Journal of Asia Entrepreneurship and Sustainability RESEARCH ARTICLE

MODELLING INTENTION AND TRUST IN AI-BASED DIGITAL PAYMENTS FOR SUSTAINABLE RURAL ENTREPRENEURSHIP AND FINANCIAL INCLUSION: A SEM STUDY IN RURAL DELHI NCR (ASIA)

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ABSTRACT
Adoption of AI-based digital payment systems plays a crucial role in advancing sustainable rural entrepreneurship, financial inclusion, and inclusive economic participation in emerging Asian economies. This study investigates the factors influencing the adoption of AI-enabled digital payments in rural Delhi NCR by extending the Technology Acceptance Model to include trust and perceived security as key socio-psychological determinants. AI-based digital payments are examined as an essential component of entrepreneurial infrastructure supporting rural microenterprises, informal entrepreneurs, and resilient economic activity. Using Partial Least Squares Structural Equation Modelling (PLS-SEM), the study analyses survey data collected from 453 rural respondents who were users or had awareness of digital payment platforms. Findings indicate that trust particularly trust in AI-driven payment security has a strong and significant influence on attitudes and intentions to adopt digital payment systems, highlighting its importance for rural entrepreneurial transactions and microenterprise sustainability. Perceived security emerges as the most influential driver of adoption, while knowledge and awareness of AI technology do not directly affect intention to use, suggesting that practical usability and experiential confidence outweigh awareness alone in rural contexts. Results further demonstrate the role of secure and user-friendly digital payment systems in strengthening financial inclusion, enterprise resilience, and sustainable digital economic development across rural Asia. Policy and managerial implications are drawn for policymakers, financial institutions, and fintech providers seeking to design entrepreneur-friendly AI-based digital payment ecosystems that promote sustainable rural entrepreneurship and inclusive growth in emerging economies.
Keywords: Sustainable Entrepreneurship, Financial Inclusion, AI-Based Digital Payments, Rural Innovation, Trust and Security, Emerging Economies (Asia)
JEL Classification: O33, D12, G21, L86, I38

1. INTRODUCTION
Digital payment systems have transformed the financial sector across the world. Increased convenience, speed, and safety of financial transactions are added to these systems-the mobile wallet systems, online banking, and mobile money applications (Sevinc & Akyildiz, 2021; Roth, 2020). Such technologies have just sprung into an extremely rapid pace in the urban locations, yet the rural corners of the Delhi NCR are still inundated with road blocks in accepting digital payments. Digital illiteracy, infrastructural gaps, and low Internet connectivity and socio-economic factors have served as a hindrance in the increased use of digital payments in rural populations (Hussain et al., 2024).
The AI-driven digital payment systems are becoming more of an entrepreneurial infrastructure in rural and semi-rural settings, and not just a convenience tool to consumers. In the case of rural microenterprises, informal entrepreneurs, self-employed people, and small traders, digital payments are facilitating such critical business operations as customer payment acceptance, supplier transactions, formal financial services, and better cash flow visibility. Secure and user-friendly AI-based payment systems are thus highly important in helping to sustain a sustainable rural entrepreneurship, financial inclusion, and inclusive economic participation, especially in the emerging Asian economies. Such aspects as trust, perceived security, and ease of use are particularly important in this respect, as they directly determine the willingness of the entrepreneurs to incorporate digital payments in daily business processes, which increases the resilience of enterprises, as well as leads to the

establishment of sustainable rural digital ecosystems.

The necessity of the use of digital payment in the rural areas cannot be overestimated. The implementation of this kind of systems would significantly improve the efficiency of financial transactions; access to government services; and economic inclusion of marginalized communities (Rana & Goel, 2025; Sindakis and Showkat, 2024). With the use of such systems, transaction costs may be maintained at a minimum and financial transactions made safer and more transparent to everyone involved in the rural regions (Au & Kauffman, 2008; Manrai et al., 2021). In addition, trust in relation to digital platforms, the role of financial literacy, and security concerns, in essence, in relation to rural users are also important factors that will act against the integration of digital payment systems (Putrevu and Mertzanis, 2024). These socio-psychological variables mediate the community-level distanced perceptions of rural consumers about the perceived usefulness and perceived ease of use of digital payment systems; therefore, cognizance of the said variables is critical in reaching the behaviour adoption (Banerji and Singh, 2024).

This research aims to fill the gaps by including other factors that the rural population would be interested in with the Technology Acceptance Model (TAM). Specifically, the current research employs Structural Equation Modelling (SEM) in testing the hypotheses that the social influence, trust in digital payment systems, financial literacy and perceived risk affect adoption of digital payment systems in rural Delhi NCR.

Research Objectives

A. To examine the role of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) in adopting AI-based digital payment systems in rural Delhi NCR considering the facilitation of rural entrepreneurial involvement and the presence of sustainable microenterprise activities

B. To examine the impact of Social Influence (SI) on the implementation of AI-based digital payment systems in rural Delhi NCR in regards to financial inclusion and diffusion among small business operators and entrepreneurs in rural area

C. To examine the impact of Social Influence (SI) on the implementation of AI-based digital payment systems in rural Delhi NCR under the conditions of financial inclusion and peer-based diffusion of rural entrepreneurs and small business operators

2. REVIEW OF LITERATURE

2.1 Overview of Digital Payment Systems

Joshi (2017) examined the development of digital payment in India in 2015-2017. It reflected the growth in the volumes of transaction in systems like UPI, BHIM-UPI, and IMPS. This expansion encouraged the transition to a cashless society which was launched by government programs. The detection of fraud cases, the decision in civil cases, or judgements in criminal cases has given AI or more specifically machine learning a chance to excel in fraud detection in digital payment platforms (Jain, 2024); Njoku et al., 2024). The detection of known cases of fraud is done through supervised learning with labelled data and unsupervised learning is applied to unknown patterns with unlabelled data. (Afriyie et al., 2023).

Sujith and Julie (2017) were interested in determining the key issues and concerns of utilizing e-payment systems in India to suggest potential solutions to enhance their efficiency in the management of digital business environment. An e-payment can be described as a system that enables a person to make payments in a form of goods and services without using cash or cheques and therefore offering the convenience of punctuality and location where the payment is made (TAREKEGN, 2019; Naeem et al., 2020). According to the study, as digital transactions are becoming the standard, it has been a strange situation not to embrace e-payments to help and maintain e-business operations (Dzarma, 2022).

2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model was developed in the 1980s as a result of the unsatisfaction with previous models on the process of adoption of information systems. An effort was put to draw a theoretical model of causal linking between such factors as: system design, perceived usefulness, ease-of-use, positive or negative user attitude, and actual behavior. TAM integrates MIS research, laboratory studies, and HCI, the basis of which are psychological theories of attitude (Hornbæk and Hertzum, 2017). The model was tested in an empirical field experiment of 112 end users in two end-user systems where it was discovered that it accounted only 36% of variance in actual use. The results indicated that the perceived usefulness played 50 percent greater role than perceived ease of use in the choice to adopt: a concept that gives greater stress on functional usefulness than on usability. The framework of development that this seminal study of TAM provided to the new research and the practical aspect of examining new technologies and enhancing their acceptance, including digital payment systems, was rather strong (Davis and others, 1989; Ashraf et al., 2014; Straub et al., 1997). Although it has certain limitations, it is a powerful backbone model applied in the cognition and improvement of the adoption of different technologies like digital payment systems (Silva, 2015; Jamil, 2012; Yousafzai et al., 2010). The literature can be taken mostly through three perspectives i.e., TAM reviews, TAM extensions and developments, and realistic adjustments and applications (S. Yousafzai and Yani-de-Soriano, 2012; Marangunica and Grani, 2015). With user-acceptance theories technical background, TAM is viewed as a fundamental model of the same, in addition to it being billed as an object of ambivalent opinion with regards to its theoretical presumptions and practical application (Ajibade, 2018; Lala and others, 2014; Davis, 1987).

2.3 Factors Influencing Digital Payment Adoption

The study by Kumar et al. (2025) is insightful to carry on an intention to use e-wallets with a mediating variable of how it is perceived to be useful. Based on the already developed technology acceptance theories, it is believed that users are more likely to keep using e-wallets when they perceive such systems to be useful, efficient, and convenient. Karmaker et al. (2025) illuminated the psychological and demographic factors that propel consumer behaviour that is essential to startups and businesses that hope to thrive in the digital payment sector (Oyeyemi et al., 2024). According to the study, motivation, attitude, perception, preference and the demographic factors (age, income, etc.) are mentioned as some of the key factors that influence consumer behaviour (Sabbir Rahman, 2012). The brand recognition, availability, and security determine patterns of consumer adoption (Pai et al., 2025).

2.4 Digital Payment Adoption in Rural Areas

Nepal et al. (2025) focus on what influences the use of digital payment in rural Nepal. It reveals that the most significant adoption factors are digital literacy, internet quality, and overall education, with the most weight being on the former, then the latter and the quality of the internet (Yang et al., 2025; Yecsilyurt and Vezne, 2023). The paper also illuminates the main obstacles including untrustworthy internet connection to low penetration of smartphones, difficulties in the registration process, and low acceptance of merchants (Macamo, 2020). As LINH (2025) demonstrates, acceptance of DPMs-Northern mountainous region is determined by the main key factors. The statistics of 811 residents claim that the most accepted DPM is a bank transfer, then Smart Banking / QR code, E-wallet, and Visa cards. Most of these techniques are tolerated in retail shopping, utility-based payment and online shopping. The value is immediate and is comparatively not hard to value. Trivedi and Sanchiher (2023) provide the analysis of the obstacles that hinder the prevalence of the use of digital payment systems, especially in rural settings. Mobile payments do not involve formal infrastructures and are largely dependent on how users accept them instead of infrastructures (Banerji and Singh, 2022). Digital payments are opposed by lower digital literacy, inadequate infrastructure, English dominance language setting, cybercrime, online fraud, low trust in digital payment, taxation, and ineffective legal frameworks.

2.5 Digital Payments, Sustainable Entrepreneurship, and Financial Inclusion

The recent literature has come to appreciate the role of digital payment systems as a key facilitator of sustainable entrepreneurship and development of rural enterprises, especially in the emerging Asian economies. In the case of rural microenterprises, informal entrepreneurs and self-employed persons, having access to secure and reliable digital payment platforms allows to conduct critical business operations which include customer payment, supplier transactions, better financial records keeping and access to formal financial services. The digital financial services made possible by AI-based payment services play a major role in financial inclusion by ensuring that previously unbanked and underbanked rural entrepreneurs get access to the formal financial system (Gomber et al., 2017). Entrepreneurial adoption of digital payment is particularly sensitive to trust, perceived security, and ease of use, because the perceived risk is greater among business users, concerning the income stability, transaction reliability, and continuity of cash flow. Digital payment systems facilitate sustainability of microenterprises in terms of resiliency and long-term economic inclusion through minimizing cash dependency, enhancing the transparency of transactions, and facilitating scaled business operations. Empirical data indicates that the spread of safe and affordable digital payment tools has a significant contribution to the empowerment of the entrepreneurial ecosystem and the promotion of an inclusive economic growth in emerging markets (Beck et al., 2018). In this respect, the technology adoption frameworks like the Technology Acceptance Model could be applied to the context beyond the individual consumer use to describe the role of AI-based digital payment adoption in enhancing entrepreneurial participation, financial inclusion, and sustainable rural economic development in the emerging Asian contexts.

2.5 Research Gaps

Although a lot of effort has been put into the explanation of the adoption of digital payments, there are still research gaps, particularly in developing nations such as India. An example is that the socioeconomic and cultural influences on adoption in villages are an area that is sparsely researched. Where the perceived usefulness and perceived ease of use are more, demographic factors such as age, income and education levels are less examined. What is more important, there is a lack of the study of adoption and utilization across the time in the areas with low digital literacy. Infrastructure wise, adoption is however curtailed by bad internet connectivity and limited access to smart phones. Statutory laws; cybersecurity laws and even data privacy-have not been sufficiently researched to have an impact on inculcating trust and creating an adoption effect. The research needs to be done on the role of issues relating to the security, credibility of merchants and perception of risk in making the decision to adopt the technology especially in underserved locations. Sealing these gaps will give the momentum to work on the strategies to advance the digital payments in various settings.

3. MATERIALS AND METHODS

3.1 Research Design

This study utilised quantitative research design and a cross-sectional study design since the primary goal was to determine the behavioural intention and trust in AI-based digital payment in the rural Delhi NCR region. It is important to note that the framework of this study is constructed on the basis of the extended variation of the Technology Acceptance Model (TAM), but these other constructs are Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Security (PS), Knowledge about AI Technology (KAAT), Customer Trust (CT), Attitude toward Adoption (ATA) and Intention to Use AI-based Digital payment systems (ITUA). The associations between the latent variables were tested with the help of SEM.

3.2 Sampling and Data Collection

Purposive sampling was used to sample target population which is digitally aware residents of the rural belt of Delhi NCR who have used or are aware of any and all types of AI-enabled digital payment systems. The questionnaire was developed into a well-designed and self-administered questionnaire that was sent via both physical and online platforms, including WhatsApp and email, and local kiosks.

Out of 500 responses obtained, 453 responses were retained to undergo the analysis following data cleaning and missing value treatments. The inclusion criteria included that the participants must be 18 and above, and must be living in any of the rural areas in Delhi NCR and should possess some basic knowledge of digital payment technologies.

Digitally conscious rural respondents who use or have been exposed to AI-based digital payment systems in the rural setting of the Delhi NCR can contribute to the study with relevant information in the dynamics of entrepreneurial and microenterprise adoption, although even the formal registration of business owners is not the focus of the study. Self-employed rural residents, people who perform informal trades of goods, individuals who have salaried jobs, and home-based economic activities often resort to digital payment systems to conduct business-related transactions including receiving payments, managing their spending and using financial services. Thus, the chosen sample will provide a valuable sample of financial inclusion and entrepreneurial involvement in rural digital ecosystems. The constructs used in this study in particular trust, perceived security, perceived usefulness, and ease of use are thus suitable in studying how the adoption of AI-based digital payments could enhance sustainable economic activity and the resilience of microenterprises in emergent rural areas.

3.3 Data Analysis

The PLS-SEM method was applied to SmartPLS version 4.0 to conduct an evaluation of measurement and structural models of proposed extended Technology Acceptance Framework (Muda et al., 2023; Shmueli et al., 2019; Chinnararaj, 2025).

Variables analysis was then carried out in two big steps. Evaluation of measurement model complied with reliability and validity of constructs. With this, the internal consistency was evaluated with Cronbach Alpha and Composite Reliability (CR), convergent validity with Average Variance Extracted (AVE), and heterotrait-monotrait ratio (HTMT) to evaluate the discriminant validity (Ab Hamid et al., 2017).

The second step was the evaluation of the structural model where the proposed relationships between constructs would be analysed. To test the significance of path coefficients in both directions, Bootstrapping using 5,000 subsamples and Bias-Corrected Percentile Confidence Intervals was used (Tibbe and Montoya, 2022). The value of R2 shows the amount of explicating variance in endogenous constructs (Janadari et al., 2016), and f 2 effect sizes are used to compute the strength of exogenous constructs (Samartha, 2020).

4. RESULTS AND ANALYSIS

4.1 Demographic Interpretation

The demographic analysis of the 453 respondents reveals that there is a high percentage of 45.5 of those in the age category of 1824 as a result of which there is a large number of heavy drinkers of the digital fund. The gender ratio is largely equal, as 54.1 are males and 44.6 females. Majority of the respondents are at least of secondary school education and 30.2 percent earn between 50,000-100,000 a month. The usual occupations offer salaried jobs (34.5%), and housewifery (19.7%). Respondents are rural (38.4%), semi-urban (33.1) and urban (28.5%). It is worth noting that 92.5% are smartphone owners, which also gives them access to digital payment, 41.2% make digital payments everyday, and as many are aware of AI functionality, this is a potential adoption in rural Delhi NCR.

An entrepreneurial approach, the sample demographics is significant to the rural microenterprise and informal economic activity. The large percentage of smartphone users and regular participation in online payments indicates that the respondents are in a good position to make use of AI-based payment solutions in their business transactions, such as the ability to receive customer payments and complete their daily financial operations. The existence of salaried and homemakers and younger respondents also indicate the various types of rural entrepreneurial engagement and self-employment that are prevalent in new economies, which support the importance of the sample in the study of the financial inclusion and sustainable rural entrepreneurship outcomes.

4.2 ASSESSMENT OF MEASUREMENT MODEL

Any external loading yielded a value above 0.70 with a range of 0.708 to 0.891 in CT 8 and KAAT 3 respectively, which actually has a good item reliability. The T values were all much higher than the 1.96 and the corresponding p-values were 0.000, all of which are extremely significant at the confidence level of 5% (Georgescu and Wren, 2018). Moreover, the VIFs are between 1.43 and 3.11, which confirms the lack of threats of multicollinearity because they are lower than 5 (Senaviratna et al., 2019). Therefore, reliability of support and validity of measurement model.

4.2.1 Construct Reliability & Validity

Table 1. Construct Reliability & Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attitude towards Adoption (ATA)	0.760	0.784	0.845	0.577
Consumer Trust (CT)	0.916	0.916	0.930	0.598
Intention to Use (ITUA)	0.897	0.898	0.924	0.709
Knowledge and Awareness (KAAT)	0.913	0.918	0.935	0.741
Perceived Ease of Use (PEOU)	0.892	0.894	0.925	0.755
Perceived Security (PS)	0.880	0.884	0.913	0.677
Perceived Usefulness (PU)	0.909	0.913	0.932	0.732

Source: Author's own creation

Interpretation:

All constructs had high reliability with Cronbach alpha of between 0.760 in ATA and 0.916 in CT, more than the recommended level of acceptance of 0.70 and hence good internal consistency (Vaske et al., 2017). The values of Composite Reliability (CR) of rho a and rho c were also higher than the value of 0.70 used as a reference of construct reliability, thus guaranteeing a good construct reliability (Hair Jr et al., 2021). All constructs met the required AVE value of 0.50 and above.

4.2.2 Discriminant Validity

Table 2. Discriminant Validity

Heterotrait-monotrait ratio (HTMT) – Matrix							
	ATA	CT	ITUA	KAAT	PEOU	PS	PU
ATA							
CT	0.656						
ITUA	0.583	0.654					
KAAT	0.417	0.410	0.398				
PEOU	0.400	0.591	0.470	0.231			
PS	0.550	0.623	0.577	0.315	0.427		
PU	0.450	0.425	0.422	0.977	0.267	0.334	
Fornell-Larcker criterion							
	ATA	CT	ITUA	KAAT	PEOU	PS	PU
ATA	0.760						

CT	0.570	0.773					
ITUA	0.495	0.595	0.842				
KAAT	0.358	0.376	0.362	0.861			
PEOU	0.345	0.534	0.423	0.212	0.869		
PS	0.463	0.561	0.515	0.287	0.380	0.823	
PU	0.381	0.389	0.384	0.589	0.244	0.303	0.856

Source: Author's own creation

Interpretation:

The values of all HTMT were considered to be below the criterion threshold of 0.85 except PU and KAAT whose value was 0.977, which required further studies. Fornell-Larcker criterion ensured discriminant validity and high correlation between PU and KAAT created an overlap of concepts.

4.2.3 Coefficient of Determination (R^2)

Table 3. Coefficient of Determination (R^2)

	R-square	R-square adjusted
ATA	0.301	0.295
CT	0.454	0.452
ITUA	0.369	0.363

Source: Author's own creation

Interpretation:

The R^2 of Attitude Towards Adoption (ATA), Consumer Trust (CT), and Intention to Use AI-enabled Digital Payments (ITUA) were 0.301, 0.454, and 0.369 respectively, and these are moderate predictors (Prairie, 1996). These values indicate that the antecedents are explaining about 30.1%, 45.4% and 36.9% variances in ATA, CT and ITUA respectively.

4.2.4 Effect Size (f^2)

Table 4. Effect Size (f^2)

	f-square
ATA -> CT	0.184
ITUA -> CT	0.237
KAAT -> ATA	0.001
KAAT -> ITUA	0.002
PEOU -> ATA	0.032
PEOU -> ITUA	0.072
PS -> ATA	0.123
PS -> ITUA	0.165
PU -> ATA	0.010
PU -> ITUA	0.008

Source: *Author's own creation*

Interpretation:

The f^2 value of ITUA on CT is 0.237, and that of ATA on CT is 0.184, demonstrates that these two variables actually have a positive contribution towards consumer trust in AI digital payments. On the other hand, perceived security provided significant effects on ATA (f^2 = 0.123) and on ITUA (f^2 = 0.165), therefore supporting its importance as a predictor of actual acceptance and intention (Gefen et al., 2003). Conversely, the effects of KAAT and PU on the constructs were very small and f^2 was nearly zero meaning that they have practically no effect in this situation.

4.2.5 Model Fit Evaluation

Table 5. Model Fit Evaluation

	Saturated model	Estimated model
SRMR	0.054	0.076
d_ULS	2.075	4.074
d_G	1.974	2.041
Chi-square	4017.494	4102.859
NFI	0.897	0.907

Source: Author's own creation

Interpretation:

SRMR of estimated model was 0.076 and 0.054 was of saturated model which fits better. It implies that the two models can be accepted as far as good fit, with the saturated model having a slight superiority in terms of the fit (Sivo et al., 2006; Hu and Bentler, 1999). In comparison to that, the values of d ULS and d G were found to be low (d ULS: 2.075 and 4.074; d G: 1.974 and 2.041), which points to a good fit of the model (Dijkstra and Henseler, 2015). Chi-square values were also high (4017.494 in the saturated model and 4102.859 in the estimated model), but it was claimed that they are not so significant in PLS-SEM due to the size of the sample and the complexity of the model (Hair and Alamer, 2022). The values of NFI were 0.897 (saturated) and 0.907 (estimated), which are beyond the standard cut-off point of 0.90 and enhance the acceptance of the model. Overall, it can be marked that model can be well-applied to the data, therefore, confirming the structural relationships provided in the research framework (Bentler and Bonett, 1980).

4.2.6 Path Coefficients Analysis

The research explains strength and direction of relationship between variables which are latent through path coefficient analysis in SEM. The importance of hypothesized paths is checked on the basis of β-values (regression weights), t-statistics and p-values (Grapentine, 2000).

Table 6. Path Coefficients

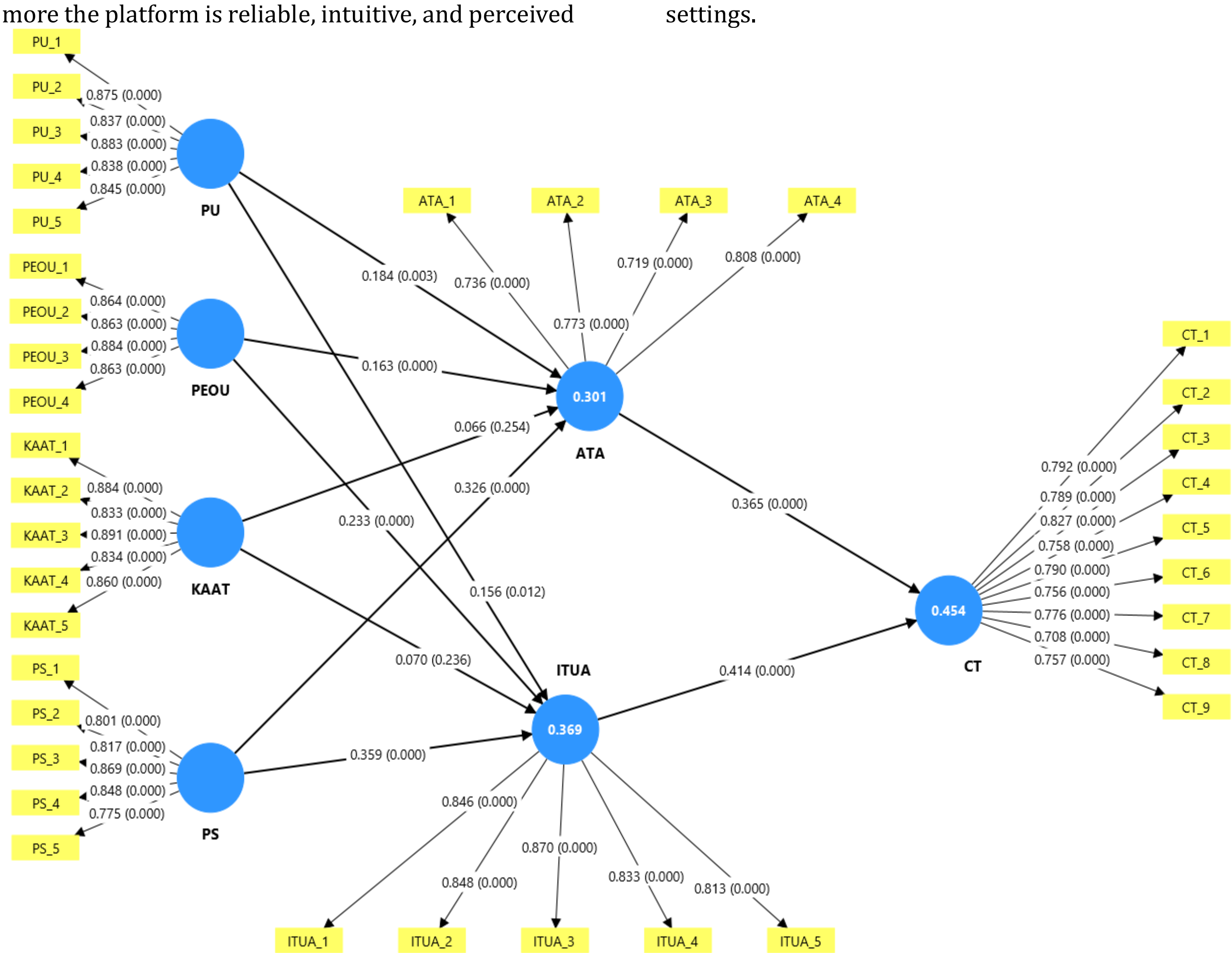
	Beta value	Mean (M)	Std Dev (STDEV)	T-Statistics (|O/STDEV|)	p- value
ATA -> CT	.365	.367	.045	8.139	.000
ITUA -> CT	.414	.415	.046	8.917	.000
KAAT -> ATA	.066	.066	.058	1.141	.254
KAAT -> ITUA	.070	.070	.059	1.186	.236
PEOU -> ATA	.163	.163	.044	3.707	.000
PEOU -> ITUA	.233	.233	.044	5.256	.000
PS -> ATA	.326	.329	.044	7.404	.000
PS -> ITUA	.359	.362	.049	7.375	.000
PU -> ATA	.184	.184	.062	2.957	.003
PU -> ITUA	.156	.155	.062	2.528	.012

Source: Author's own creation

Interpretation:

The path coefficients demonstrate all the important relations as the Intention to Use (ITUA) and Attitude Toward Adoption (ATA) have a strong impact on Consumer Trust (CT). Perceived Security has a positive impact on ATA and ITUA. Perceived ease of use & perceived usefulness also has some considerable impacts. But Knowledge and Awareness (KAAT) have no significant influences on ATA and ITUA which implies that knowledge alone cannot be effective without a working experience. The attitude and intention, and perceptions about the security, ease of use, and usefulness, therefore, constitute trust in AI-based payments (Choung et al., 2023; Kandoth and Shekhar, 2022).

Interpreted in terms of sustainable entrepreneurship, these results suggest that the concepts of trust and perceived security are important facilitators of the adoption of digital payment systems by rural microenterprises. The high impact of perceived security, ease of use, and usefulness on attitude and intention imply that the more the platform is reliable, intuitive, and perceived to be safe, the more likely are the rural entrepreneurs to adopt AI-based digital payments in their business. The meaninglessness of knowledge and awareness also suggests that it is not technical knowledge but practical usability and experience that causes entrepreneurship to be adopted. All these findings bring out the importance of AI-based digital payment systems in facilitating enterprise resilience, financial inclusion, and inclusive regional economic development in rural and emerging economy settings.



Source: Author's own creation

Figure 1. Measurement Model

4.2.7 Hypothesis Testing and Mediation Analysis

H1: Attitude towards Adoption (ATA) affects positively Consumer Trust (CT).

The analysis confirmed that a positive attitude towards adoption of AI-enabled digital payment systems leads to an increase in consumer trust ($\beta=0.365$, $p<0.001$).

H2: Intention to Use AI-based digital payments (ITUA) affects positively Consumer Trust (CT).

A firm intention to use AI-enabled digital payment services substantially fosters the building of consumer trust ($\beta=0.414$, $p<0.001$).

H3: Knowledge and Awareness of AI Technology (KAAT) positively affect Attitude towards Adoption (ATA).

Contrary to theoretical postulations, the relationship between awareness of AI applications and attitudes toward the adoption was probed and found to be statistically insignificant ($\beta = 0.066$, $p = 0.254$).

H4: Knowledge and Awareness of AI Technology (KAAT) positively affect Intention to Use AI-based payments (ITUA).

Knowledge and awareness do not seem to have a direct impact on the intention to use AI-enabled payments, paralleling the prior hypothesis (β = 0.070, p = 0.236).

H5: Perceived ease of use (PEOU) positively influences attitude toward adoption (ATA).

Ease of use has a significant influence on users' feeling toward adopting AI-based digital payments (β = 0.163, p < 0.001).

H6: Intention to Use (ITUA) is positively affected by Perceived Ease of Use (PEOU).

Users' stronger intention to adopt AI-based digital payments is accounted for by bargaining with an easy interface and intuitive interaction (β = 0.233, p < 0.001)

H7: Perceived Security (PS) positively influences Attitude towards Adoption (ATA).

Perceived security was found affecting consumers' attitude towards adoption of digital payment system (β = 0.326, p < 0.001). The greater the perception of safety and data protection in an AI-enabled transaction, the more the individual attitudes of acceptance toward such systems.

H8: Perceived Security (PS) positively influences Intention to Use (ITUA).

Security concerns significantly affect how one intends to behave (β = 0.359, p < 0.001). In adopting rural digital payment, trust in the safety of system encourages the users to actively choose AI-based platforms, pertaining to the provision of strong cyber protections and user confidence.

H9: Attitude towards Adoption (ATA) is positively affected by Perceived Usefulness (PU).

The more useful individuals see AI-enabled digital payments (e.g., saving time or buying accuracy), the more positively they view adopting them (β = 0.184, p = 0.003).

H10: Intention to Use (ITUA) is positively affected by Perceived Usefulness (PU).

The belief among users that AI-based digital payments are efficient and effective makes them more likely to express the intent to use them (β = 0.156, p = 0.012).

In a sustainable entrepreneurship context, the hypotheses supported by them all show that the attitude, intention, trust, perceived security, and usability are the predetermined factors of rural entrepreneurial adoption of AI-based digital payment systems. These constructs are strongly and significantly related, indicating that the rural microenterprises and informal entrepreneurs will be more inclined to incorporate digital payments into their business operations when the platform is perceived as secure, useful, and easy to operate. The fact that knowledge and awareness are not significant further supports the fact that the driving forces of adoption in the cases of entrepreneurship are not the technical familiarity but the experiential confidence and operational reliability. The results of these findings highlight the applicability of the hypotheses under test to the study of the role of digital payment adoption in financial inclusion, enterprise resilience, and economic participation sustainability in rural and emerging economy environments.

4.2.8 Mediation Analysis

Table 7. Total Effects

Total effects					
	Original-Sample (O)	**Sample-mean (M)**	**Std. Dev. (STDEV)**	**T-Statistics (|O/STDEV|)**	**P values**
ATA -> CT	0.365	0.367	0.045	8.139	0.000
ITUA -> CT	0.414	0.415	0.046	8.917	0.000
KAAT -> ATA	0.066	0.066	0.058	1.141	0.254
KAAT -> CT	0.053	0.054	0.039	1.361	0.173
KAAT -> ITUA	0.070	0.070	0.059	1.186	0.236
PEOU -> ATA	0.163	0.163	0.044	3.707	0.000
PEOU -> CT	0.156	0.157	0.030	5.237	0.000
PEOU -> ITUA	0.233	0.233	0.044	5.256	0.000
PS -> ATA	0.326	0.329	0.044	7.404	0.000

PS -> CT	0.268	0.271	0.032	8.307	0.000
PS -> ITUA	0.359	0.362	0.049	7.375	0.000
PU -> ATA	0.184	0.184	0.062	2.957	0.003
PU -> CT	0.132	0.132	0.041	3.245	0.001
PU -> ITUA	0.156	0.155	0.062	2.528	0.012

Source: Author's own creation

Interpretation:

CT is highly affected by ATA and ITUA ($\beta = 0.365$, $p < 0.001$; $\beta = 0.414$, $p < 0.001$). PEOU, PS and PU mediate CT indirectly and directly, implying their partial mediation. Thus, KAAT is not an intermediary of trust because it is not assigned any signification in the statistical perspective. These outcomes indicate that the formation of the attitude and intention towards rare has a more significant impact on the trust in the AI-based digital payment systems. The ease of use, usefulness and security have a role to play in establishing trust particularly in digital financial inclusion in rural India.

5. DISCUSSION

The research identifies important psychological and behavioural factors that determine consumer trust in AI-based system payment modes of transaction in rural India. This paper has determined that Attitude Towards Adoption (ATA) and Intention to Use AI (IUA) have the greatest impact on Consumer Trust (CT) and that trust blossoms to a large extent on psychological preparedness and willingness of the users to adopt AI. Perceived security was among the most important factors as it had a valuable influence on trust by itself directly and indirectly via attitude and intention. A secure AI platform gives a sense of safety; this is in line with the fact that security is a valuable parameter in the adoption of the digital technologies (Gefen et al., 2003).

There were also other factors that may have impacted on consumer trust indirectly, and these were PEOU and PU, primarily via attitude and intention. The results confirm the assumptions of Technology Acceptance Model (Davis and others, 1989), which means that users believe in AI-based payment systems as they believe that they are convenient to use and that it is worth being used. Quite to the contrary, it appears that KAAT had no real effect on trust, whether directly or via mediators, to any significant degree. This can imply that awareness can be not enough to create trust and behavioural intention unless some value perception, experience, or usability element gets into the picture (Venkatesh et al., 2012).

In the sustainable entrepreneurship perspective of the findings, it suggests that the trust, perceived security, and usability are not just drivers of adoption but enabling factors of rural entrepreneurship. In the case of rural microenterprises, informal entrepreneurs, and people who do not work, AI-based digital payment systems support the most critical business processes, including the management of daily operations, customer payments, and financial sustainability. The significant role of attitude and intention on trust implies that entrepreneurial adoption is defined by the trust in the reliability of operations, which supports the role of secure and convenient digital payment infrastructure in maintaining business operations and entrepreneurial ecosystems in rural settings (Ahlstrom et al., 2007; Audretsch and Belitski, 2017).

Regarding a larger sustainability and regional development view, the findings point to the importance of AI-driven digital payment systems to promote the development of financial inclusion, decreased cash dependency, and stable rural economic ecosystems in emerging Asian economies. Accessible and secure fintech-based payment systems facilitate transparency, effectiveness, and inclusion of rural entrepreneurs in formal financial systems, which enhances access to financial services and credit facilities (Beck et al., 2008; Taherdoost, 2023). Such dynamics help to achieve inclusive growth and innovation diffusion, making AI-based digital payments a vital entrepreneurial infrastructure to help to become an economic participant over the long term and develop sustainably in rural and resource-constrained settings (Audretsch and Belitski, 2017; Ahlstrom et al., 2007).

6. CONCLUSION

This study examines consumer confidence in AI-powered digital payment systems, and rural adoption in India has been infrastructural or psychological. Within an extended Technology Acceptance Model, this proposed model incorporated such constructs as Perceived Security, Perceived Usefulness, Perceived Ease of Use, Knowledge and Awareness of AI, Attitude Towards Adoption, as well as Intention to Use. The results indicated that Attitude Towards Adoption and Intention to Use have a direct impact on trust. Trust is mediated by Perceived Security, Perceived Ease of

Use, and Perceived Usefulness, but not by Knowledge and Awareness of AI, meaning that being aware of AI does not cause one to be confident in these types of technologies. The mediation analysis emphasized that development of trust must have a user experience and clear perception. Therefore, the problem of AI digital payment systems is more of a psychological, perception and experience problem than a technology problem. In the case of rural regions, security, ease, and usability are required to form negative attitudes and intentions toward digital financial inclusion. In a more general entrepreneurship and sustainability sense, the results show that AI-based digital payment systems go beyond the individual consumer level of usage to serve as an essential infrastructure of sustainable rural entrepreneurship and microenterprise involvement. Such platforms facilitate informal entrepreneurs, small businesses and self-employed people to become part of formal financial systems, thus enhancing financial inclusion and resilience of businesses, by allowing them to conduct safe, efficient and accessible financial transactions. The creation of reliable and convenient AI-based digital payment infrastructure in emerging Asian settings can support sustainable economic growth in the region, decrease cash reliance, and enhance economic stability in the region in the long term, which makes the strategic significance of digital payments in the promotion of sustainable rural development.

Contribution of the Authors

This manuscript's conception, methodology, data collecting, analysis, and writing were all contributed by writers. Before submitting the manuscript, she also checked and verified it.

Conflict of Interest

The authors declare that there is no conflict of interest in regard to publishing this paper.

Funding Acknowledgments

No specific grants from governmental, private, or nonprofit funding organisations have been awarded for this study.

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