category	Frequency	Percent (%)
Gender	Male	72	35.29
	Female	132	64.71
Age	18–23	19	9.31
	24–29	20	9.80
	30–35	33	16.18
	36–41	40	19.61
	42–47	31	15.20
	48–53	30	14.71
	54–59	18	8.82
	60–65	8	3.92
	66–71	5	2.45
Education	High School	143	70.10
	Vocational	37	18.14
	Bachelor's	22	10.78
	Master's	2	0.98

Descriptively, respondents showed agreement toward perceived usefulness (mean 3.94) and intention to use (mean 3.70), while perceived security had a relatively lower mean (3.48), suggesting that security concerns may remain a notable friction even when usefulness is acknowledged.

4.2. Measurement Model Assessment

Before testing the structural model, the quality of the measurement (outer) model was evaluated in accordance with established PLS-SEM guidelines [72], [73]. The assessment was conducted sequentially and covered: (1) indicator reliability and internal consistency reliability, (2) convergent validity, and (3) discriminant validity. All estimates were generated using SmartPLS [74], [75].

4.2.1. Indicator Reliability and Internal Consistency

Indicator reliability was assessed using outer loadings, where values ≥ 0.70 indicate that an indicator explains at least 50% of the variance in its corresponding construct [76]. All retained indicators met the recommended threshold (≥ 0.70), demonstrating adequate indicator reliability. Internal consistency was evaluated using Cronbach's alpha and composite reliability (CR). Values ≥ 0.70 indicate acceptable reliability, whereas values ≥ 0.95 may suggest item redundancy [77]. Table 3 show Cronbach's alpha (CA) (0.747–0.861) and CR (0.853–0.906) exceeded the minimum criteria, indicating satisfactory internal consistency across all constructs [78], [79].

Table 3. Reliability and Convergent Validity

Construct	AVE	CR	CA
Intention to use fintech application	0.660	0.853	0.747
Perceived security	0.707	0.906	0.861
Perceived usefulness	0.605	0.859	0.781
Trust	0.670	0.859	0.754

Table 3 indicates that all constructs exhibit strong measurement quality. Specifically, composite reliability values (0.853–0.906) exceed the recommended threshold, demonstrating high internal consistency. Cronbach's alpha values (0.747–0.861) likewise meet accepted standards, suggesting reliable measurement without evidence of excessive item redundancy. Regarding convergent validity, all average variance extracted (AVE) values (0.605–0.860) surpass the 0.50 criterion, indicating that each construct explains more than half of the variance in its indicators.

4.2.2. Discriminant Validity

Discriminant validity indicates that each construct is empirically distinct from the others. In this study, discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio, which is widely recommended for PLS-SEM because of its sensitivity [75], [80]. Common cut-off values are HTMT < 0.90 (more liberal) or HTMT < 0.85 (more conservative), depending on the conceptual similarity among constructs [76], [81].

Table 4. Heterotrait–Monotrait (HTMT) Ratio

Construct	ITU	PS	PU	TR
Intention to use fintech application	—			
Perceived security	0.717	—		
Perceived usefulness	0.647	0.683	—	
Trust	0.722	0.821	0.714	—

Table 4 reports the HTMT values among Intention to Use (ITU), Perceived Security (PS), Perceived Usefulness (PU), and Trust (TR). All HTMT values range from 0.647 to 0.821, satisfying both the conservative threshold (< 0.85) and the liberal threshold (< 0.90). These results provide strong evidence that each construct is empirically distinct and that the indicators exhibit stronger associations with their intended construct than with other constructs. Therefore, discriminant validity is established.

4.3. Structural Model Assessment

Following the evaluation of the measurement model, the structural (inner) model was assessed in accordance with established PLS-SEM recommendations. This evaluation focuses on the model's explanatory power and predictive relevance, which are typically examined using R^2 and Q^2 values [82].

4.3.1. Explanatory Power (Coefficient of Determination)

The coefficient of determination (R^2) represents the proportion of variance in each endogenous construct explained by its predictors, thereby indicating the model's explanatory power. Although R^2 values should be interpreted in context, commonly used benchmarks classify values of 0.75 as substantial, 0.50 as moderate, and 0.25 as weak [71], [83]. As shown in Table 5, the model explains 42.4% of the variance in Intention to Use (R^2 = 0.424), 31.6% in Perceived Security (R^2 = 0.316), and 48.5% in Trust (R^2 = 0.485).

Table 5. Coefficient of Determination (R^2) Estimates

Construct	R-square (R^2)
Intention to use fintech application	0.424
Perceived security	0.316
Trust	0.485

Overall, the R^2 values indicate moderate explanatory power for Intention to Use (0.424) and Trust (0.485), suggesting that the model accounts for a meaningful proportion of variance in these constructs. Perceived Security shows a weak-to-moderate level of explained variance (0.316). Taken together, these results imply that the proposed predictors provide a reasonable explanation of users' intention and trust in the fintech context, although additional antecedents may be necessary to further strengthen the explanation of perceived security [84].

4.3.2. Predictive Relevance (Stone–Geisser's Q^2)

Beyond in-sample explanatory power, PLS-SEM also emphasizes predictive capability. Stone–Geisser's Q^2 assesses predictive relevance using a blindfolding procedure (cross-validated redundancy). A Q^2 value greater than zero indicates that the model has predictive relevance for a given endogenous construct [79], [85], [86]. As additional guidance, Q^2 values of approximately 0.02 (small), 0.15 (medium), and 0.35 (large) are often used to describe the magnitude of predictive relevance [81], [84]. As reported in Table 6, the Q^2 values are 0.263 for Intention to Use, 0.218 for Perceived Security, and 0.316 for Trust.

Table 6. Stone–Geisser's (Q^2) Estimates

Construct	Stone–Geisser's (Q^2)
Intention to use fintech application	0.263
Perceived security	0.218
Trust	0.316

All Q^2 values exceed zero, confirming that the model demonstrates predictive relevance for each endogenous construct. In terms of magnitude, the Q^2 estimates fall within the medium range, with Trust (0.316) showing the strongest predictive relevance, followed by Intention to Use (0.263) and Perceived Security (0.218). These findings indicate that the structural model not only explains variance (R^2) but also provides meaningful predictive capability for the outcomes examined in this study [79], [85], [86].

4.4. Hypothesis Testing and Mediation Results

Hypothesis testing was performed by examining the t-statistics obtained from the PLS output using a bootstrapping procedure. The significance level was set at $\alpha = 0.05$; therefore, relationships were considered statistically significant when $p < 0.05$ (equivalently, $t > 1.96$ for a two-tailed test). In addition to direct effects, the study also evaluated indirect (mediating) effects to clarify the mechanisms through which the constructs influence one another.

The path coefficient results indicate that all hypothesized direct relationships are positive and statistically significant ($p < 0.05$), as summarized in Table 7. Beyond the direct effects, the study also examined the indirect influence of perceived usefulness on intention to use through two mediators—perceived security and trust. Bootstrapping results indicate that both mediating pathways are statistically significant.

Table 7. Path coefficients and hypothesis results

Path	β	t-value	p-value	Results
Perceived usefulness → Trust	0.259	4.372	0.000	Supported (H1)
Perceived usefulness → Perceived security	0.562	10.712	0.000	Supported (H2)

Path	β	t-value	p-value	Results
Perceived usefulness → Intention to use	0.208	2.789	0.005	Supported (H3)
Trust → Intention to use	0.213	3.098	0.002	Supported (H4)
Perceived security → Intention to use	0.337	5.122	0.000	Supported (H5)
Perceived security → Trust	0.517	9.114	0.000	Supported (H6)
Perceived usefulness → Trust → Intention to use	0.055	2.596	0.010	Supported (H7)
Perceived usefulness → Perceived security → Intention to use	0.189	4.669	0.000	Supported (H8)

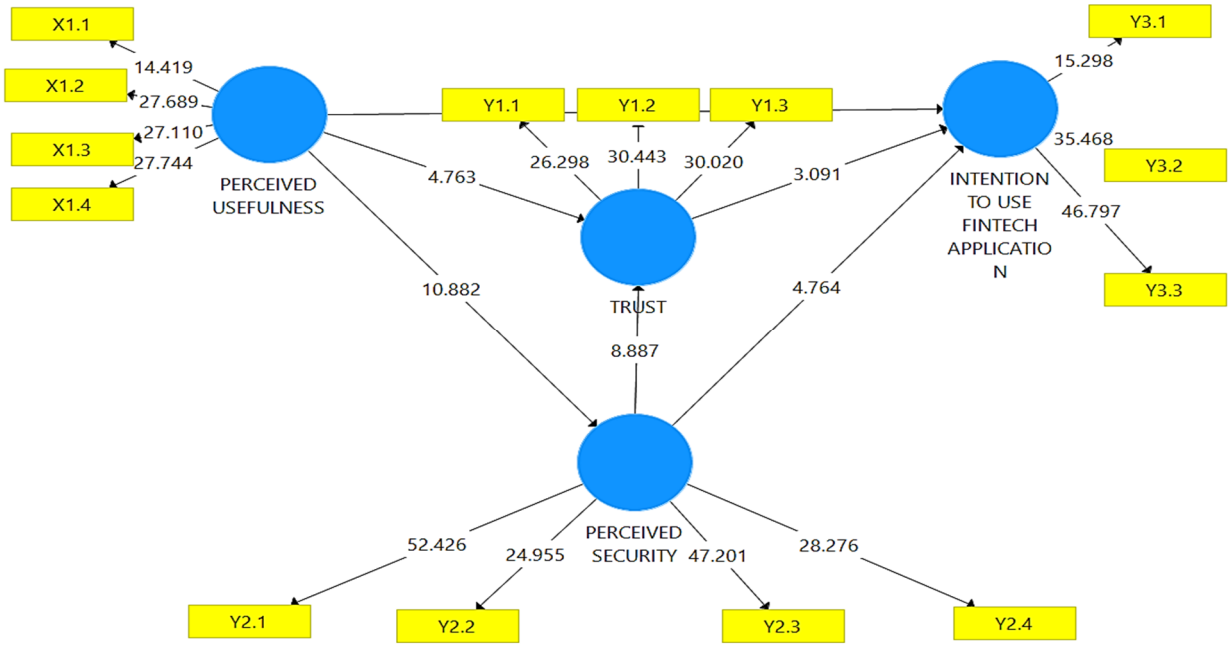

Figure 2. Structural model results (output Smart-PLS)

As shown in Figure 2, all indicators for each construct exhibit t-statistics well above the 1.96 threshold. This finding indicates that each indicator contributes significantly to measuring its respective latent construct, thereby supporting the adequacy of the measurement (outer) model for Perceived Usefulness, Trust, Perceived Security, and Intention to Use.

The outer (measurement) model shows that all indicators load significantly on their respective constructs, confirming adequate measurement quality. The inner (structural) model further indicates that all direct effects are positive and significant: perceived usefulness increases trust (β = 0.259, p < 0.001) and perceived security (β = 0.562, p < 0.001), and perceived security, in turn, strengthens trust (β = 0.517, p < 0.001). Intention to use is significantly predicted by perceived security (β = 0.337, p < 0.001), trust (β = 0.213, p = 0.002), and perceived usefulness (β = 0.208, p = 0.005). These findings suggest that adoption intention increases when users perceive the application as useful, secure, and trustworthy. Mediation analyses further confirm two significant indirect effects of perceived usefulness on intention to use: through perceived security (β = 0.189, p < 0.001) and through trust (β = 0.055, p = 0.010). Because the direct path from perceived usefulness to intention to use remains significant, the results support partial mediation, with perceived security and trust jointly explaining how perceived usefulness translates into intention.

5. DISCUSSION

The findings indicate that Perceived Security (PS) is the strongest determinant of Intention to Use (ITU). The positive and significant path coefficient (β = 0.337; t = 5.122; p < 0.001) supports H5, confirming that users are more inclined to adopt the application when they perceive it as secure—an especially critical consideration in digital contexts involving sensitive personal and financial information.

In addition, PS has a strong and significant effect on Trust (TR) (β = 0.517; t = 9.114; p < 0.001), supporting H6. This suggests that stronger security perceptions substantially enhance trust by reducing uncertainty and perceived risk, reinforcing the view that security constitutes a key foundation for trust in technology-based services.

The results also underscore the multifaceted role of Perceived Usefulness (PU). First, PU exerts a direct positive effect on ITU (β = 0.208; t = 2.789; p = 0.005),

supporting H3 and confirming that functional value remains an important driver of adoption. However, this effect is weaker than that of PS, implying that usefulness alone may be insufficient to maximize intention in the absence of strong security assurances.

Second, PU significantly increases both PS ($\beta = 0.562$; $t = 10.712$; $p < 0.001$) and TR ($\beta = 0.259$; $t = 4.372$; $p < 0.001$), supporting H2 and H1, respectively. This indicates that when users perceive the application as beneficial, they also tend to evaluate it as more secure and more trustworthy, thereby strengthening overall confidence in the system.

Furthermore, TR significantly predicts ITU ($\beta = 0.213$; $t = 3.098$; $p = 0.002$), supporting H4. This finding suggests that, beyond security and usefulness, adoption intention increases when users believe the application is reliable.

The mediation analysis provides additional theoretical insight. PU exhibits two significant indirect effects on ITU: through PS (PU → PS → ITU: $\beta = 0.189$; $t = 4.669$; $p < 0.001$, supporting H8) and through TR (PU → TR → ITU: $\beta = 0.055$; $t = 2.596$; $p = 0.010$, supporting H7). Because the direct PU → ITU path remains significant (H3), these results indicate partial mediation: usefulness influences intention both directly and indirectly, primarily by enhancing perceived security, and to a lesser extent by strengthening trust.

The finding that PU influences ITU aligns with the core proposition of the Technology Acceptance Model (TAM). When users perceive a technology as useful (i.e., improving performance and effectiveness), they are more likely to intend to adopt it [18]. This result is also consistent with broader technology-acceptance research, which shows that PU remains a stable predictor of intention. However, its relative strength can vary by context and service characteristics (e.g., extensions of TAM/TAM2 across digital domains) [64].

However, this study reveals a context-specific pattern: in P2P lending, PS emerges as a more dominant predictor than PU. This "security-dominance" pattern is not anomalous; it is consistent with a well-established stream of e-commerce research demonstrating that when adoption decisions involve uncertainty and potential loss, particularly involving money and personal data security, beliefs can outweigh purely utilitarian considerations. A classic study found that perceived web security exerts a stronger influence on purchase intention than ease of use and usefulness [66]. Similarly, e-commerce research emphasizes that security and privacy are foundational attributes shaping perceived trustworthiness in online transactions [87], [88]. Collectively, these findings position P2P lending as a risk-salient digital service: users evaluate not only "how beneficial it is," but also "how safe the consequences are."

Research integrating trust with TAM in online shopping likewise shows that adoption intention is jointly shaped by technology evaluations (PU/PEOU) and trust in the vendor or transaction environment. That trust adds explanatory power beyond TAM alone [63], [89]. In addition, e-commerce acceptance models incorporating trust and perceived risk identify these constructs as central mechanisms linking user beliefs to transaction intentions [34]. At the psychological level, trust-based consumer decision-making models further suggest that trust and perceived risk directly shape online purchasing decisions, while security and privacy function as antecedents that build trust and reduce risk perceptions [15]. Within this lens, the significant PS → TR and PS → ITU pathways are theoretically well grounded: security operates both as a risk-reducer (lowering uncertainty) and as a trust cue (signaling competence and integrity), thereby increasing intention to use.

In the specific domain of FinTech and P2P lending, more recent evidence supports the view that adoption is often driven by a benefit–risk trade-off (net valence), in which users weigh value creation against financial, legal, and privacy risks. For example, benefit–risk framework studies of FinTech adoption show that perceived risks (e.g., legal risk) can be highly constraining even when perceived benefits are substantial [90]. Empirical work on P2P lending in Indonesia similarly indicates that adoption is shaped by a combination of TAM/IDT-related variables, service factors, trust, and perceived risk [91], [92]. More specifically, Indonesian studies extending TAM by incorporating data security and privacy suggest that stronger security/privacy perceptions correspond with more favorable evaluations and higher acceptance [93], [94]. Thus, the present findings are not merely consistent with prior work; they sharpen the positioning of P2P lending as a FinTech domain in which trust and security form the central axis of adoption.

By contrast, in non-credit FinTech services (e.g., payments and mobile payment systems), many studies reports that utilitarian factors such as performance expectancy/perceived usefulness, along with convenience and ease of use, are strong determinants of intention. At the same time, trust and risk play important complementary roles. For example, mobile payment research highlights the importance of usefulness-related beliefs in predicting adoption and intention to recommend [95], [96]. Studies of remote mobile payments likewise show that adoption models are strengthened by innovativeness, trust, and risk; however, the decision context differs because the perceived downside consequences are often less severe than those associated with committing to debt [97]–[99]. This cross-context contrast reinforces the argument that service type (credit vs. non-credit) can shift the "center of gravity" of intention predictors from usefulness dominance (payments) toward security/trust dominance (lending).

This interpretation is also consistent with the policy and consumer-protection literature, which emphasizes that digital credit risks extend beyond pricing to include data protection, transparency, and collection practices. Industry and development-policy standards for digital

credit stress fair treatment, data privacy, and safeguards against harmful collection practices [9], [100], while guidance on responsible digital credit highlights major consumer risks that should be mitigated through service design and governance [101], [102]. Consequently, the stronger role of PS relative to PU in this study can be framed as a rational consumer response. When worst-case outcomes are financially and socially consequential, users prioritize transaction and data safety before the service's functional benefits fully translate into adoption intention.

Theoretically, these findings are best explained by integrating TAM's utilitarian logic with uncertainty-reduction mechanisms typical of digital credit services. In TAM, PU increases intention because users believe the technology enhances efficiency and performance [18]. In the present model, PU not only affects ITU directly but also strengthens risk-salient evaluations PS and TR such that perceived benefits may initiate intention while simultaneously shaping judgments about platform safety and provider credibility. The significant PU → PS, PU → TR, and PU → ITU paths indicate that perceived benefits may "open the door," but intention formation in digital credit remains filtered through security and trust considerations.

In P2P lending, adoption decisions are inherently high-stakes, prompting users to engage in risk calculus in which perceived benefits are weighed against potential losses (e.g., data leakage, misuse of personal information, fraud, and financial consequences). Prior research shows that when transactions involve sensitive data and monetary stakes, perceived security can outweigh usefulness or ease of use in shaping intention [66], and that security/privacy are central to perceived trustworthiness in digital services [87]. This aligns with the observed pattern—relatively high usefulness and intention alongside comparatively lower security perceptions—suggesting persistent security frictions that inhibit the conversion of perceived benefits into intention. The mediation results further clarify the mechanism: significant indirect effects via PS and TR indicate that security and trust are key channels through which benefit evaluations translate into intention, with trust functioning as psychological assurance that enables users to tolerate uncertainty [34], [63].

This study contributes to FinTech adoption research by clarifying how intentions are formed in high-stakes digital credit services such as P2P lending. Theoretically, it extends TAM by demonstrating that PS should be treated as a core construct that directly predicts intention and shapes relational evaluations, such as trust. This accords with evidence that, in transactions involving sensitive data and money, security can outweigh purely utilitarian beliefs in explaining intention, and that security/privacy serve as foundational cues of digital trustworthiness. The study further specifies an asymmetric mediation mechanism, showing that PU translates into intention primarily through PS and, secondarily, through TR, thereby reinforcing integrated trust–TAM accounts in which online intentions reflect both technology evaluations and trust in the provider.

Practically, the findings imply that P2P platforms should prioritize security-by-design (e.g., data protection, encryption, access control, and fraud mitigation) and translate these safeguards into visible trust cues (e.g., clear data policies, transparent fee disclosures, responsive grievance handling with defined service levels, and credible audits or certifications). For regulators, effective enforcement and clear public communication are critical to translating regulation into institution-based trust, particularly under Indonesia's strengthened framework set out in POJK No. 40/2024 (effective 27 December 2024). Finally, because the study targets pre-adopter micro-entrepreneurs, literacy programs should emphasize risk and security competence (e.g., legitimacy checks, data-permission awareness, cost comprehension, and complaint channels) to support adoption that is not only higher, but also safer and more sustainable.

6. CONCLUSION AND IMPLICATIONS

This study concludes that the interplay between instrumental benefits and perceived protection mechanisms shapes vulnerable micro-entrepreneurs' intention to adopt FinTech peer-to-peer (P2P) lending. The results indicate that perceived usefulness affects intention both directly and indirectly via perceived security and trust. Perceived security emerges as the strongest determinant: it increases intention to use and also strengthens trust, suggesting that in high-risk digital credit contexts, security perceptions are a prerequisite for trust formation and, ultimately, technology acceptance. Overall, the extended Technology Acceptance Model (TAM) applied in this study offers a more context-sensitive explanation by positioning security and trust as central mediating constructs.

From a practical and policy standpoint, the findings suggest that expanding financial inclusion through P2P lending requires more than technological efficiency or functional innovation. FinTech platforms should prioritize security-by-design features, transparent data governance, and clear consumer-protection mechanisms to reduce perceived vulnerability among micro-entrepreneurs. Regulators, in turn, should ensure consistent enforcement of digital financial regulations and implement visible institutional safeguards to strengthen trust and protect financially vulnerable users. Enhancing perceived security and trust alongside perceived usefulness may enable platforms to support sustainable financial inclusion, strengthen micro-entrepreneurial resilience, and advance broader development objectives aligned with the Sustainable Development Goals.

Several limitations warrant acknowledgement. First, the study focuses on Malang City, which may limit the generalizability of the findings to other settings. Second,

the cross-sectional, self-report design precludes causal inference and may be susceptible to response bias. Third, because the sample comprises pre-adopters, the results may not fully reflect post-adoption dynamics, including continued use and repayment behavior. Future research should therefore employ longitudinal designs to link intention with actual adoption and repayment outcomes; expand sampling to multiple cities or regions; incorporate additional predictors such as perceived ease of use (PEOU), financial literacy, and regulatory trust; and use experimental vignette methods to test how disclosure practices and security cues causally shape perceived security, trust, and adoption decisions.

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CONFLICTS OF INTEREST

The authors declare that no conflicts of interest are associated with this study. All aspects of the research were conducted with the utmost integrity and transparency.

DATA AVAILABILITY

The datasets utilized and analyzed during this research are available from the corresponding author upon reasonable request.

ETHICAL STATEMENTS

The authors confirm that the study complied with all applicable local laws, ethical standards, and institutional guidelines, including obtaining approval from relevant ethics committees.

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