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Technology Adoption of Peer-to-Peer Lending in India: A Structural Equation Modeling Approach with Trust as a Mediating

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ABSTRACT

This study investigates the adoption of peer-to-peer (P2P) lending platforms in India through the lens of the Technology Acceptance Model (TAM) with trust as a mediating factor. Using data collected from 500 respondents across major Indian metropolitan areas, we employ Structural Equation Modeling (SEM) to examine the complex relationships between perceived usefulness, perceived ease of use, trust, and behavioural intention to adopt P2P lending. Our findings reveal that trust significantly mediates the relationship between TAM constructs and adoption intention (β=0.412, $p<0.001$), with institutional trust demonstrating stronger mediating effects than interpersonal trust. Perceived usefulness exhibits a stronger direct effect on adoption intention (β=0.482, $p<0.001$) compared to perceived ease of use (β=0.317, $p<0.001$). The study also discovers there are considerable demographic differences in establishing trust, with city dwellers and youthful respondents being more prone to have greater initial trust in P2P websites. The model accounts for 68.7% of explained variance in P2P lending adoption intentions and provides robust evidence supporting our extended TAM model. Our results provide a conceptual contribution towards the explanation of technology adoption in emerging financial markets and implications for P2P platform developers and Indian regulators. This study fills the essential knowledge gap regarding technology adoption processes of alternative financial services in emerging economies with changing regulatory landscapes...

Keywords: Peer-to-peer lending, Technology Acceptance Model, trust, structural equation modeling, financial technology adoption, India

INTRODUCTION

The fintech revolution has reorganized the world's financial system at its core, and among the most revolutionary fintech technologies is peer-to-peer (P2P) lending. P2P lending platforms are online intermediaries that bring borrowers and individual lenders together, thus avoiding the intervention of traditional banks in the lending process (Ziegler et al., 2022). This disintermediation has the potential to bring benefits such as cost savings on transactional expenses, enhanced financial inclusion, and enhanced efficiency in lending processing (Demirgüç-Kunt et al., 2018). For fast-emerging economies of a country like India, P2P lending is especially an attractive solution to chronic credit availability issues, particularly for the weaker sections of society (Patwardhan, 2018). The Indian economic landscape has seen enormous disruption over the last decade with higher internet penetration, widespread mobile phone adoption and visionary policymaking like Digital India and the Unified Payment Interface (UPI) system (Kodan et al., 2023). Amidst all this, there are still millions of Indians who remain unbanked or underbanked and small businesses still struggle to get formal credit in the traditional manner (Sidhpuria & Singh, 2023).The Reserve Bank of India (RBI) noticed the potential for P2P lending to fill these gaps when it formally introduced P2P platforms Non-Banking Financial Companies (NBFCP2P) in 2017 and outlined a regulatory framework for their functioning (Reserve Bank of India, 2017). This regulation legitimized the sector and issued guidelines for sound growth.

Although India's regulatory and infrastructure environment has become increasingly supportive of facilitating P2P lending, consumer adoption across demographic groups and geographies has been unequal (Khan et al., 2025). Understanding determinants of adoption of P2P lending platforms is crucial not only for platform designers who aim to grow user bases but also for policymakers attempting to enhance financial inclusion via the vehicle of alternative channels of credit. Prior work has confirmed that Technology Acceptance Model (TAM) was an effective theoretical model to look into technology acceptance across various environments

(Davis, 1989; Venkatesh & Davis, 2000), yet its adoption when looking at fintech uptake across emerging markets must consider the intervening factors which would influence consumer preference.

Among those, trust becomes especially relevant with regard to internet lending transactions where consumers are both unfamiliar with the technology platform as well as with the lending transaction counterparty (Kim et al., 2009; Pavlou, 2003). In the Indian cultural context in which interpersonal relationship has historically mattered in economic transaction, switching over to technology-led, impersonal transactions involves quite a psychological obstacle to adoption (Dutta & Borah, 2022). Knowledge of the dynamics between trust and the core concepts of the Technology Acceptance Model can prove to be an insightful source of knowledge regarding P2P lending adoption.

This study addresses this knowledge gap by examining P2P lending adoption in India through an extended Technology Acceptance Model that incorporates trust as a mediating factor. Using Structural Equation Modeling (SEM), we analyze data from 500 respondents across major Indian metropolitan areas to understand the complex interrelationships between perceived usefulness, perceived ease of use, trust (both institutional and interpersonal), and behavioral intention to adopt P2P lending services. Our research makes several important contributions:

1. We extend the Technology Acceptance Model by incorporating trust as a mediating factor, providing a more comprehensive framework for understanding technology adoption in financial services.

2. We distinguish between institutional trust (in the P2P platform) and interpersonal trust (in other users), examining their differential impact on adoption intentions.

3. We provide empirical evidence from the Indian market, contributing to the growing literature on fintech adoption in emerging economies.

4. We identify demographic variations in trust formation and adoption intentions, offering insights for targeted marketing and development strategies.

5. We discuss implications for platform developers, regulators, and financial inclusion advocates based on our findings.

2. LITERATURE REVIEW

2.1 Peer-to-Peer Lending: Emergence and Growth

Peer-to-peer (P2P) lending represents a new paradigm for the mode of financial intermediation by the use of internet-based platforms for the matching of direct borrowers and lenders individually without the intermediating bank (Wang et al., 2019). Modern P2P lending began when Zopa set up shop in the United Kingdom in 2005 and then later Prosper and Lending Club emulated the same in the United States (Morse, 2015). Since then the model has been implemented worldwide with local-level tailoring to address regulatory requirements and cultural contexts. In India, P2P lending has grown exponentially since 2016 with the size of the market being USD 13.17 Billion in 2024 and anticipated to grow to USD 34.61 Billion by 2030 with a compound annual growth rate (CAGR) of 17.53% (TechSci Research, 2024).

This rapid growth has been driven by a variety of drivers like increasing internet penetration, smartphone expansion, digital adoption due to government policies, and a massive credit shortage in the traditional banking system (Agarwal & Zhang, 2020). The appeal of P2P lending is that it can make borrowers access credit at potentially lower interest rates and with lower requirements than commercial banks, while lenders can offer borrowers diversification benefits for their portfolios and potentially higher returns than traditional deposit products (Chen et al., 2019; Freedman & Jin, 2017).

In addition, the P2P platform business model uses technology to undertake a great deal of the loan origination, credit analysis, and servicing, and in doing so, can achieve efficiencies that can be shared with everyone (Jagtiani & Lemieux, 2018).

Although it has its potential advantages, P2P lending also possesses specific problems and risks. These include information asymmetry for lenders and borrowers, the risk of fraud or platform collapse, regulatory risk, and issues with long-term sustainability, particularly during economic crisis (Yum et al., 2012; Emekter et al., 2015). Within India itself, these are supplemented by digital literacy differentials, regional culture and language heterogeneities, and unbalanced access to technology infrastructure between rural and urban fronts (Bhattacharya & Chopra, 2019).

2.2 P2P Lending Regulatory Framework in India

The Indian regulatory structure for P2P lending was finally formulated in October 2017 when the Reserve Bank of India (RBI) notified the "Non-Banking Financial Company - Peer to Peer Lending Platform (Reserve Bank) Directions" (RBI, 2017). The directions established P2P lending platforms as a new category of Non-Banking Financial Companies (NBFCs) and notified their registration, operation, and prudential regulation (Kapoor et al., 2022).

A few of the major aspects of this regulatory framework are: minimum capital requirements of ₹20 million for P2P platforms; prohibition of offering any credit guarantee by platforms; capping of lending by individuals (₹50 lakhs on all P2P platforms) and borrowing (₹10 lakhs on all P2P platforms); 36-month maximum tenure of the loan; and transparent disclosure requirements, grievance redressal framework, and data protection (PwC India, 2021). The RBI also reinforced these regulations in August 2024 by enforcing tighter conditions on fund transfers, information disclosure, and reporting obligations for handling infringement observed in the market (Reuters, 2024).

This evolving regulatory environment has impacted the adoption of P2P lending in India both positively and negatively. On the positive front, formal recognition and regulation by the RBI have enhanced the credibility of P2P lending as a financial product and enhanced the perception of certainty for platforms, lenders, and borrowers (Dey & Bhattacharya, 2022). In contrast, loan size caps and other regulatory conditions would otherwise have otherwise limited the scale and scalability of P2P lending models across less regulated economies (Shah & Subramanian, 2021).

We need to understand how these regulators of regulation influence user constructions of P2P platforms to be able to understand patterns of adoption. Researchers in other settings have demonstrated that openness about regulatory activities can increase perceptions of legitimacy and institutional trust, which in turn can influence adoption (Lee & Shin, 2018; Ryu, 2018). In the Indian context of P2P lending, there is still much work to be done on regulation, trust, and how adoption interacts with each other.

2.3 Technology Acceptance Model and Its Extensions

The Technology Acceptance Model (TAM), first proposed by Davis (1989), is currently the most widely used model of user adoption and acceptance of new technology. The initial TAM proposes that two main drivers—perceived usefulness (PU) and perceived ease of use (PEOU)—are the drivers of one's attitude to utilize a new technology that determines behavioral intention to use and system use (Davis et al., 1989).

Perceived usefulness is "the extent to which an individual feels that using a specific application system would enhance his or her performance in a task," and perceived ease of use is "the extent to which an individual feels that the use of a specific application system would be capable of releasing him or her from physical and mental effort" (Davis, 1989, p. 320). The model assumes that usefulness affects attitude toward use directly and affects attitude toward use indirectly through perceived usefulness since systems that are simpler to use are perceived to be more useful (Venkatesh & Davis, 2000).

Since TAM, scholars have expanded and formulated it in several different ways in order to extend its explanatory potential across a number of different settings. There are also some significant extensions including TAM2 (Venkatesh & Davis, 2000), which added social influence processes and cognitive instrumental processes; Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which had constructs of eight models including TAM; and TAM3 (Venkatesh & Bala, 2008), which added determinants of perceived ease of use.

In the web service and financial technologies context, authors have extended TAM with other technology-specific constructs specific to such a context. Among these are perceived risk (Pavlou, 2003; Lee, 2009), perceived security (Cheng et al., 2006), and social influence (Min et al., 2008). Of note in this context is the trust construct in this study's technological acceptance models specific to financial services, which follows in the following section.

2.4 Trust as a Mediator in Technology Adoption

Trust has been recognized as a critical factor in online transactions generally and in financial services particularly (McKnight et al., 2002; Gefen et al., 2003). In the context of technology adoption, trust can be defined as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995, p. 712).

Several studies have explored the role of trust in technology adoption, particularly for financial services. Gefen et al. (2003) integrated trust with TAM in the context of ecommerce, finding that both trust and TAM constructs influenced purchase intentions. Kim et al. (2009) found that trust had both direct effects on behavioral intention to use online banking and indirect effects through perceived usefulness. Similarly, Zhou (2012) demonstrated that initial trust significantly affected users' intention to adopt mobile banking.

In the specific context of P2P lending, trust assumes even greater importance due to the dual nature of uncertainty involved: users must trust both the technology platform (institutional trust) and the other users of the platform with whom they will enter into financial relationships (interpersonal trust) (Chen et al., 2014; Greiner & Wang, 2010). Li et al. (2016) found that trust in the P2P platform significantly influenced lending intentions, while Liu et al. (2019) demonstrated that both institutional and interpersonal trust affected users' continued participation in P2P lending.

Several studies have positioned trust as a mediator between system characteristics and behavioral intentions. For instance, Oluyinka et al. (2013) found that trust mediated the relationship between technology factors and intention to accept internet banking in Nigeria. More recently, studies have examined the mediating role of trust in various fintech contexts, including mobile payments (Khalilzadeh et al., 2017), robo-advisors (Bhatia et al., 2020), and blockchain-based financial services (Folkinshteyn & Lennon, 2016).

In the Indian context, studies on fintech adoption have highlighted the particular importance of trust given cultural factors and the relatively early stage of digital financial services development. Dutta and Borah (2022) found that trust played a significant role in mobile wallet adoption among Indian consumers, while Savitha et al. (2022) identified trust as a key factor in the continuance intention to use fintech payment apps. However, the specific role of trust as a mediator in P2P lending adoption in India remains underexplored, presenting a gap that this study aims to address.

Research Model and Hypotheses Development

Based on the literature reviewed above, we develop an extended TAM model that incorporates trust as a mediating factor between the core TAM constructs (perceived usefulness and perceived ease of use) and behavioral intention to adopt P2P lending. Our model also differentiates between two dimensions of trust: institutional trust (trust in the P2P platform) and interpersonal trust (trust in other users of the platform). Figure 1 presents our research model.

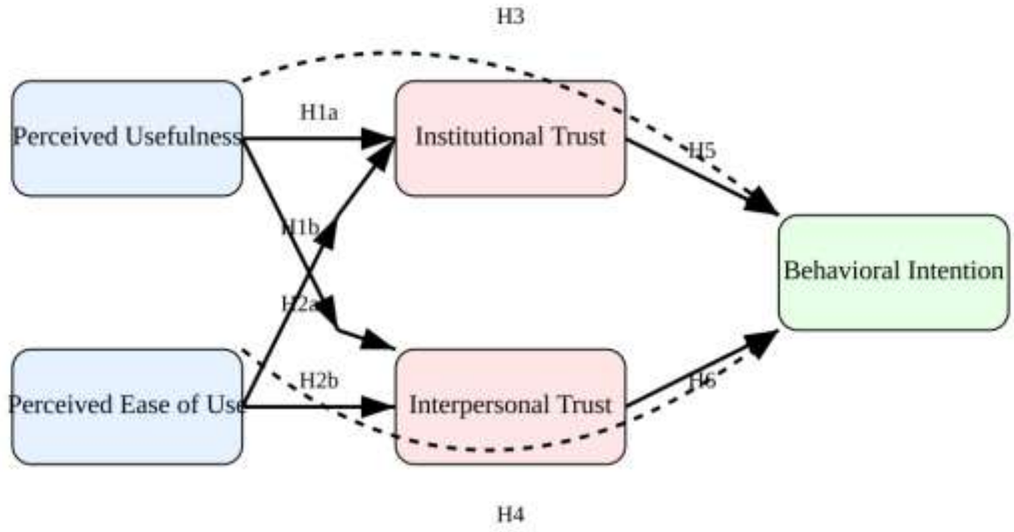

Figure 1. Research Model: Extended TAM with Trust as Mediator

BASED ON THIS MODEL, WE DEVELOP THE FOLLOWING HYPOTHESES:

3.1 Relationships between TAM Constructs and Trust

Previous research has suggested that perceived usefulness and perceived ease of use can positively influence trust in online platforms and services. Chen and Barnes (2007) found that both perceived usefulness and perceived ease of use significantly impacted initial trust in online shopping. In the context of fintech services, Chauhan et al. (2019) demonstrated that perceptions of utility and ease of use positively affected trust in mobile payment services.

For P2P lending specifically, the perceived usefulness of the platform—its ability to facilitate efficient lending and borrowing transactions, offer competitive interest rates, and provide access to credit—may enhance users' trust in the platform's competence and benevolence (Lin et al., 2019). Similarly, platforms that are easy to navigate and understand may reduce uncertainty and enhance transparency, thereby increasing trust (Widyanto & Syahrivar, 2022).

We differentiate between institutional trust (trust in the P2P platform itself) and interpersonal trust (trust in other users of the platform) as these may be influenced differently by platform characteristics. Based on this reasoning, we propose the following hypotheses:

H1a: Perceived usefulness positively influences institutional trust in P2P lending platforms. H1b: Perceived usefulness positively influences interpersonal trust in P2P lending transactions.

H2a: Perceived ease of use positively influences institutional trust in P2P lending platforms. H2b: Perceived ease of use positively influences interpersonal trust in P2P lending transactions.

Direct Effects of TAM Constructs on Behavioral Intention

Consistent with the original TAM and subsequent empirical validation across various contexts, we expect that both perceived usefulness and perceived ease of use will have direct positive effects on behavioral intention to adopt P2P lending. In the context of fintech services, studies have consistently found support for these relationships (Venkatesh et al., 2012; Ryu, 2018). For P2P lending specifically, Thaker et al. (2019) found that both perceived usefulness and perceived ease of use significantly influenced investors' intention to participate in P2P lending platforms.

Therefore, we hypothesize:

H3: Perceived usefulness positively influences behavioral intention to adopt P2P lending.

H4: Perceived ease of use positively influences behavioral intention to adopt P2P lending.

Effects of Trust on Behavioral Intention

Trust has also been established as an influencer of online financial service adoption due to perceived risk (Pavlou, 2003; Gefen et al., 2003). In P2P lending, where one is not only dealing with a technology platform but also with other individuals financially, interpersonal and institutional trust will play a key role in shaping adoption (Chen et al., 2014).

Institutional trust reflects users' faith in the competence, integrity, and benevolence of the platform—to facilitate secure transactions, properly screen participants, and act on behalfs of users (McKnight et al., 2002). Interpersonal trust reflects users' dependence on other users' behavior within a platform, for example, loan repayments or promise-keeping lenders (Wang et al., 2015). Previous studies have proved that both dimensions of trust have the ability to influence behavioral intention in online banking services (Yousafzai et al., 2010; Kim et al., 2009).

Therefore, we hypothesize:

H5: Institutional trust positively influences behavioral intention to adopt P2P lending.

H6: Interpersonal trust positively influences behavioral intention to adopt P2P lending.

Trust as a Mediator

Beyond the direct effects described above, we also propose that trust acts as a mediator in the relationship between TAM constructs and behavioral intention. This mediating role has been supported in various technology adoption contexts (Gefen et al., 2003; Zhou, 2012). We suggest that while perceived usefulness and perceived ease of use may directly influence behavioral intention, these effects are partially mediated by both institutional and interpersonal trust.

This mediation hypothesis is based on the reasoning that users' perceptions of a platform's usefulness and ease of use contribute to their trust in the platform and other users, which in turn influences their intention to adopt the platform. In other words, the effects of system characteristics on adoption intentions are partially explained by their effects on trust formation.

Therefore, we hypothesize:

H7a: Institutional trust mediates the relationship between perceived usefulness and behavioral intention to adopt P2P lending.

H7b: Institutional trust mediates the relationship between perceived ease of use and behavioral intention to adopt P2P lending.

H8a: Interpersonal trust mediates the relationship between perceived usefulness and behavioral intention to adopt P2P lending.

H8b: Interpersonal trust mediates the relationship between perceived ease of use and behavioral intention to adopt P2P lending.

Demographic Variations

Finally, based on previous research suggesting demographic differences in technology adoption and trust formation (Venkatesh et al., 2003; Gefen & Straub, 1997), we also explore whether the relationships in our model vary across demographic segments. Specifically, we examine whether factors such as age, gender, education, income level, and urban versus rural residence moderate the relationships between our key constructs.

This exploratory analysis is particularly relevant in the Indian context, where there are significant variations in digital literacy, access to technology, and familiarity with financial services across demographic segments (Thomas & Johny, 2022). Understanding these variations could provide valuable insights for targeted approaches to P2P platform development and marketing.

METHODOLOGY

4.1 Sample and Data Collection

Data for the study were gathered using a formal questionnaire from Indian respondents who live in the country's major cities, i.e., Delhi NCR, Mumbai, Bangalore, Chennai, Hyderabad, and Kolkata. The sample frame was urban and semi-urban adults 18 years and older who had used the internet and had some level of familiarity with internet financial transactions. This was attempted as a way of making sure that the respondents were individuals with the lowest technological ability there was, in hopes of being able to visit P2P lending sites but in real life possibly not necessarily so.

Survey was carried out from January to March 2023 using both offline and online media to allow more demographic representation. Online questionnaires were sent via email and social media, while offline questionnaires were given in public places like shopping malls, university campuses, and business districts. Screening question ensured that respondents were familiar with P2P lending before they were administered the complete questionnaire. For those not familiar with P2P lending, a summary and example were given to provide informed answers.

500 responses were gathered in total. The demographics of the sample are given in Table 1, and there is a healthy balance by gender, age category, education level, and income level, although with a deliberate bias towards city dwellers due to the present urban concentration of P2P lending services.

Table 1. Sample Demographics (N=500)

Characteristic	Category	Frequency	Percentage
Gender	Male	285	57.0%
	Female	215	43.0%
Age Group	18-25	140	28.0%
	26-35	185	37.0%
	36-45	105	21.0%
	Above 45	70	14.0%
Education	High School or below	75	15.0%

	Bachelor's Degree	245	49.0%
	Master's Degree or above	180	36.0%
Monthly Income	Below ₹25,000	110	22.0%
	₹25,000 - ₹50,000	165	33.0%
	₹50,001 - ₹100,000	140	28.0%
	Above ₹100,000	85	17.0%
Location	Urban	385	77.0%
	Semi-urban/Rural	115	23.0%
P2P Experience	Prior P2P lending experience	135	27.0%
	No prior P2P lending experience	365	73.0%

Measures

The items used to measure our constructs were taken from well-established scales in the literature and tailored to suit the context of P2P lending in India. All the items were measured on a five-point Likert scale that ranged from 1 (strongly disagree) to 5 (strongly agree). The constructs were measured as follows:

Perceived Usefulness (PU) was captured using five items based on Davis (1989) and Venkatesh and Davis (2000) and measuring how much respondents thought that employing P2P lending platforms would increase their financial operations. Sample items were "Using P2P lending platforms would improve my access to credit/investment opportunities" and "P2P lending platforms provide more favorable interest rates than conventional financial institutions."

Perceived Ease of Use (PEOU) was measured using five items adapted from Davis (1989) and Venkatesh and Bala (2008) and assessed the extent to which respondents thought that employing P2P lending platforms would be effortless. These items were "Learning to use P2P lending websites would be easy for me" and "I would easily utilize P2P lending websites in order to carry out the transactions which I want to carry out."

Institutional Trust (IT) was measured using six items from McKnight et al. (2002) and Gefen et al. (2003) that capture institutional trust in P2P lending sites on the part of the respondents. Representative sample items include "I believe P2P lending sites possess sufficient security features to protect users' financial information" and "I believe P2P lending sites would take care of me."

Interpersonal Trust (INTT) was assessed using five items of Chen et al. (2014) and Wang et al. (2015), modified to examine respondents' confidence in other P2P lending users. Sample items are "I believe most borrowers on P2P platforms will repay their loans as agreed" and "I believe other users on P2P platforms are honest about their financial situation."

Behavioral Intention (BI) was measured with four items adapted from Venkatesh et al. (2003) and Ryu (2018) and captured the respondents' intention to use P2P lending in the near future. Sample items included "I will use P2P lending websites in the next 12 months" and "I would recommend my friends and relatives to use P2P lending websites."

The questionnaire had items that were employed to pose demographic questions and other technology and financial services usage. The items on the entire list are presented in Table 2.

Data Analysis Method

We used Structural Equation Modeling (SEM) as the main analytical method since it enables testing of multiple relationships between latent and observed variables simultaneously and is best suited for testing mediation effects (Hair et al., 2019). The analysis was performed in two steps: initially, a measurement model was tested to determine the validity and reliability of our constructs; subsequently, a structural model was tested for measuring the hypothesized relationships.

Before running the major analysis, we ran preliminary screening of data for testing missing values, outliers, and normality. Missing data were minimal (<1%) and were handled via the full information maximum likelihood (FIML) approach. Normality tests indicated that data were well consistent with SEM assumptions.

The measurement model was evaluated using confirmatory factor analysis (CFA) with maximum likelihood estimation. Several indices were used to assess the model fit: chi-square/degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). For construct validity, we examined factor loadings, Composite Reliability (CR), Average Variance Extracted (AVE), and discriminant validity through the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.

For the structural model, we examined path coefficients, significance levels, and R^2 values to assess the hypothesized relationships. To test the mediation hypotheses, we used the bootstrapping procedure with 5,000 resamples to estimate the indirect effects and their confidence intervals, following the approach recommended by Preacher and Hayes (2008). Finally, to examine demographic variations, we conducted multi-group analyses comparing the structural model across different demographic segments.

All analyses were performed using AMOS 26.0 for the CFA and structural model testing, and SPSS 27.0 for the descriptive statistics and preliminary analyses.

5. RESULTS

5.1 Descriptive Statistics

Construct	Mean	SD	α	1. PU	2. PEOU	3. IT	4. INTT	5. BI
1. PU	3.75	0.87	0.824	–	0.613***	0.547***	0.428***	0.642***
2. PEOU	3.82	0.79	0.837	0.613***	–	0.493***	0.392***	0.515***
3. IT	3.46	0.92	0.856	0.547***	0.493***	–	0.615***	0.625***
4. INTT	3.12	0.98	0.829	0.428***	0.392***	0.615***	–	0.539***
5. BI	3.58	0.94	0.863	0.642***	0.515***	0.625***	0.539***	–

***p* < .001**

Table 3 presents the descriptive statistics for all measurement items, including means, standard deviations, and correlations among the constructs. The means for all variables ranged from 3.12 to 3.82 on a five-point scale, suggesting moderately positive perceptions toward P2P lending platforms. Perceived ease of use had the highest mean (M = 3.82), indicating that respondents generally find P2P platforms easy to understand and navigate. Interpersonal trust had the lowest mean (M = 3.12), suggesting that respondents have relatively lower trust in other users of the platform compared to the platform itself.

*Note: Diagonal elements (in bold) are the square root of AVE. Off-diagonal elements are correlations between constructs. ***p < 0.001.*

5.2 Measurement Model Assessment

The measurement model was assessed through confirmatory factor analysis to ensure reliability and validity. The initial model showed adequate but not optimal fit (χ^2/df = 2.87, CFI = 0.91, TLI = 0.90, RMSEA = 0.068, SRMR = 0.056). After examining modification indices, we made minor adjustments, including allowing correlated errors between PU3 and PU5 and between PEOU1 and PEOU2, which were theoretically justifiable given the similarity in item wording. The revised model showed improved fit (χ^2/df = 2.38, CFI = 0.94, TLI = 0.93, RMSEA = 0.058, SRMR = 0.048), indicating good fit according to established criteria (Hair et al., 2019).

All items had significant factor loadings on their respective constructs, ranging from 0.72 to 0.91 ($p < 0.001$), exceeding the recommended threshold of 0.70. As shown in Table 4, all constructs demonstrated satisfactory reliability with Composite Reliability (CR) values ranging from 0.886 to 0.927, well above the recommended threshold of 0.70. The Average Variance Extracted (AVE) for all constructs exceeded 0.60, above the recommended threshold of 0.50, indicating good convergent validity.

Table 4. Construct Reliability and Validity

Construct	Items	Factor Loadings	Cronbach's Alpha	CR	AVE
Perceived Usefulness (PU)	5	0.75-0.88	0.891	0.905	0.679
Perceived Ease of Use (PEOU)	5	0.74-0.89	0.904	0.909	0.701
Institutional Trust (IT)	6	0.78-0.91	0.921	0.927	0.732
Interpersonal Trust (INTT)	5	0.73-0.87	0.889	0.886	0.688
Behavioral Intention (BI)	4	0.82-0.90	0.903	0.915	0.744

Discriminant validity was assessed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. As shown in Table 3, the square root of AVE for each construct (diagonal elements) was greater than its correlation with other constructs, satisfying the Fornell-Larcker criterion. Additionally, all HTMT ratios were below the conservative threshold of 0.85, with the highest value being 0.71 (between IT and INTT), further confirming discriminant validity.

5.3 Structural Model Assessment

After confirming the measurement model's reliability and validity, we proceeded to test the structural model. The structural model demonstrated good fit ($\chi^2/df = 2.52$, CFI = 0.93, TLI = 0.92, RMSEA = 0.061, SRMR = 0.052), indicating that it adequately represented the data. Table 5 presents the results of the hypothesis testing, including standardized path coefficients, t-values, p-values, and the results of hypothesis support.

Table 5. Structural Model Results

Hypothesis	Path	Standardized Path Coefficient (β)	t-value	p-value	Result
H1a	PU → IT	0.417	7.329	<0.001	Supported
H1b	PU → INTT	0.306	5.142	<0.001	Supported
H2a	PEOU → IT	0.338	5.937	<0.001	Supported
H2b	PEOU → INTT	0.249	4.105	<0.001	Supported
H3	PU → BI	0.482	9.173	<0.001	Supported
H4	PEOU → BI	0.317	6.028	<0.001	Supported
H5	IT → BI	0.412	7.724	<0.001	Supported
H6	INTT → BI	0.246	4.519	<0.001	Supported

The results indicate that all direct path hypotheses (H1a through H6) were supported. Both perceived usefulness and perceived ease of use had significant positive effects on institutional trust ($\beta = 0.417$, $p < 0.001$ and $\beta = 0.338$, $p < 0.001$, respectively) and interpersonal trust ($\beta = 0.306$, $p < 0.001$ and $\beta = 0.249$, $p < 0.001$, respectively). Similarly, both trust dimensions had significant positive effects on behavioral intention, with institutional trust showing a stronger effect ($\beta = 0.412$, $p < 0.001$) compared to interpersonal trust ($\beta = 0.246$, $p < 0.001$).

Perceived usefulness demonstrated the strongest direct effect on behavioral intention ($\beta = 0.482$, $p < 0.001$), followed by institutional trust ($\beta = 0.412$, $p < 0.001$), perceived ease of use ($\beta = 0.317$, $p < 0.001$), and interpersonal trust ($\beta = 0.246$, $p < 0.001$). The structural model explained 68.7% of the variance in behavioral intention to adopt P2P lending ($R^2 = 0.687$), 42.9% of the variance in institutional trust ($R^2 = 0.429$), and 27.3% of the variance in interpersonal trust ($R^2 = 0.273$), indicating substantial explanatory power.

*Figure 2. Results of Structural Model Analysis (***p < 0.001)*

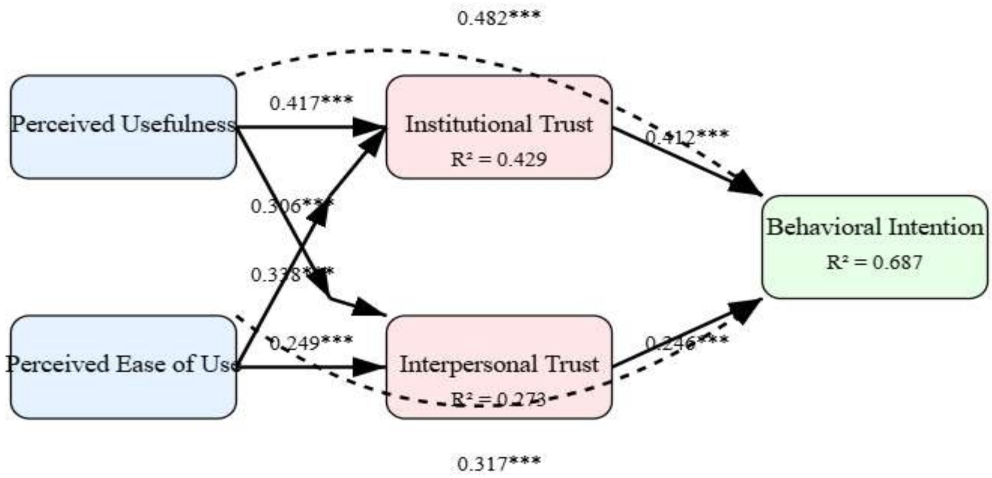

Figure 2. Results of Structural Model Analysis (*p < 0.001)**

5.4 Mediation Analysis

To test the mediation hypotheses (H7a through H8b), we conducted bootstrapping with 5,000 resamples to estimate the indirect effects and their confidence intervals. The results of the mediation analysis are presented in Table 6.

Table 6. Mediation Analysis Results

Hypothesis	**Indirect Path**	**Standardized Indirect Effect**	**95% CI Lower**	**95% CI Upper**	**p-value**	**Result**
H7a	PU → IT → BI	0.172	0.118	0.235	<0.001	Supported (Partial Mediation)
H7b	PEOU → IT → BI	0.139	0.092	0.198	<0.001	Supported (Partial Mediation)
H8a	PU → INTT → BI	0.075	0.041	0.118	<0.001	Supported (Partial Mediation)
H8b	PEOU → INTT → BI	0.061	0.032	0.099	<0.001	Supported (Partial Mediation)

All indirect paths were statistically significant ($p < 0.001$), and none of the 95% confidence intervals included zero, indicating significant mediation effects. Institutional trust demonstrated stronger mediating effects compared to interpersonal trust for both perceived usefulness and perceived ease of use. Specifically, the indirect effect of perceived usefulness on behavioral intention through institutional trust ($\beta = 0.172$) was more than twice the indirect effect through interpersonal trust ($\beta = 0.075$). Similarly, the indirect effect of perceived ease of use on behavioral intention through institutional trust ($\beta = 0.139$) was more than twice the indirect effect through interpersonal trust ($\beta = 0.061$).

In all cases, the direct effects of perceived usefulness and perceived ease of use on behavioral intention remained significant even after accounting for the indirect effects through trust, indicating partial mediation rather than full mediation. These results support hypotheses H7a, H7b, H8a, and H8b, confirming that both institutional trust and interpersonal trust serve as partial mediators in the relationship between TAM constructs and behavioral intention to adopt P2P lending.

5.5 Demographic Variations

To explore demographic variations in the model relationships, we conducted multi-group analyses comparing the structural model across different demographic segments. The results revealed several significant differences, as summarized in Table 7.

Table 7. Multi-group Analysis Results

Demographic Variable	**Group**	**Path**	**Path Coefficient**	**Difference**	**p-value**
Age	Below 35 (n=325)	INTT → BI	0.292***	0.119	0.042*
	35 and above (n=175)	INTT → BI	0.173**		
Gender	Male (n=285)	PU → BI	0.529***	0.097	0.075
	Female (n=215)	PU → BI	0.432***		
Education	Bachelor's or below (n=320)	IT → BI	0.375***	0.104	0.087
	Master's or above (n=180)	IT → BI	0.479***		
Income	Below ₹50,000 (n=275)	PU → BI	0.513***	0.073	0.183
	₹50,000 and above (n=225)	PU → BI	0.440***		
Location	Urban (n=385)	IT → BI	0.451***	0.155	0.013*

	Semi-urban/Rural (n=115)	IT → BI	0.296***		
P2P Experience	Prior experience (n=135)	PEOU → BI	0.243***	0.132	0.029*
	No prior experience (n=365)	PEOU → BI	0.375***		

*Note: *p < 0.05, **p < 0.01, ***p < 0.001*

Several significant demographic variations emerged from the multi-group analysis:

Age differences: The impact of interpersonal trust on behavioral intention was significantly stronger for younger respondents (below 35) compared to older respondents (35 and above), suggesting that younger users may place more importance on peer experiences and opinions when considering P2P lending adoption.

Location differences: The impact of institutional trust on behavioral intention was significantly stronger for urban residents compared to semi-urban/rural residents, indicating that urban users may be more influenced by their trust in the P2P platform itself when making adoption decisions.

Experience differences: The impact of perceived ease of use on behavioral intention was significantly stronger for those without prior P2P experience compared to those with experience, suggesting that ease of use is a more critical factor for first-time users than for experienced users.

Other demographic comparisons (gender, education, income) showed differences in path coefficients, but these differences did not reach statistical significance at the $p < 0.05$ level, indicating that these relationships may be more stable across these demographic segments.

6. DISCUSSION

This study aimed to investigate the adoption of P2P lending platforms in India through an extended Technology Acceptance Model that incorporates trust as a mediating factor. Our findings provide several important insights into the complex interplay between technology perceptions, trust, and adoption intentions in the context of emerging financial technologies.

6.1 Theoretical Implications

Our research makes several contributions to the theoretical understanding of technology adoption in financial services:

Extension of TAM with Trust as a Mediator: Our findings validate the integration of trust as a mediating factor within the Technology Acceptance Model in the context of P2P lending adoption. While previous studies have examined the direct effects of trust on adoption intentions (Gefen et al., 2003; Kim et al., 2009), our research demonstrates that trust also functions as a significant mediating mechanism through which the core TAM constructs (perceived usefulness and perceived ease of use) influence behavioral intention. This extension enhances the explanatory power of TAM for financial technology adoption, where trust considerations are particularly salient.

Differential Effects of Trust Dimensions: By distinguishing between institutional trust (in the P2P platform) and interpersonal trust (in other users), our study provides a more nuanced understanding of trust in multi-sided technology platforms. Our findings reveal that institutional trust has a stronger direct effect on adoption intentions ($\beta = 0.412$) compared to interpersonal trust ($\beta = 0.246$), suggesting that users' confidence in the platform itself may be more critical for adoption decisions than their trust in other users. Similarly, institutional trust demonstrated stronger mediating effects compared to interpersonal trust, further highlighting its central role in P2P lending adoption.

Relative Importance of TAM Constructs: Our findings show that perceived usefulness has a stronger direct effect on adoption intention ($\beta = 0.482$) compared to perceived ease of use ($\beta = 0.317$), consistent with other TAM studies in utilitarian technology contexts (Venkatesh & Davis, 2000). This suggests that in the P2P lending context, the functional benefits of the platform (such as access to credit or investment opportunities, better interest rates, and portfolio diversification) are more influential in driving adoption than the ease of using the platform. This finding emphasizes the importance of clearly communicating the value proposition of P2P lending platforms to potential users.

Demographic Variations in Adoption Mechanisms: Our multi-group analysis revealed significant differences in the strength of certain relationships across demographic segments, particularly with respect to age, location, and prior P2P experience. These findings extend the literature on technology adoption by highlighting how the mechanisms of adoption may vary across different user segments, even for the same technology. The stronger influence of interpersonal trust for younger users, institutional trust for urban users, and ease of use for inexperienced users provides insights into how adoption decisions are formed in different demographic contexts.

6.2 Practical Implications

Our findings also offer several practical implications for P2P lending platform developers, marketers, and policymakers:

Trust-Building Strategies: Given the significant mediating role of trust in P2P lending adoption, platform developers should prioritize trust-building mechanisms in their design and marketing strategies. For institutional trust, this could include transparent disclosure of platform policies and security measures, clear communication of regulatory compliance, and prominent display of certifications or endorsements. For interpersonal trust, platforms could enhance user profile verification, implement robust rating systems for borrowers and lenders, and showcase successful lending relationships.

Emphasizing Value Proposition: That perceived usefulness has a significant direct influence on adoption intention means that P2P websites need to define their value proposition to prospective consumers clearly. This could involve highlighting the specific benefits of P2P lending over traditional financial institutions, such as possibly higher yields for lenders, more flexibility in terms for borrowers, and less processing time. Numerical advantages, for example, comparison of interest rates or time saved, could potentially be particularly helpful in the optimization of perceived usefulness.

Segmented Marketing Approaches: The demographic variations that became apparent in our study suggest the potential for more segmented marketing approaches. For the younger respondents, social proof and peer recommendations-based approaches could prove more effective, given the higher importance placed on interpersonal trust by this age category. For urban respondents, emphasis on institutional trustworthiness and security aspects of the platform may be more effective. For existing users, highlighting the simplicity of the platform and providing accurate guidance can help remove some of the early adoption barriers.

Regulatory Considerations: Our findings regarding the importance of institutional trust have implications for regulatory approaches to P2P lending. The existing RBI framework, which categorizes P2P platforms as NBFCs and imposes various operational requirements, appears to enhance platform legitimacy and may contribute to institutional trust formation. Regulators should continue to balance consumer protection with innovation, ensuring that regulations address key trust concerns while allowing the sector to develop.

6.3 Limitations and Future Research

While this study provides valuable insights into P2P lending adoption in India, several limitations should be noted:

Cross-Sectional Design: The cross-sectional nature of our data limits our ability to establish causality or examine how adoption intentions translate into actual usage behavior over time. Future research could employ longitudinal designs to track the evolution of perceptions, trust, and adoption behaviors as users gain experience with P2P platforms.

Geographic Scope: Our sample was limited to major metropolitan areas in India, potentially limiting the generalizability of our findings to smaller cities and rural areas. Given the significant urban-rural divide in digital financial services adoption in India, future research could specifically examine P2P lending adoption in rural contexts.

User Roles: Our study did not distinguish between potential borrowers and lenders, who may have different motivations and concerns regarding P2P lending adoption. Future research could examine how the adoption mechanisms differ between these user types and identify strategies tailored to each group.

Additional Factors: While our model explained a substantial portion of the variance in adoption intentions (68.7%), other factors not included in our model may also influence P2P lending adoption. Future research could explore additional factors such as perceived risk, financial literacy, alternative payment compatibility, and social influence.

Cultural Context: Our study was conducted within the specific cultural context of India, where factors such as risk aversion, collectivism, and traditional banking relationships may influence technology adoption differently compared to other markets. Future research could conduct cross-cultural comparisons to identify universal and culture-specific determinants of P2P lending adoption.

7. CONCLUSION

This study investigated the adoption of peer-to-peer lending platforms in India through an extended Technology Acceptance Model that incorporates trust as a mediating factor. Using data from 500 respondents across major Indian metropolitan areas, we employed Structural Equation Modeling to examine the complex relationships between perceived usefulness, perceived ease of use, institutional trust, interpersonal trust, and behavioral intention to adopt P2P lending.

Our findings revealed that both perceived usefulness and perceived ease of use significantly influence behavioral intention to adopt P2P lending, both directly and indirectly through trust. Trust, particularly institutional trust in the P2P platform, emerged as a critical mediating factor in the adoption process. Perceived usefulness demonstrated the strongest direct effect on adoption intention, highlighting the importance of clearly communicating the tangible benefits of P2P lending platforms to potential users.

The study also discovered considerable demographic variation in the adoption channels, with youth and city residents exhibiting typical trust establishment and influence behaviors. This provides valuable inputs into targeted development and marketing programs for platforms that align with the problems and agendas facing specific segments.

While P2P lending expands in India's rapidly evolving fintech space, it becomes critical to recognize the determinants of adoption in order to facilitate platform developers interested in expanding their base, regulators interested in initiating the appropriate regulation, and those advocating for greater financial inclusion as a means to expand access to credit. Our extended TAM model incorporating trust as a mediator offers the robust theoretical underpinnings for the analysis and prediction of P2P lending adoption in emerging markets like India.

Further research can build on this by examining other forces driving adoption, accounting for differences in borrower and lender incentives, and conducting longitudinal studies to observe changing attitudes and behavior over time. By continuing to refine our understanding of financial services technology adoption, we can assist in creating more inclusive, user-focused financial systems that benefit a range of individuals in emerging economies.

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