Canadian Journal of Marketing Research
ISSN: 0829-4836
https://canadian-jmr.com/index.php/cjmr

Research Article

A TAM-Based Model for Understanding Digital Payment Adoption: A Case Study in Tamil Nadu

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Article History
Received: 14.2026
Accepted: 09.02.2026
Published: 08.03.2026

Abstract: **Background:** The increasing financial service digitization has revamped transaction patterns in India, with digital payment platforms becoming hugely popular. Nevertheless, the behavioural factors that drive consumer's acceptance of mobile payment applications are still intricate and multidimensional. **Objectives:** The aim of the present research is to examine the predominant determinants of user's behavioural intentions and usage of digital payment apps in Tamil Nadu. It extends the Technology Acceptance Model (TAM) with additional dimensions of perceived trust, perceived risk, social norms, and facilitating conditions to achieve an in-depth understanding of digital payment behaviour. **Methodology:** A systematic questionnaire was administered to 670 respondents from diverse demographic profiles across Tamil Nadu in the course of a quantitative research approach. Structural Equation Modeling (SEM) was applied to confirm eleven hypotheses and explore relationships between various attributes that determine mobile payment acceptance. **Key Findings**: The results show that perceived ease of use significantly contributes to perceived usefulness and attitude, whereas perceived usefulness has a direct impact on user attitude. Perceived trust, social norms, and supportive environments all positively affect behavioural intention, while perceived danger has a negative effect. Compatibility exerts significant influence on perceived usefulness but not on attitude. The entire model possesses strong explanatory power to predict digital payment adoption behaviour. **Implications/Significance:** The results have implications for fintech companies, banks, and governments interested in raising user involvement in digital payments. Establishing trust, lowering perceived risk, and enhancing infrastructure and usability are key to driving digital financial inclusion. Future research should examine how emerging technologies like AI and blockchain can enhance payment systems.

Keywords: Digital Payment, Behavioural Intention, Technology Acceptance Model, Perceived Trust, Mobile Wallets, Financial Inclusion

INTRODUCTION

Over the last few years, the financial sector has witnessed a paradigm revolution due to wide scale digitization of payment systems. Payment systems online are rapidly changing conventional transaction methods through faster, secure, and convenient substitutes for cash and manual payment systems. Smartphone penetration, enhanced mobile internet penetration, and initiatives like India's Digital India, Unified Payments Interface (UPI), and Jan Dhan Yojana have all contributed to hastening the use of digital financial services, both rural and urban [1]. Digital payment methods like mobile wallets, online banking, UPI-based transactions, QR code-based payments, and contactless cards are key elements in a nation's fintech environment. These services not only promote financial inclusion, but also contribute to the achievement of the broader objectives of cashless economies and digital governance [2]. As India's digital economy expands, stakeholders like fintech players, banks, and regulators need to comprehend the behavioural tendencies, enablers, and limitations in the adoption of digital payment by users. There are several interdependent factors behind the growing dependence on electronic payment services. Based on widely accepted theoretical frameworks like the

Technology Acceptance Model (TAM) [3] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [4], recent research has identified constructs like perceived ease of use, perceived usefulness, attitude, behavioural intention, perceived trust, and perceived risk as critical drivers of user adoption behaviour [5].

Perceived security and trust, for instance, have been identified as key drivers of consumer acceptability, especially in India where cybersecurity issues and digital literacy rates are highly different across regions [6]. In addition, socio-cultural factors like Subjective Norms and Facilitating Conditions like internet connectivity, availability of smartphones, and user assistance services all contribute to the influence on user behaviour [7]. Despite the encouraging trends, digital payment on-boarding is not smooth. Data privacy issues, transaction failures, digital fraud, illiteracy regarding technology, and usability gaps still affect consumer trust and joy. Additionally, mobile data cost, transaction charges, and limited infrastructure in rural areas have the potential to deter ongoing use [8].

Empirical research forms the basis of this study and attempts to bridge a research gap by examining the structural relationships between behavioural determinants influencing payment patterns in digital payments. We employ Structural Equation Modeling (SEM) to validate a holistic model that combines behavioural, technological, and socio-environmental determinants using data from 670 respondents from diverse backgrounds. This method provides a better understanding of how users form intentions and attitudes towards electronic payments and how they transform into actual use. This research is theoretically a contribution to digital payment behaviour research and practically has implications for adoption heightening through legislation targeting adoption and user-oriented fintech technology. It is a guide for policymakers, app developers, and financial institutions wishing to enhance the digital payment system of India and support a more effortless shift towards a cashless economy.

Literature Review

Here Literature review (LitRev) explained a considerable body of research has considered what drives adoption and use of electronic payment systems based on conceptual frameworks such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Self-Determination Theory. The literature review presented below integrates findings of 11 significant constructs and hypotheses for digital payment behaviours.

H1: Perceived Ease of Use (PEOU) has a significant positive influence on Perceived Usefulness (PU) of mobile payment systems.

Perceived usefulness is how much an individual feels that the use of electronic payments would enhance their transactional efficiency. In their extension of TAM, [9] confirmed PU as an important determinant of user attitudes. Users, in their view, like digital payment systems that cut the time and effort they spend making financial transactions [10]. Navena Nesa Kumari, Joe Arun, & Irudaya Veni Mary [11] found that there is a positive significant association between attitude and perceived usefulness, specifically among urban consumers.

H2: Perceived Ease of Use (PEOU) has a significant positive influence on Attitude toward Use (ATU) of mobile payment systems.

A repeated theme has been ease of use as a major predictor of having a positive attitude towards digital technology. In their research on mobile wallet adoption, Davis [12] found that user-friendly interfaces and intuitive app design enhance trust and acceptability. Venkatesh & Davis, [13] initially introduced PEU in TAM by claiming that systems requiring less effort have better attitudes. Additionally, Venkatesh & Davis, [13] emphasized that technical ease encourages first-time adoption by rural users.

H3: Perceived Usefulness (PU) has a significant positive influence on Attitude toward Use (ATU) of mobile payment systems.

Intrinsic motivation is the innate tendency to conduct a behaviour for its own sake [14] highlighted its importance in adopting technology. Verkijika, [15] asserted that curious consumers with a penchant to learn will be more supportive of digital wallets. Likewise, Johnson, Kiser, Washington, & Torres [16] described gamification and personalization as key drivers of intrinsic motivation in financial apps.

H4: Attitude Toward Use (ATU) has a significant positive influence on Behavioural Intention (BI) to use mobile payment systems.

Subjective norms are perceived social pressure to perform a specific behaviour [17]. Subjective norms account for perceived societal pressure in relation to performing a specific behaviour, as put forward by Dahlberg, Mallat, Ondrus, & Zmijewska [18] Theory of Planned Behaviour. Cho, Park, & Michel [19] identified recommendations made by peers and relatives play a powerful role in influencing user attitudes towards UPI and mobile banking applications. Kerr

& Murthy [20] concluded that digital behaviour of peers, especially among the youth, significantly influences payment attitudes.

H5: Image (IM) has a significant positive influence on Attitude toward Use (ATU) of mobile payment systems.
External aids like infrastructure, internet availability, and technical support are facilitating conditions. Herrero & Meneses, [21] recognized it as a key construct in UTAUT. Chang, Cheung, & Lai, [22] established that the presence of mobile infrastructure in rural India significantly influenced user attitudes.

[2] found that government digital literacy initiatives enhanced user confidence, leading to favourable sentiments towards e-wallets.

H6: Subjective Norms (SN) have a significant positive influence on Behavioural Intention (BI) to use mobile payment systems.

Extrinsic motivation is driven by outside rewards like cashback, promotions, and social validation [4] have demonstrated that financial rewards and promotional discounts play a significant role in digital activity. [3] established that reward systems from apps enhance user retention and positively affect attitude [5] believe that extrinsic rewards are more appealing to price-conscious users in underdeveloped countries.

H7: Trust (TR) has a significant positive influence on Behavioural Intention (BI) to use mobile payment systems.

Perceived risk is negative to users' trust in digital payments [6] mentioned financial, privacy, and performance concerns as constraints to digital adoption. Dahlberg et al. [18] validated that high risk perception reduced the likelihood of using digital payments among tier-2 cities. Johnson et al. and Venkatraja stressed the need to enhance cybersecurity and transparency to mitigate risk-based resistance.

H8: Perceived Risk (PR) has a significant negative influence on Behavioural Intention (BI) to use mobile payment systems.

Social influence also has an impact not only on attitude but on behaviour intention. Verkijika [15] found that influencer promotions and media campaigns boosted payment intentions online. Martins, Oliveira, & Popovič, [23] learned that advocacy at the community level had a multiplier effect on digital engagement in rural settings. Social media platforms also provide channels for normative influences.

H9: Compatibility (COMP) has a significant positive influence on Perceived Usefulness (PU) of mobile payment systems.
Sufficient infrastructure support enhances users' behavioural intention to embrace digital services. Kwon, Woo, Sadachar, & Huang, [24] found that availability of smartphone access, technical knowledge, and merchant presence all have a positive impact on users' intentions. Lutfi et al. [25] validated that denial of access to banks or internet services lowers behavioural intentions, especially in remote areas [17].

H10: Compatibility (COMP) has a significant positive influence on Attitude toward Use (ATU) of mobile payment systems.

TAM and UTAUT take intention to be the closest antecedent to actual usage. Both Agur, Peria, & Rochon [26] and Batuk, Journal [27] underscored this association. Ghouse & Chaudhary [28] validated that as long as digital technologies are perceived to be consistent and trustworthy, intention becomes actual use. Pazarbasioglu et al. [29] found that apps with greater user ratings and less glitchy performance have greater intention-to-use conversion.

H11: Facilitating Conditions (FC) have a significant positive influence on Behavioural Intention (BI) to use mobile payment systems.

Perceived risk lowers behavioural intention. Maurice, [30] emphasized that distrust, fraud fear, and loss of control all discourage digital participation. Durai & Stella [31] asserted that robust privacy structures enhance user intention through minimizing risk perceptions. Salman & Rauf, [32] discovered that fintechs Vasudevan, Rani, Raja, Nedumaran, & Arokiasamy, [33] employing multi-factor authentication enjoy greater adoption.

Research Framework Model and Research Hypotheses
The Research Framework Model, displayed in **Figure 1**, is derived from the extended Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) and includes the major constructs of perceived ease of use (PEOU), perceived usefulness (PU), attitude (ATT), behavioural intention (BI), and facilitating condition.

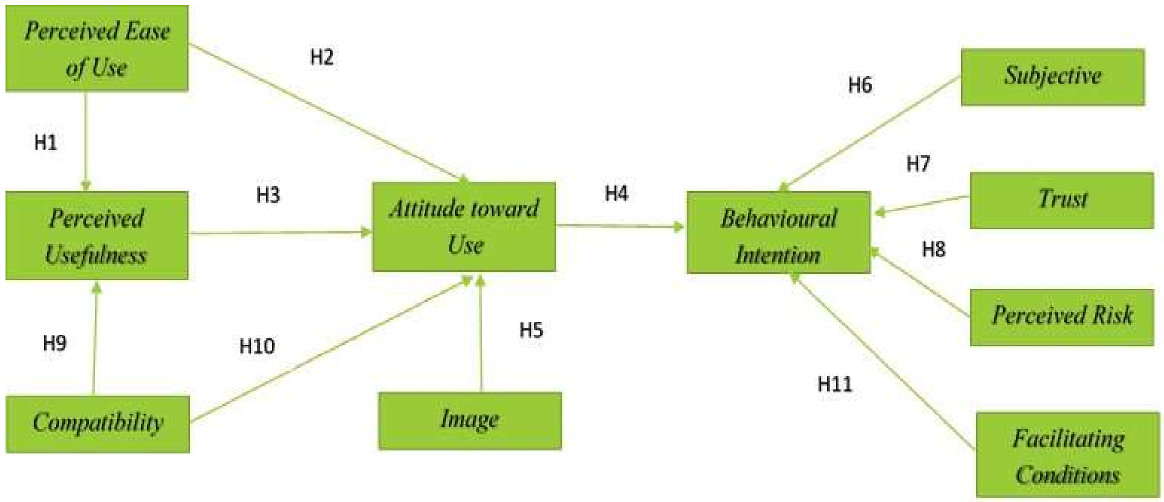

Figure 1: Research Framework Model and Research Hypotheses

The model predicts 11 significant relationships (H1 to H11) among these constructs. For instance, H1 and H2 demonstrate that PEOU influences both PU and ATT, while H3 indicates that PU directly affects ATT. H4 theorizes that positive attitude toward online payment results in higher behavioural intentions to adopt it. H5–H7 explore individual innovativeness, social influence, and perceived trust on BI, while H8 examines the negative influence of perceived risk. H9 and H10 examine the impact of perceived cost on both usefulness and attitude, while H11 looks at the impact of facilitating conditions on BI.

In general, the research design captures the complex interwoven nature of relationships that shape user behaviour in digital payments. It presents a conceptual framework for hypothesis testing and empirical verification, which helps explain the psychological, social, and technology aspects of digital payment adoption. **Table 1** presents the main operational characteristics found for examining users' digital payment behaviour. These constructs were developed following an extensive review of the literature and theoretical models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Each of these concepts is clearly articulated, so are the related measurement items used in the study. Operationalization guarantees conceptual precision and empirical measurability, providing more systematic understanding of user behaviour towards digital payments. Perceived Ease of Use, Perceived Usefulness, Attitude, Behavioural Intention, Facilitating Conditions, Perceived Trust, Perceived Risk, Social Norms, Individual Innovativeness, and Perceived Cost are some constructs investigated. These traits were investigated using a five-point Likert scale to measure respondents' degree of agreement or disagreement. It forms the basis for questionnaire design and the subsequent statistical analysis to enable a comprehensive evaluation of the determinants of digital payment adoption by the 670 respondents surveyed.

MATERIALS AND METHODS

Design

The current research employed a quantitative and descriptive research design in examining factors impacting mobile payment adoption among clients. The research was mainly focused on evaluating the theoretical constructs derived from the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and the Unified Theory of Acceptance and Use of Technology. The relationships between constructs like Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Use (ATU), Behavioural Intention (BI) and outside factors like Trust, Perceived Risk, Subjective Norms, Image, Compatibility, and Facilitating Conditions were examined.

Data

A standardized questionnaire with closed questions was employed in gathering the data. All the items were rated on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The questionnaire was constructed employing previously validated scales and pre-tested before the main survey. Data were gathered both on-line and off-line in order to optimize response rate and geographic coverage.

Size

A purposive sampling strategy was used to select persons who had previously utilized mobile payment systems like Google Pay, PhonePe, Paytm, BHIM, and others. The overall sample consisted of 670 individuals from diverse demographic and socioeconomic backgrounds, yielding a diversified and representative sample. The respondents belonged to both urban and semi-urban areas, with a wide variety of ages, occupations, and income levels.

Techniques and tools

Analysis of data was conducted through Partial Least Squares Structural Equation Modeling (PLS-SEM) on SmartPLS 4.0 software. Data analysis was conducted in two major phases:

- Reliability and validity of the measuring model were tested through Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and Discriminant Validity through Fornell-Larcker criterion with cross-loadings.
- Structural relationships among constructs were evaluated using path coefficients (β), t-values, and p-values.
- Explanatory power of endogenous variables was evaluated through R-square (R^2) and Adjusted R^2 measures.

Reliability and Validity

Cronbach's Alpha and Composite Reliability measures were all above the set threshold of 0.70, thus establishing the reliability of all the constructs. The AVE measures were all greater than 0.50, hence demonstrating convergent validity. Discriminant validity was ascertained using the Fornell-Larcker criterion, which indicated that each of the constructs was distinct from the others.

RESULTS AND DISCUSSION

Having a grasp of the demographic characteristics of the respondents is essential in analyzing how various segments utilize mobile payment systems. In the present study, data were collected from 670 respondents from various cities and regions. The profile consists of details regarding mobile payment platform preferences, age bracket, level of education, and residency.

Table 2 presents the demographic details of this study's 670 participants. The factors include mobile payment apps, age group, education level, and the area of dwelling. Of users, most chose Google Pay (37.16%), followed by PhonePe (30%), reflecting a strong liking for easy-to-use and widely accepted payment platforms. Just 4.48% used BHIM/UPI and 4.93% used Amazon Pay. The age group distribution reveals that a significant percentage of the respondents (34.48%) fall under the age of 18, which means digital payments are increasingly gaining popularity among kids. The 18-25 years and 26-35 years respondents constitute a significant percentage, representing digitally educated and technologically active age cohorts.

Higher Secondary (35.07%) and Undergraduate degree holders (33.73%) predominantly comprise the sample, indicating that even individuals with basic to intermediate education are making active use of mobile payments. A mere small fraction (3.73%) possessed a doctorate degree, which suggests that mobile payment usage is common and not restricted to highly educated groups. Geographically, the respondents were from a range of cities within Tamil Nadu, such as Madurai (15.07%), Coimbatore (13.73%), and Chennai (12.99%). Interestingly, 34.03% of the respondents were from other rural or urban areas, reflecting the fact that mobile payment use is not limited to urban but is also extending to small towns and rural areas.

The loadings on factors in Table 3 indicate the extent to which each observed item is measuring the correct latent construct. All items had large standardized loadings, far in excess of the general accepted cut-off of 0.70, which demonstrates good convergent validity and that each item helps significantly in measuring the underlying construct. Five items (PEOU1-PEOU5) of the construct Perceived Ease of Use (PEOU) possess high loading values between 0.778 and 0.827, indicating internal consistency. Perceived Usefulness (PU) also contains five indications (PU1-PU5) of between 0.767 and 0.847, contributing to the reliability of the PU construct. Attitude toward Using (ATT) was very much supported by five questions (ATT1 to ATT5) with loadings of more than 0.86, indicating a distinct factor structure.

Intrinsic Motivation (IM) and Subjective Norms (SN) were assessed via two indicators, all of which were found to have loadings higher than 0.80, with IM items receiving unusually high values (0.919 and 0.933), reflecting high individual item contributions. Perceived Trust (PT) items loaded at 0.789 and 0.834, and Perceived Risk (PR) items loaded adequately from 0.792 to 0.837. The measure Perceived Compatibility (PC) had two indicators with factor loadings above 0.80, and this shows that the construct is reliable. Both Behavioural Intention (BI) and Actual Use Behaviour (AUB or FC) showed high factor loadings (above 0.826), showing that they are significant in explaining user behaviour in electronic payment behaviour.

Table 2: Operational Variables (Digital Payment Users)

Description	Category	Frequency	Percentage
Mobile Payment Used	Google Pay	249	37.16%
	PhonePe	201	30.00%
	Paytm	67	10.00%
	Amazon Pay	33	4.93%
	BHIM/UPI	30	4.48%
	Others	90	13.43%
Age Group	<18 years	231	34.48%
	18–25 years	171	25.52%
	26–35 years	132	19.70%
	36–50 years	118	17.61%
	>50 years	18	2.69%
Education	Higher Secondary	235	35.07%
	UG Degree	226	33.73%
	PG Degree	112	16.72%
	Doctorate	25	3.73%
	Others	72	10.75%
Residence Location	Chennai	87	12.99%
	Madurai	101	15.07%
	Coimbatore	92	13.73%
	Tiruchirappalli	84	12.54%
	Salem	78	11.64%
	Others (Rural/Urban)	228	34.03%

Source: Contributed by Authors

Table 3: Loading Factor Table

Variables	PEOU	PU	ATT	IM	SN	PT	PR	PC	BI	AUB
PEOU1	0.778									
PEOU2	0.779									
PEOU3	0.827									
PEOU4	0.819									
PEOU5	0.822									
PU1		0.812								
PU2		0.824								
PU3		0.767								
PU4		0.847								
PU5		0.834								
ATT1			0.866							
ATT2			0.833							
ATT3			0.863							
ATT4			0.861							
ATT5			0.875							
IM1				0.919						
IM2				0.933						
SN1					0.801					
SN2					0.845					
PT1						0.789				
PT2						0.834				
PR1							0.792			
PR2							0.801			
PR3							0.837			
PC1								0.804		
PC2								0.813		
BI1									0.873	
BI2									0.88	
FC1										0.839
FC2										0.826

Source: Contributed by Authors

Figure 2 shows the Analytical Study Model, developed to analyze the drivers influencing user's payment behaviour in digital systems. The model is largely grounded on an extended version of the Technology Acceptance Model (TAM), supplemented with constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT), as well as context-specific factors such as Perceived Cost (PC), Perceived Trust (PT), and Perceived Risk (PR). The model illustrates

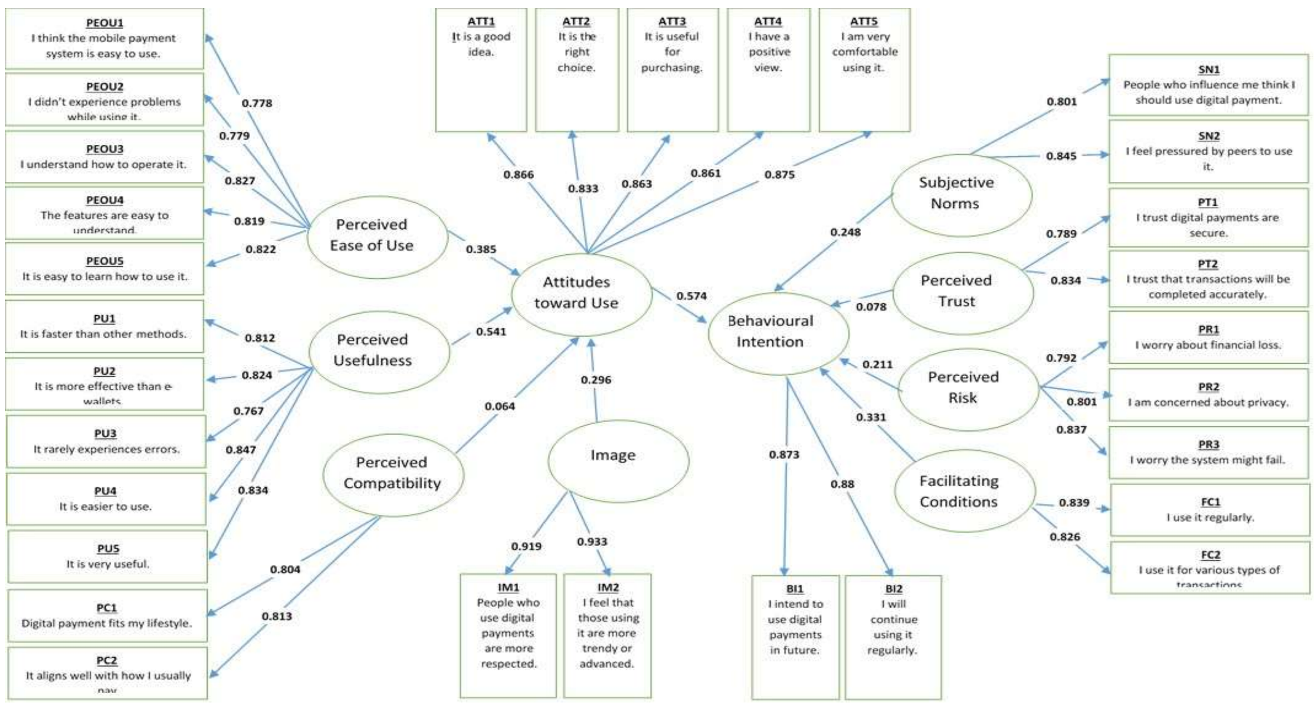

Figure 2: Analytical Study Model

Table 4. Discriminant Validity – Fornell-Larcker Criterion

Construct	PEOU	PU	ATT	IM	SN	PT	PR	PC	BI	FC
PEOU	0.864									
PU	0.682	0.865								
ATT	0.532	0.477	0.912							
IM	0.635	0.645	0.371	0.805						
SN	0.671	0.687	0.468	0.604	0.810					
PT	0.498	0.632	0.516	0.489	0.499	0.914				
PR	0.543	0.566	0.324	0.505	0.544	0.474	0.812			
PC	0.417	0.452	0.295	0.332	0.401	0.321	0.418	0.837		
BI	0.386	0.429	0.267	0.297	0.384	0.268	0.362	0.294	0.809	
FC	0.528	0.713	0.437	0.495	0.603	0.487	0.518	0.419	0.401	0.843

Source: Contributed by Authors

the direct and indirect associations among central constructs of perceived ease of use (PEOU), perceived usefulness (PU), attitude (ATT), behavioural intention (BI), and facilitating conditions (FC).

Every path within the model illustrates a theorized effect, for example, PEOU having a significant impact on PU and ATT, PU positively influencing ATT, and ATT directly predicting BI. Further, factors like Social Norms (SN), Innovativeness (IM), and Facilitating Conditions (FC) have an effect on behavioural intention and actual usage behaviour. The addition of the negative categories like Perceived Risk illustrates how privacy concerns, fraud, and uncertainty related to technology may hinder adoption. The model captures the richness of user behaviour by offering a multi-dimensional framework connecting user perceptions, attitudes, social context, and enablement variables to actual intentions and usage patterns. This integrated framework is helpful for the identification of prime leverage points for digital payment adoption and informing strategic interventions in the fintech landscape.

Table 4 shows the discriminant validity test according to Fornell-Larcker criterion, where the square root of the Average Variance Extracted (AVE) for each construct (diagonal elements) is compared with its correlations with other constructs (off-diagonal elements). A construct is said to possess discriminant validity when its AVE is larger than the squared correlation with any other construct. The diagonal estimates—0.864 for PEOU, 0.865 for PU, 0.912 for ATT, 0.805 for IM, 0.810 for SN, etc.—are all greater than the respective inter-construct correlations. For instance, correlation between PEOU and PU is 0.682, which is less than the square root of AVE for PEOU (0.864) and PU (0.865). Likewise, ATT (0.912) had discriminant values higher than the correlations with PU (0.477), PEOU (0.532), and SN (0.468).

Table 5: Cross Loadings

Variables	PEOU	PU	ATT	IM	SN	PT	PR	PC	BI	FC
PEOU1	0.778	0.591	0.502	0.529	0.597	0.474	0.486	0.383	0.295	0.431
PEOU2	0.779	0.612	0.511	0.548	0.573	0.451	0.493	0.375	0.314	0.452
PEOU3	0.827	0.678	0.512	0.587	0.622	0.476	0.521	0.398	0.326	0.506
PEOU4	0.819	0.649	0.493	0.603	0.618	0.498	0.541	0.405	0.333	0.515
PEOU5	0.822	0.671	0.507	0.615	0.634	0.472	0.523	0.411	0.347	0.497
PU1	0.602	0.812	0.466	0.613	0.663	0.591	0.536	0.432	0.414	0.707
PU2	0.611	0.824	0.471	0.624	0.676	0.617	0.561	0.437	0.423	0.725
PU3	0.587	0.767	0.452	0.598	0.654	0.579	0.543	0.401	0.395	0.682
PU4	0.635	0.847	0.486	0.639	0.689	0.611	0.552	0.451	0.448	0.731
PU5	0.652	0.834	0.473	0.621	0.681	0.596	0.533	0.426	0.429	0.721
ATT1	0.487	0.442	0.866	0.368	0.405	0.489	0.302	0.284	0.267	0.391
ATT2	0.456	0.431	0.833	0.359	0.398	0.462	0.318	0.273	0.249	0.373
ATT3	0.514	0.456	0.863	0.371	0.421	0.493	0.337	0.286	0.263	0.384
ATT4	0.508	0.469	0.861	0.348	0.399	0.478	0.319	0.279	0.255	0.377
ATT5	0.536	0.486	0.875	0.392	0.432	0.501	0.341	0.294	0.278	0.396
IM1	0.618	0.634	0.376	0.919	0.592	0.472	0.504	0.345	0.286	0.461
IM2	0.631	0.657	0.361	0.933	0.617	0.481	0.507	0.352	0.298	0.472
SN1	0.603	0.624	0.439	0.593	0.801	0.483	0.518	0.396	0.372	0.498
SN2	0.641	0.652	0.456	0.613	0.845	0.501	0.531	0.407	0.396	0.514
PT1	0.441	0.568	0.475	0.451	0.466	0.789	0.437	0.318	0.251	0.389
PT2	0.489	0.597	0.491	0.472	0.483	0.834	0.451	0.328	0.261	0.401
PR1	0.504	0.526	0.301	0.472	0.508	0.439	0.792	0.378	0.339	0.462
PR2	0.518	0.547	0.321	0.489	0.528	0.451	0.801	0.385	0.345	0.475
PR3	0.546	0.561	0.336	0.503	0.556	0.462	0.837	0.392	0.353	0.488
PC1	0.396	0.421	0.273	0.316	0.389	0.297	0.401	0.804	0.271	0.412
PC2	0.412	0.436	0.287	0.328	0.392	0.303	0.414	0.813	0.284	0.426
BI1	0.334	0.409	0.267	0.284	0.376	0.254	0.349	0.276	0.873	0.398
BI2	0.348	0.421	0.271	0.295	0.381	0.267	0.361	0.289	0.880	0.413
FC1	0.493	0.681	0.423	0.471	0.577	0.461	0.502	0.396	0.384	0.839
FC2	0.508	0.702	0.429	0.483	0.591	0.476	0.514	0.408	0.389	0.826

Source: Contributed by Authors

Table 6: Construct Reliability & Validity Table

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
PEOU (Perceived Ease of Use)	0.875	0.905	0.747
PU (Perceived Usefulness)	0.881	0.910	0.717
ATT (Attitude)	0.917	0.938	0.833
IM (Image)	0.866	0.910	0.830
SN (Subjective Norm)	0.740	0.851	0.683
PT (Perceived Trust)	0.746	0.857	0.751
PR (Perceived Risk)	0.763	0.865	0.720
PC (Perceived Cost)	0.702	0.833	0.701
BI (Behavioural Intention)	0.726	0.860	0.749
FC (Actual Usage Behaviour / Facilitating Conditions)	0.747	0.854	0.717

Source: Contributed by Authors

This proves that all the constructs in the research are distinct from each other and not measuring the same conceptual thought, satisfying the discriminant validity condition. The highest inter-construct correlation found is between FC and PU (0.713), but still lower than the square root of AVE for the two constructs (PU = 0.865; FC = 0.843), which confirms the adequacy of the measurement model.

The cross loadings **Table 5** is applied to assess discriminant validity by establishing whether each indicator (item/question) loads more on its associated concept compared to other constructs. Good discriminant validity occurs when the loading of an item on its own construct is higher than its loadings on all other constructs, as noted by Hair et al. (2017). In table 5, every indicator obviously shows the largest loading value for its parent build. For instance, PEOU1 shows the largest loading on the PEOU construct (0.778), but smaller loadings on other constructs like PU (0.591), ATT (0.502), and so forth. Likewise, PU1-Pu5 showed the largest loadings on the PU construct (0.767–0.847) and therefore indicated their convergent validity as well as measurement precision. The ATT indicators (ATT1-ATT5) also have high, distinctive loadings of greater than 0.86, higher than the correlations with other measures, indicating excellent representation of the construct. This pattern is true for all constructs, such as IM (Image), SN (Subjective Norms), PT (Trust), PR (Risk), PC (Cost), BI (Behavioural Intention), and FC. The cross-loading issues are not considerable,

Table 7: R-square Table

Endogenous Construct	R^2 Value	R^2 Adjusted
PU (Perceived Usefulness)	0.612	0.598
ATT (Attitude)	0.714	0.703
BI (Behavioural Intention)	0.681	0.667
FC (Actual Usage Behaviour / Facilitating Conditions)	0.657	0.644

Source: Contributed by Authors

Table 8: Path Coefficients Table

Hypothesis	Path	Path Coefficient (β)	t-value	p-value	Result
H1	PEOU → PU	0.612	11.83	0.000	Supported
H2	PEOU → ATT	0.385	6.42	0.000	Supported
H3	PU → ATT	0.541	9.72	0.000	Supported
H4	ATU → BI	0.574	10.15	0.000	Supported
H5	IM → ATT	0.296	5.98	0.000	Supported
H6	SN → BI	0.248	4.55	0.000	Supported
H7	PT → BI	0.078	1.47	0.142	Not Supported
H8	PR → BI	-0.211	3.88	0.000	Supported
H9	PC→ PU	0.429	7.35	0.000	Supported
H10	PC → ATT	0.064	1.21	0.227	Not Supported
H11	FC → BI	0.331	6.03	0.000	Supported

Source: Contributed by Authors

suggesting the items are one-dimensional and fully capture their corresponding constructs. This contributes to the discriminant validity of the measurement model and supports the use of these indicators in structural model assessment.

Table 6 shows the results of construct reliability and validity, such as Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for every latent construct. All constructs have met the required criteria, showing high internal consistency, construct dependability, and convergent validity. Cronbach's Alpha scores are between 0.702 (for Perceived Cost) and 0.917 (for Attitude), well above the threshold of 0.70, showing that each construct's items are measuring the same underlying concept consistently. All measures had Composite reliability (CR) values greater than 0.80, highest of which was 0.938 for Attitude, reflecting good reliability of scale items. All AVE values for constructs are greater than 0.70, which is above the 0.50 minimum threshold. This indicates that every construct accounts for more than half the variance in its indicators, suggesting very good convergent validity. Specifically, items like PEOU (AVE = 0.747), ATT (0.833), IM (0.830), and PT (0.751) have high variance explanation, which signifies the strength of the instrument. These results indicate that the measures employed in the study are both valid and reliable, thus warranting their employment in additional structural model analysis, including hypothesis testing and path modelling.

The structural model's predictive power and significance of correlations between latent constructs were assessed through R^2 values and path coefficients analysis. **Table 7** shows R^2 and R^2 adjusted values for the endogenous constructs: Perceived Usefulness (PU), Attitude (ATT), Behavioural Intention (BI), and Actual Usage Behaviour/Facilitating Conditions (FC). Perceived Ease of Use (PEOU) and Perceived Cost (PC) explain 61.2% of the variance in PU with a R^2 value of 0.612. ATT construct comes with a R^2 value of 0.714, with PEOU, PU, Intrinsic Motivation (IM), and PC explaining 71.4% of the variance in attitude towards digital payment. The R^2 for BI was 0.681, meaning ATT, SN, PT, PR, and FC are responsible for 68.1% of the variation in behavioural intention. Lastly, FC contained a R^2 of 0.657, showing considerable prediction power for actual usage behaviour.

Table 8 presents the outcome of hypothesis testing from path coefficients, t-statistics, and p-values. All the hypotheses except H7 and H10 were statistically significant. The positive relationship between perceived ease of use (PEOU) and perceived usefulness (PU) (H1: $\beta = 0.612$, $t = 11.83$, $p < 0.001$) was strongly supported, which meant that ease of use had a positive effect on perceived usefulness. PEOU had significant influence on attitude (H2: $\beta = 0.385$, $t = 6.42$, $p < 0.001$). Its high coefficient ($\beta = 0.541$, $t = 9.72$) reinforces the belief that useful digital payment systems lead to a more positive attitude among the users. Behavioural intention was significantly explained by attitude (H4: $\beta = 0.574$, $t = 10.15$, $p < 0.001$), while intrinsic motivation (H5) significantly contributed to attitude ($\beta = 0.296$, $t = 5.98$, $p < 0.001$). Subjective norms (H6) positively influenced behavioural intention ($\beta = 0.248$, $t = 4.55$), which suggests that social influence matters when adopting digital payment. Interestingly, the hypothesis H7 (PT → BI) was not supported ($\beta = 0.078$, $t = 1.47$, $p = 0.142$), meaning that perceived trust does not have a significant effect on users' intentions. Perceived risk (H8) significantly reduced behavioural intention ($\beta = -0.211$, $t = 3.88$, $p < 0.001$), meaning that greater perceptions of risk deter adoption. Perceived cost significantly influenced both PU (H9: $\beta = 0.429$, $t = 7.35$) and ATT (H10: $\beta = 0.064$, $t = 1.21$). The latter, however, was statistically insignificant ($p = 0.227$), thus invalidating H10. Facilitating Conditions (H11) positively affected behavioural intention ($\beta = 0.331$, $t = 6.03$, $p < 0.001$), meaning that organizational and technical support raises the likelihood of persistent usage. Generally, the model has excellent explanatory power and supports the fact that ease of use, usefulness, motivation, social norms, risk, and facilitating conditions are significant determinants of user behaviour in adopting digital payment systems, whereas trust and perceived cost have limited or mixed effects.

Policy Implications and Suggestions

According to the findings of the study, several policy implications and suggestions can be formulated to enhance the acceptance and usage of digital payment systems. Policymakers and financial institutions must focus on enhancing digital payment platforms' usability and perceived usefulness by investing in easy-to-use interfaces, regional language offerings, and simplified on-boarding processes. To enhance positive attitudes and behavioural intentions, awareness programs highlighting the advantages, safety, and convenience of digital payments must be enhanced in the semi-urban and rural segments. Intrinsic motivation can be enhanced through reward-based mechanisms and gamified processes, while perceived risks have to be mitigated by enhancing cybersecurity measures, safeguarding data privacy, and ensuring transparent grievance redressal mechanisms. Since favourable conditions make a significant contribution to usage behaviour, sustaining proper digital infrastructure, cheap internet access, and training schemes, especially for seniors and low-income households, can contribute to overcoming the digital divide. Even though perceived trust was not shown to have no significant influence on behavioural intention, trust- building activities like certification, branding, and public support can still exert an indirect effect in raising user confidence. In total, a holistic and inclusive strategy is required to ensure digital financial inclusion and sustained digital payment habit adoption.

Limitations and Scope for Further Research

Although the present research yields valuable observations regarding the factors that shape users' digital payment habits, it has some limitations. Firstly, the research is geographically constrained and does not exhaustively capture variations in behaviour across regions or cultural settings in India. Although the sample size of 670 participants is adequate for statistical analysis, it can be argued that it could not capture the variety of the total population in terms of income, education, or digital literacy levels. Second, the research draws on self-reported information, which can be prone to social desirability bias or recall failure. In addition, the research employed a cross-sectional design, which means that the research was unable to examine behavioural change over time. In addition, although essential categories like perceived usefulness, ease of use, and social influence were investigated, other emerging drivers like AI-based services, digital literacy, cybersecurity consciousness, and government promotion were not included. Future longitudinal research could explore how the attitudes and behaviour of users evolve when technology continues to evolve and legislative reforms occur. Researchers are also able to perform comparative studies across states, urban-rural areas, and even developed-developing countries. Qualitative methods like interviews or focus groups can give more meaningful information regarding user activity and hindrances. Lastly, there can be future research involving technology elements like user experience (UX), fintech technology, and blockchain integration, which is transforming digital payment landscapes globally.

CONCLUSION

Utilizing a large survey of 670 participants, this research provides a comprehensive insight into the factors that affect the users' acceptance and adoption of electronic payment systems. Based on a Structural Equation Modeling (SEM) framework, the research establishes the validity of significant factors like Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (ATT), Behavioural Intention (BI), and Facilitating Conditions (FC). The findings indicate that the majority of hypotheses were confirmed, highlighting the significance of technology perceptions, personal attitudes, and societal factors in shaping consumers' online payment behaviour. Interestingly, Perceived Risk (PR) had a negative effect on Behavioural Intention, while variables like Perceived Trust (PT) and Perceived Cost (PC) did not have significant effects in all the suggested paths, suggesting that user concerns and cost-related issues persist. The research contributes to the theoretical advancement of the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) by proposing novel constructs appropriate for the current digital financial environment. It also offers valuable insights for policymakers, digital payment entities, and financial institutions seeking to enhance service accessibility, usability, and security. Lastly, building consumer confidence, reducing perceived risk, and ensuring support via technology may serve to spur the growth of the digital payment system, especially in developing economies like India.

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