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Factors Shaping the Adoption of UPI-Enabled Mobile Payment Systems: An Empirical Investigation through the UTAUT2 Lens with Performance Risk Moderation

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Abstract

India's push toward a cashless economy has placed the Unified Payments Interface (UPI) at the very centre of everyday financial life yet the behavioural story behind why millions of citizens choose to keep using, or walking away from, UPI-based Mobile Payment Systems (MPS) remains only partially told. Drawing on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), this study builds and tests a model that treats Performance Risk not merely as a background nuisance but as an active boundary condition shaping whether positive intentions actually translate into real-world usage. Structured questionnaires were administered to 686 active UPI users across India between November 2025 and February 2026, and the data were analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM). Every hypothesised path held up: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation and Habit each contributed meaningfully to Behavioural Intention, which went on to strongly predict Usage Behaviour. Crucially, Performance Risk weakened the intention-to-usage link in a statistically and practically significant way—a finding with direct implications for how platforms, regulators and marketers should think about consumer trust. The model accounts for roughly 41% of variance in intentions and 30% in actual usage, both classified as substantial.

Keywords: UPI Payment Systems; UTAUT2; Performance Risk; Mobile Payment Adoption; PLS-SEM; Digital Financial Inclusion; Behavioural Intention

1. Introduction

Somewhere between 2016 and today, cash lost its monopoly on Indian life. That shift did not happen quietly or by accident it was engineered, accelerated by demonetisation, and then handed a permanent vehicle in the form of UPI, a real-time interoperable payment architecture that the National Payments Corporation of India (NPCI) quietly launched and then watched explode. By the close of financial year 2023–24, UPI was processing north of 131 billion transactions a year, moving roughly USD 2.2 trillion through mobile screens, QR codes, and feature phones across the country (Reserve Bank of India, 2024). Globally, this kind of traction is exceptional. Most countries attempting large-scale digital payment transitions have struggled with fragmentation, merchant resistance, or simply the inertia of a cash-addicted population. India, for all its diversity and connectivity gaps, managed something different though not without complications, and certainly not uniformly across demographics.

The international literature on mobile payment adoption is extensive, and frameworks like TAM (Davis, 1989), TPB (Ajzen, 1991), and more recently UTAUT2 (Venkatesh et al., 2012) have done considerable explanatory work. What these models collectively show is that adoption is never monocausal: people pick up or put down a payment technology based on a web of perceived usefulness, social pressure, habitual reinforcement, ease-of-use perceptions and importantly what they fear might go wrong. That last dimension is where Indian UPI scholarship has been conspicuously thin. Studies exploring adoption drivers in India tend to treat risk as an afterthought, a control variable or a footnote, rather than as something that could actively moderate whether someone who wants to use UPI actually goes ahead and does so (Rana et al., 2019; Sharma et al., 2020; Singh & Srivastava, 2020). This study was designed to close that gap or at least meaningfully narrow it.

Three objectives organise the inquiry. First, we examine how the six core UTAUT2 constructs Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Habit shape users' Behavioural Intention toward UPI-based MPS. Second, we assess how strongly that intention cascades into actual Usage Behaviour. Third, and most distinctively, we test whether Performance Risk moderates the intention-to-behaviour pathway that is, whether risk perceptions erode what would otherwise be a reliable link between wanting to use UPI and actually doing so. The theoretical contribution here is modest but precise: we introduce Performance Risk as a boundary condition within a UTAUT2 framework validated specifically in the Indian UPI context, something that, to the best of our knowledge, has not been done in this configuration before. Practically, the findings speak to platform engineers, fintech marketers, NPCI strategists, and policymakers who are still working to make digital payments genuinely universal not just technically available, but behaviourally embedded across a population of 1.4 billion.

2. Literature Review

2.1 Theoretical Grounding: Why UTAUT2?

The Unified Theory of Acceptance and Use of Technology 2 was developed by (Venkatesh et al., 2012) specifically to address a gap in consumer-facing technology research. The earlier UTAUT (Venkatesh et al., 2003) was strong in organisational contexts but missed dimensions that matter when individuals choose technology for personal, discretionary use. UTAUT2 remedied this by adding Hedonic Motivation, Price Value, and Habit to the established quartet of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. The resulting model explained considerably more variance in consumer intention than its predecessor, and it has since been applied with modifications across mobile banking (Baptista & Oliveira, 2015), e-commerce (Hew et al., 2015), and digital payments in multiple geographies (Slade et al., 2015; Alalwan et al., 2017).

For this study, Price Value was set aside: UPI transactions carry no user-side fees, which makes price-related perceptions largely irrelevant to the decision architecture we are examining. In its place, Performance Risk drawing conceptually from Featherman and (Pavlou, 2003) was incorporated as a moderating condition on the intention-to-behaviour relationship. This modification is not arbitrary; it reflects what Indian consumers actually report worrying about when they hesitate before making a UPI transfer. Transaction failures, server timeouts during peak hours, and delayed reversals of erroneous debits are documented realities of the UPI ecosystem (Agarwal et al., 2020), and they matter more to adoption continuance than to initial intention formation hence the moderation role rather than a direct effect.

2.2 Performance Expectancy

Performance Expectancy (PE) captures the degree to which a person believes a technology will help them accomplish tasks better or faster (Venkatesh et al., 2012). It is the conceptual heir to perceived usefulness in TAM (Davis, 1989) and has consistently emerged as the strongest driver of adoption intention across technology contexts and national settings (Liébana-Cabanillas et al., 2021). In the Indian UPI context specifically, the value proposition is concrete and immediate: faster transactions, no need to carry cash or remember account numbers, and seamless integration with everyday merchant interactions from vegetable vendors to premium online retailers. Srivastava et al. (2019) confirmed PE as the leading predictor of mobile wallet intention among Indian urban consumers, and similar patterns have been observed in rural and peri-urban samples as broadband connectivity expanded. There is no reason to expect this relationship to weaken in a 2025–26 sample; if anything, UPI's deepening integration into government benefit transfers, taxation, and healthcare payments has broadened the range of tasks it can meaningfully assist, likely strengthening the PE–intention link further.

H1: Performance Expectancy significantly influences Behavioural Intention to use UPI-based MPS.

2.3 Effort Expectancy

Effort Expectancy (EE) is essentially about how hard a system feels to use its conceptual lineage runs through perceived ease of use in TAM (Davis, 1989) and the complexity construct in Innovation Diffusion Theory (Rogers, 1995). For UPI, this is a nuanced question. Among tech-savvy urban millennials, UPI is often described as intuitive to the point of being unconscious they scan and pay without thinking. For a first-generation smartphone user in a tier-3 town, the same interface may involve multiple barriers: navigating the app language, understanding VPA-based transfers, or trusting that a payment marked 'pending' will eventually resolve. Singh and Srivastava (2020) found EE to be a significant predictor of UPI adoption intention. The argument for including EE in this study, then, is not that UPI is objectively difficult it is that the experience of effort is subjectively variable, and that variance predicts intention meaningfully.

H2: Effort Expectancy significantly influences Behavioural Intention to use UPI-based MPS.

2.4 Social Influence

Social Influence (SI) reflects how strongly a person feels that people who matter to them think they should use a given technology (Venkatesh et al., 2012). In a society where financial decisions are frequently made within family councils, recommended by neighbourhood shopkeepers, and endorsed through WhatsApp groups, SI arguably carries more weight in India than in many of the Western contexts where UTAUT2 was originally developed. Bhattacherjee and Sanford (2006) made the case that normative pressure from trusted others is particularly potent during the initial phases of adoption and for large segments of India's population, UPI is still in those initial phases. Sharma et al. (2020) documented significant SI effects on mobile payment adoption in India, and Rana et al. (2019) observed parallel patterns in e-government services. The proposed hypothesis is therefore well-grounded.

H3: Social Influence significantly influences Behavioural Intention to use UPI-based MPS.

2.5 Facilitating Conditions

Facilitating Conditions (FC) in UTAUT2 refer to the enabling environment infrastructure, compatible technology, access to support without which intended use cannot become actual use (Venkatesh et al., 2012). India's UPI ecosystem has seen dramatic improvement in FC since 2016: smartphone penetration crossed 800 million by 2024, 4G and 5G coverage extended to most districts, and the UPI merchant network grew to over 350 million acceptance points (NPCI, 2024). Still, FC is not uniformly positive across the population. Users in remote areas still contend with intermittent connectivity; older adults often lack access to the customer support they need; and small merchants occasionally run devices that are incompatible with specific UPI apps. Agarwal et al. (2020) documented these FC gaps and found they meaningfully suppressed adoption intention among underserved segments. FC thus remains a relevant predictor even in a maturing payment ecosystem.

H4: Facilitating Conditions significantly influence Behavioural Intention to use UPI-based MPS.

2.6 Hedonic Motivation

Hedonic Motivation (HM) is the enjoyment dimension the fun and pleasure that consumers derive from using a technology, as distinct from any task performance benefit (Venkatesh et al., 2012). It draws conceptually from intrinsic motivation research (Davis et al., 1992) and hedonic consumption theory (Hirschman & Holbrook, 1982). In the UPI context, HM manifests in ways that are not always obvious on the surface: the satisfaction of watching a transfer confirm in under a second, the gamified scratch-card rewards embedded in Google Pay or PhonePe, the small delight of splitting a restaurant bill without the usual awkwardness. Alalwan et al. (2018) confirmed that HM is a significant predictor of mobile payment intention. What is interesting is that HM's influence is likely underestimated in self-report studies because people do not always consciously attribute their payment choices to enjoyment yet behavioural studies suggest the hedonic pull is real.

H5: Hedonic Motivation significantly influences Behavioural Intention to use UPI-based MPS.

2.7 Habit

Habit in UTAUT2 refers to automatic behavioural responses actions triggered by situational cues rather than conscious deliberation (Venkatesh et al., 2012). The automaticity theory underlying this construct (Limayem et al., 2007) suggests that once a behaviour has been performed enough times in consistent contexts, it shifts from a considered choice to a default routine. For UPI, this transition has already happened for tens of millions of Indians: the reflex to open a payment app when handed a bill, or to initiate a transfer rather than withdraw cash, reflects embedded habit rather than active decision-making. (Singh, N., & Srivastava, S. 2020) confirmed habit as a meaningful predictor of UPI adoption continuance, and (Baptista & Oliveira, 2015) found consistent habit effects in mobile banking contexts. This study expects similar results and also expects that habit formation will be differentially distributed across age groups, which the demographic analysis can partially illuminate.

H6: Habit positively and significantly influences Behavioural Intention to use UPI-based MPS.

2.8 Behavioural Intention and Usage Behaviour

The proposition that what people intend to do predicts what they actually do is foundational to virtually every attitude-behaviour theory in the social sciences from TPB (Ajzen, 1991) to TRA to UTAUT2 (Venkatesh et al., 2012). In technology adoption research specifically, the intention–behaviour link is one of the most replicated relationships in the literature, though its strength varies with context, time lag, and moderating conditions (Maruping et al., 2017). In the Indian UPI context, (Rana et al. 2019) and (Sharma et al. 2020) both confirmed that strong adoption intention translates reliably into actual usage frequency. The current study expects this relationship to hold but also expects it to be conditioned by Performance Risk, which is why the moderation hypothesis is as theoretically important as the direct effect.

H7: Behavioural Intention positively and significantly influences Usage Behaviour of UPI-based MPS.

2.9 Performance Risk as a Moderator on the BI–UB Pathway

Performance Risk is defined as the probability, as perceived by the consumer, that a product or service will fail to deliver expected outcomes and thereby create problems (Pavlou, 2003). In the mobile payment space, this translates into fears about transaction failures mid-payment, double debits, app crashes during transfers, and delays in resolving disputes. The conceptual argument for treating PR as a moderator rather than a direct antecedent of intention is that risk perceptions are more likely to intervene at the point where intention meets action. A consumer might fully intend to use UPI for a significant payment but hesitate at the last moment because they remember a failed transaction at the same merchant, or because they cannot afford to have the payment stuck in limbo. (Kim et al. 2008) demonstrated exactly this moderating pattern in mobile commerce, (Pavlou 2003) showed that performance risk was the most potent inhibitor among various risk dimensions in e-services. India's documented UPI outages and transaction reversal delays make this moderating pathway particularly relevant to the current study.

H8: Performance Risk negatively moderates the relationship between Behavioural Intention and Usage Behaviour.

3. Research Methodology

3.1 Design, Sampling, and Sample Size

This study follows a quantitative, cross-sectional, deductive research design. The target population is Indian adults who had actively used any UPI-based application Google Pay, PhonePe, Paytm, BHIM, or similar for at least one financial transaction in the three months before the survey. Non-probability convenience sampling was adopted as the primary sampling strategy, a choice that warrants brief justification. No comprehensive, publicly available sampling frame of UPI users exists in India, making probability sampling practically infeasible for an academic study of this scope. Convenience sampling is widely used and accepted in technology adoption research under such conditions, provided the resulting sample is demographically diverse enough to limit systematic bias (Hair et al., 2019).

The sample size of 686 respondents was determined through the sample-to-indicator ratio recommended by Joseph Hair and colleagues (Hair et al., 2010) commonly referred to as the 1:10 rule which requires at minimum ten respondents per indicator in PLS-SEM models. With 27 measured indicators across nine latent constructs, a strictly minimum sample would be 270 responses. However, the study inflated this substantially to 686, following Hair et al.'s (2019) guidance that larger samples improve the stability and precision of PLS-SEM estimates, reduce the influence of non-normality, and strengthen the credibility of bootstrapped confidence intervals. Data collection ran from November 2025 through February 2026, spanning a four-month window that covered both pre-holiday peak payment activity and the quieter January–February period, providing a reasonably representative slice of UPI usage behaviour across seasonal variation.

3.2 Survey Instrument and Measurement

All constructs were operationalised using items adapted from Venkatesh et al. (2012) for the UTAUT2 dimensions and from Featherman and Pavlou (2003) for Performance Risk. Adaptation involved rewording items to reflect the UPI context explicitly replacing generic phrases like 'the system' with 'UPI-based MPS' while preserving the original semantic intent. This approach maintains conceptual fidelity while improving respondent relatability. All items were scored on a five-point Likert scale running from 1 (Strongly Disagree) to 5 (Strongly Agree). A five-point rather than seven-point scale was chosen deliberately: Indian survey research has documented response compression and mid-point preference on longer scales, particularly in rural and semi-urban samples with limited English proficiency (Rana et al., 2019). Content validity was confirmed through expert review involving three IS and consumer behaviour scholars, and a 35-person pilot test produced Cronbach's alpha values above 0.70 for all constructs before main data collection began.

3.3 Respondent Profile

Table 1: Demographic Profile of Survey Respondents (N = 686)

Variable	Category	Frequency	Percentage (%)
Gender	Male	316	46.1
	Female	370	53.9
	Total	**686**	**100**
Age Group	18–25 years	220	32.1
	26–45 years	247	36
	46–65 years	96	14
	66–75 years	69	10.1
	>75 years	54	7.8
	Total	**686**	**100**
Occupation	Student	123	17.9
	Private Employee	212	30.9
	Self-Employed	151	22
	Government Employee	89	13
	Other	111	16.2
	Total	**686**	**100**
Monthly Income	Below ₹25,000	267	38.9
	₹25,001–₹50,000	212	30.9
	₹50,001–₹75,000	158	23
	Above ₹75,000	49	7.2
	Total	**686**	**100**
UPI Apps Used	One	309	45
	Two	234	34.1
	Three	96	14
	>Three	47	6.9
	Total	**686**	**100**

Source: Primary survey data.

Table 1 summarises who answered the survey. Female respondents formed a slight majority at 53.9%, compared to 46.1% male a distribution that mirrors the growing female participation in digital payments documented in recent NPCI reports. The 26–45 age bracket contributed the largest share (36.0%), closely followed by the 18–25 cohort (32.1%), consistent with the demographic skew of active UPI users toward younger, economically active adults (Sharma et al., 2020). Occupationally, private-sector employees dominated (30.9%), with self-employed individuals forming the second-largest group (22.0%) a finding that makes intuitive sense given that self-employed workers often transact across both formal and informal markets where UPI has expanded rapidly. The income distribution is noteworthy: nearly two-fifths of respondents (38.9%) earned below ₹25,000 per month,

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underscoring that UPI penetration has reached well into lower-middle-income segments. Finally, 45.0% of respondents reported using a single UPI application, while 34.1% used two apps a pattern suggesting that multi-homing on UPI platforms is common, possibly driven by differential cashback offers and merchant acceptance patterns.

3.4 Analytical Approach

Partial Least Squares Structural Equation Modelling (PLS-SEM) implemented in SmartPLS 4.0 was the chosen analytical technique, and the choice warrants explanation. CB-SEM (covariance-based SEM) requires multivariate normality and works best when theory is mature and the primary goal is confirmatory. PLS-SEM is better suited to the current study because: the research objective is partly predictive; the sample, while large, does not satisfy strict multivariate normality assumptions; and the model is complex, with nine latent constructs and one moderation term (Hair et al., 2019). The analysis followed the two-stage procedure outlined by Anderson and Gerbing (1988): first, the measurement model was evaluated for reliability and validity; second, the structural model was tested for hypothesis support. Bootstrapping with 5,000 resamples generated bias-corrected confidence intervals for all path coefficients.

4. Results

4.1 Measurement Model

Before testing the structural paths, the measurement model needed to demonstrate that each construct was being reliably and validly captured by its indicators. Three criteria were applied. Convergent validity was assessed through outer loadings (all should exceed 0.708, per Hair et al., 2019), Composite Reliability (CR > 0.70), and Average Variance Extracted (AVE > 0.50). Discriminant validity was examined using the Fornell-Larcker criterion (Fornell & Larcker, 1981), where the square root of each construct's AVE must exceed its highest correlation with any other construct. Common Method Variance was assessed via Harman's single-factor test; the first unrotated factor captured only 32.7% of total variance, safely below the 50% threshold, indicating CMV was not a meaningful concern (Podsakoff et al., 2003). Table 2 presents the complete measurement model results.

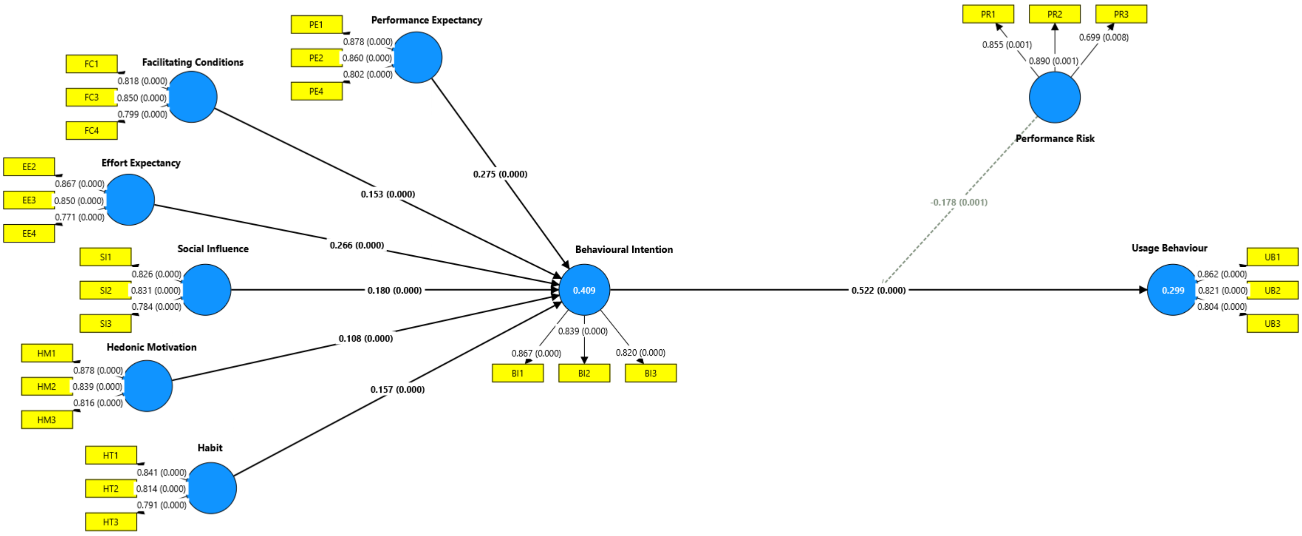

Figure 1: Structural Model Illustrating the Determinants Influencing Behavioural Intention and Usage Behaviour towards UPI-Enabled Mobile Payment Systems with Performance Risk Moderation.

Source: Authors' own computation using SmartPLS 4 based on primary survey data (n = 686).

Table 2: Outer Loadings, Reliability Coefficients, and Convergent Validity Statistics

Item	Statements	loadings
	Behavioural Intention	
BI1	I intend to continue using UPI MPS in the future.	0.867
BI2	I will always try to use UPI MPS in my daily life.	0.839
BI3	I plan to continue to use UPI MPS frequently.	0.820
	alpha = 0.795, CR = 0.798, AVE = 0.709	
	Effort Expectancy	
EE2	My interaction with UPI enabled MPS would be clear and understandable.	0.867
EE3	I find UPI enabled MPS easy to use.	0.850
EE4	It is easy for me to become skilful at using UPI enabled MPS.	0.771
	alpha = 0.775, CR = 0.79 , AVE = 0.689	
	Facilitating Conditions	
FC1	I have the resources necessary to use UPI enabled MPS.	0.818
FC3	UPI enabled MPS is compatible with other technologies I use.	0.850
FC4	I can get help from others when I have difficulties using UPI enabled MPS.	0.799
	alpha = 0.763, CR = 0.772, AVE = 0.677	
	Hedonic Motivation	
HM1	Using UPI is fun.	0.878
HM2	Using UPI is enjoyable.	0.839
HM3	Using UPI is very entertaining.	0.816
	alpha = 0.8 , CR = 0.815, AVE = 0.714	
	Habit	
HT1	The use of UPI Apps becomes a habit for me.	0.841
HT2	I am addicted to using UPI Apps.	0.814

HT3	I must use UPI Apps	0.791
	alpha = 0.749, CR = 0.754, AVE = 0.665	
	Performance Expectancy	
PE1	I find UPI MPS useful in my daily life.	0.878
PE2	Using UPI MPS increases my chances of achieving things that are important to me.	0.860
PE4	Using UPI MPS increases my productivity.	0.802
	alpha = 0.804, CR = 0.817, AVE = 0.718	
	Performance Risk	
PR1	The probability that something will go wrong with the performance of UPI MPS is high.	0.855
PR2	UPI MPS might not perform well and create problems with my payment process during purchasing.	0.890
PR3	Considering the expected level of service performance of UPI MPS, for me to sign up and use it would be risky.	0.699
	alpha = 0.773, CR = 0.862, AVE = 0.67	
	Social Influence	
SI1	People who are important to me think that I should use UPI enabled MPS.	0.826
SI2	People who influence my behavior think that I should use UPI enabled MPS.	0.831
SI3	People whose opinions that I value prefer that I use UPI enabled MPS.	0.784
	alpha = 0.746, CR = 0.75, AVE = 0.663	
	Usage Behaviour	
UB1	I often use UPI MPS to do payments.	0.862
UB2	I often use UPI MPS to transfer and remit money.	0.821
UB3	I often use UPI MPS to pay my bills.	0.804
	alpha = 0.773, CR = 0.781, AVE = 0.688	

Source: Authors' own computation using SmartPLS 4 based on primary survey data (n = 686).

Every indicator loading exceeded the 0.708 threshold, with values ranging from 0.699 (PR3, marginally retained given its theoretical necessity) to 0.890 (PR2). Cronbach's alpha values ranged from 0.749 (Habit) to 0.804

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(Performance Expectancy), all comfortably above 0.70. CR values ranged from 0.750 to 0.862, and AVE values spanned 0.663 to 0.718 every construct exceeding the 0.50 minimum, meaning each latent variable accounts for more than half the variance in its own indicators. The convergent validity picture is, in short, satisfactory across the board. Table 3 provides the discriminant validity evidence.

Table 3: Discriminant Validity Assessment via Fornell-Larcker Criterion (√AVE on Diagonal)

Construct	BI	EE	FC	HT	HM	PE	PR	SI	UB
Behavioural Intention	**0.842**								
Effort Expectancy	0.393	**0.830**							
Facilitating Conditions	0.310	0.128	**0.823**						
Habit	0.320	0.126	0.150	**0.816**					
Hedonic Motivation	0.280	0.165	0.171	0.200	**0.845**				
Performance Expectancy	0.420	0.178	0.162	0.179	0.147	**0.847**			
Performance Risk	-0.041	-0.071	-0.015	-0.057	-0.015	-0.040	**0.819**		
Social Influence	0.335	0.115	0.203	0.198	0.165	0.160	-0.054	**0.814**	
Usage Behaviour	0.516	0.279	0.225	0.152	0.183	0.312	-0.039	0.271	**0.829**

Source: Authors' own computation using SmartPLS 4 based on primary survey data (n = 686).

The bolded diagonal entries in Table 3 each representing the square root of a construct's AVE uniformly exceed the off-diagonal inter-construct correlations in their respective rows and columns. Discriminant validity is therefore established for all nine constructs. Two patterns in the correlation matrix are theoretically interesting and worth noting. First, Performance Risk shows negative correlations with Behavioural Intention (−0.041) and Usage Behaviour (−0.039), which is directionally consistent with the moderation hypothesis risk perceptions and adoption behaviour run in opposite directions. Second, Performance Expectancy and Effort Expectancy show the highest positive correlations with Behavioural Intention (0.420 and 0.393 respectively), foreshadowing what the structural model will confirm about their relative influence.

4.2 Structural Model and Hypothesis Testing

The structural model was evaluated by examining R^2, Q^2predict, and the significance, magnitude, and effect sizes of path coefficients obtained through bootstrapping. Table 4 reports the endogenous variable statistics.

Table 4: R^2 and Q^2predict Values for Endogenous Constructs

Endogenous latent variable	R-square	Q^2predict	Interpretation
Behavioural Intention	0.409	0.395	substantial
Usage Behaviour	0.299	0.200	substantial

Source: Authors' own computation using SmartPLS 4 based on primary survey data (n = 686).

Behavioural Intention achieved an R^2 of 0.409 meaning the six UTAUT2 predictors collectively explain roughly 41% of the variation in how strongly UPI users intend to continue using the service. Usage Behaviour reached an R^2 of 0.299, with Behavioural Intention and the PR moderation term explaining about 30% of actual usage variance. Both values are classified as 'substantial' by Cohen (1988), and the Q^2predict values of 0.395 and 0.200 (both clearly positive) confirm the model has genuine out-of-sample predictive relevance (Hair et al., 2019). Table 5 presents the full path coefficient results and hypothesis verdicts.

Table 5: Bootstrapped Path Coefficients and Hypothesis Testing Results (5,000 Resamples)

Hyp. No.	Path	Beta	Std. Dev.	T Value	P Value	CI		f^2	Effect Size	Supported
						2.50%	97.50%			
H1	PE → BI	0.275	0.03	9.208	0.00	0.217	0.333	0.117	Medium	Yes
H2	EE → BI	0.267	0.031	8.498	0.00	0.205	0.328	0.112	Medium	Yes
H3	SI → BI	0.181	0.03	6.004	0.00	0.121	0.240	0.050	Small	Yes
H4	FC → BI	0.153	0.032	4.852	0.00	0.091	0.214	0.036	Small	Yes
H5	HM → BI	0.11	0.03	3.555	0.00	0.051	0.171	0.018	Small	Yes
H6	HT → BI	0.158	0.03	5.214	0.00	0.098	0.217	0.038	Small	Yes
H7	BI → UB	0.522	0.027	18.982	0.00	0.466	0.575	0.388	Large	Yes
H8	PR × BI → UB	-0.155	0.052	3.41	0.00	-0.231	-0.015	0.047	Small	Yes

Source: Authors' own computation using SmartPLS 4 based on primary survey data (n = 686).

Note: All paths are significant at $p < 0.001$. Effect sizes follow Cohen (1988): $f^2 \geq 0.35$ = Large; 0.15–0.35 = Medium; 0.02–0.15 = Small. 95% bias-corrected confidence intervals are reported.

5. Discussion

The discussion of the study indicates that all eight proposed hypotheses received empirical support, although the magnitude of their influence differed considerably across the structural model. H1 proposed that Performance Expectancy positively influences Behavioural Intention towards UPI-enabled Mobile Payment Systems, and the findings confirmed this relationship ($\beta = 0.275$, $t = 9.208$, $p < 0.001$, $f^2 = 0.117$), establishing Performance Expectancy as the strongest predictor of Behavioural Intention. This suggests that users are more inclined to adopt UPI platforms when they perceive them as efficient, useful, and capable of enhancing transaction convenience, which is consistent with prior technology adoption studies (Liébana-Cabanillas et al., 2021; Srivastava et al., 2019). H2 examined the influence of Effort Expectancy on Behavioural Intention and revealed a significant positive relationship ($\beta = 0.267$, $t = 8.498$, $p < 0.001$, $f^2 = 0.112$). The result demonstrates that simplicity, ease of navigation, and user-friendly interfaces substantially contribute to consumers' willingness to use UPI applications, thereby supporting earlier findings reported by Singh and Srivastava (2020). H3 stated that Social Influence positively affects Behavioural Intention, and the empirical findings supported this hypothesis ($\beta = 0.181$, $t = 6.004$, $p < 0.001$, $f^2 = 0.050$). The findings indicate that recommendations from peers, family members, merchants, and social networks continue to shape consumer decisions regarding digital payment adoption, particularly within socially connected environments (Sharma et al., 2020). H4 proposed a positive relationship between Facilitating Conditions and Behavioural Intention, and the results confirmed this association ($\beta = 0.153$, $t = 4.852$, $p < 0.001$,

$f^2 = 0.036$). Although the effect size remained relatively small, the findings suggest that infrastructure availability, internet access, technical support, and smartphone compatibility continue to influence adoption behaviour. H5 examined the influence of Hedonic Motivation on Behavioural Intention and revealed a statistically significant relationship ($\beta = 0.110$, $t = 3.555$, $p < 0.001$, $f^2 = 0.018$). This indicates that enjoyment, entertainment, and positive user experiences associated with UPI applications marginally contribute to adoption intention, especially among digitally engaged consumers. H6 investigated the relationship between Habit and Behavioural Intention, and the findings supported the hypothesis ($\beta = 0.158$, $t = 5.214$, $p < 0.001$, $f^2 = 0.038$), implying that repeated usage behaviour and routine reliance on UPI applications strengthen consumers' continued intention to use digital payment systems, consistent with the observations of Limayem et al. (2007). H7 proposed that Behavioural Intention positively influences Usage Behaviour, and this relationship emerged as the strongest effect within the structural model ($\beta = 0.522$, $t = 18.982$, $p < 0.001$, $f^2 = 0.388$). The findings demonstrate that stronger behavioural intention substantially increases actual UPI usage behaviour, thereby supporting the theoretical assumptions of the UTAUT2 framework and earlier empirical evidence reported by Venkatesh et al. (2012) and Maruping et al. (2017). Finally, H8 examined the moderating effect of Performance Risk on the relationship between Behavioural Intention and Usage Behaviour. The results confirmed a significant negative moderating effect ($\beta = -0.155$, $t = 3.410$, $p < 0.001$, $f^2 = 0.047$), indicating that higher levels of perceived performance-related uncertainty weaken the positive relationship between intention and actual usage behaviour. This finding suggests that concerns regarding transaction failures, system inefficiency, technical disruptions, and payment errors reduce consumers' likelihood of translating favourable intentions into actual digital payment usage, which aligns with the arguments presented by Featherman and Pavlou (2003) and Kim et al. (2008). Overall, the findings provide substantial empirical support for the applicability of the UTAUT2 framework in explaining UPI-enabled Mobile Payment System adoption behaviour while also highlighting the critical role of perceived performance-related risk in influencing actual usage behaviour.

6. Managerial Implications

The findings of this study carry several actionable messages for the varied set of actors platform developers, digital marketers, NPCI strategists, and government policymakers who share a stake in UPI's continued growth.

Starting with the two strongest predictors: Performance Expectancy and Effort Expectancy together account for the largest share of variation in adoption intention, and they pull in a consistent direction. Marketing communications that lead with concrete, relatable use-case narratives 'pay your electricity bill in twelve seconds without logging into a website' are likely to outperform abstract 'digital India' messaging. Similarly, product teams that treat interface simplicity as a first-order business metric rather than an aesthetic preference will see real adoption returns. For Effort Expectancy specifically, the evidence suggests that the most underserved segment is not the digitally alienated elderly (who may have limited intent regardless) but the large cohort of semi-skilled workers and rural migrants who have smartphones and UPI access but find the current onboarding experience confusing. Targeted, vernacular, video-based tutorials distributed through existing community structures self-help groups, cooperative societies, common service centres could meaningfully improve EE perceptions for this segment.

Social Influence findings suggest that peer-driven marketing consistently outperforms broadcast advertising for UPI adoption at the community level. Merchant incentive programmes that turn local shopkeepers into de facto UPI ambassadors deserve continued investment; a recommendation from someone a customer transacts with daily carries more weight than a television advertisement featuring a celebrity. NPCI's existing ambassador programmes are a step in the right direction, but the current data suggest the mechanism works well enough to justify significant scale-up.

The Performance Risk moderation finding has the most urgent operational implication. Reducing performance risk is not simply a matter of improving server uptime though that matters. It also requires making the resolution of failed transactions faster, more transparent, and more user-communicable. Currently, Indian consumers who experience a UPI failure often have no clear way to know whether the money has been debited, when it will be reversed, or whom to contact. That ambiguity is the lived experience of performance risk, and it directly erodes the intention-to-usage conversion. A consumer-facing transaction status dashboard, standardised resolution timelines across banks and apps, and proactive SMS notifications at each stage of a disputed transaction would collectively reduce perceived risk even before a single additional server is provisioned.

7. Limitations And Future Research Directions

No study is without its boundaries, and being honest about them helps the field build on the work more productively. First, convenience sampling constrains generalisation. Despite the sample's size and demographic diversity, it was not drawn from a probability-based sampling frame and may systematically over-represent urban, educated, and already-digitally-confident users. Future work with stratified random sampling across pin codes and household income quintiles would produce a more representative picture.

Second, the cross-sectional design captures a moment rather than a trajectory. UPI adoption is a dynamic process: habits deepen, risk perceptions evolve as platforms improve, and social norms shift as peer networks update their technology practices. A longitudinal panel design surveying the same respondents at, say, six-month intervals over two years would capture these dynamics far better than any cross-sectional snapshot, however large.

Third, this study operationalises Usage Behaviour through self-report items rather than objective transaction data. Self-reports are cognitively reconstructed, subject to social desirability bias, and tend to overstate actual usage frequency (particularly for new technology adopters who want to present as competent). Access to anonymised transactional data from NPCI or a partner bank would allow future researchers to validate self-reported usage against actual behaviour a methodological upgrade that would substantially strengthen causal claims.

Fourth, Performance Risk was operationalised narrowly as functional/performance risk the probability of operational failure. The risk landscape for digital payments is broader: it includes financial risk (losing money through fraud), privacy risk (data exposure), and psychological risk (the anxiety of being responsible for an irreversible digital transaction). Disaggregating these risk dimensions in future studies perhaps as separate moderators or mediators would provide a richer and more actionable risk profile for platform designers and regulators. Additionally, trust-related constructs such as institutional trust in NPCI, app-level trust, and bank-level trust are conspicuously absent from UTAUT2 but may prove to be significant complements to, or substitutes for, risk perceptions in explaining the intention-behaviour gap.

8. Conclusion

This study set out to do something specific: test whether the UTAUT2 framework, extended with Performance Risk as a moderating boundary condition, could explain UPI adoption behaviour among a large and demographically varied Indian sample and it did, reasonably well. All six UTAUT2 predictors contributed significantly to Behavioural Intention, with Performance Expectancy and Effort Expectancy carrying the heaviest explanatory load. Behavioural Intention, in turn, powerfully predicted actual Usage Behaviour. And Performance Risk did exactly what the theory predicted it would: it attenuated the intention-to-usage conversion, confirming that Indian UPI users' fears about transaction failures are not irrelevant background noise they are active inhibitors that can keep a willing adopter from becoming an actual user.

Taken together, these findings paint a picture of a digital payment ecosystem that has made extraordinary progress in a short time, but that still has friction points concentrated in perceived effort, infrastructural gaps, and, most importantly, the chronic anxiety around things going wrong when money is involved. Addressing these friction points through better interfaces, stronger social proof, improved infrastructure in underserved areas, and above all more transparent and faster dispute resolution—would likely yield adoption gains that no cashback programme or celebrity endorsement can match. India's UPI story is genuinely impressive. Making it universal will require attending not just to the people who have not yet started using it, but to the millions who have started, harbour lingering doubts, and could still be lost to a single bad transaction experience.

References

[1] Agarwal, S., Sinha, A., & Siddiqui, M. W. (2020). Determinants of digital payment system adoption in India. Journal of Electronic Commerce Research, 21(3), 178–196.

[2] Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

[3] Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers. Journal of International Information Management, 26(3), 253–273.

[4] Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking. Information Systems Management, 35(2), 240–250.

[5] Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin, 103(3), 411–423.

[6] Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. Computers in Human Behavior, 50, 418–430.

[7] Bhattacherjee, A., & Sanford, C. (2006). Influence processes for information technology acceptance: An elaboration likelihood model. MIS Quarterly, 30(4), 805–825.

[8] Chin, W. W. (1998). The partial least squares approach to structural equation modelling. In G. A. Marcoulides (Ed.), Modern Methods for Business Research (pp. 295–336). Lawrence Erlbaum.

[9] Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Lawrence Erlbaum Associates.

[10] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

[11] Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology, 22(14), 1111–1132.

[12] Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human–Computer Studies, 59(4), 451–474.

[13] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

[14] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.

[15] Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis: A Global Perspective (7th ed.). Pearson Education.

[16] Hew, J. J., Lee, V. H., Ooi, K. B., & Wei, J. (2015). What catalyses mobile apps usage intention: An empirical analysis. Industrial Management & Data Systems, 115(7), 1269–1291.

[17] Hirschman, E. C., & Holbrook, M. B. (1982). Hedonic consumption: Emerging concepts, methods and propositions. Journal of Marketing, 46(3), 92–101.

[18] Kim, G., Shin, B., & Lee, H. G. (2008). Understanding dynamics between initial trust and usage intentions of mobile banking. Information Systems Journal, 19(3), 283–311.

[19] Liébana-Cabanillas, F., Muñoz-Leiva, F., Molinillo, S., & Higueras-Castillo, E. (2021). Do biometric payment systems work during the COVID-19 pandemic? Financial Innovation, 7(1), 1–25.

[20] Limayem, M., Hirt, S. G., & Cheung, C. M. (2007). How habit limits the predictive power of intention: The case of information systems continuance. MIS Quarterly, 31(4), 705–737.

[21] Maruping, L. M., Bala, H., Venkatesh, V., & Brown, S. A. (2017). Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology. Journal of the Association for Information Science and Technology, 68(3), 623–637.

[22] National Payments Corporation of India. (2024). Annual Report 2023–24. NPCI. https://www.npci.org.in

[23] Nunnally, J. C. (1978). Psychometric Theory (2nd ed.). McGraw-Hill.

[24] Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. Computers in Human Behavior, 61, 404–414.

[25] Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

[26] Rana, N. P., Dwivedi, Y. K., Lal, B., Williams, M. D., & Clement, M. (2019). Citizens' adoption of an electronic government system: Towards a unified view. Information Systems Frontiers, 19(3), 549–568.

[27] Reserve Bank of India. (2024). Annual Report 2023–24. RBI. https://www.rbi.org.in

[28] Rogers, E. M. (1995). Diffusion of Innovations (4th ed.). Free Press.

[29] Sharma, S., Singh, G., Pratt, S., & Narayan, J. (2020). Exploring consumer behavior to purchase travel online in Fiji and Solomon Islands. Tourism Management Perspectives, 34, 100636.

[30] Singh, N., & Srivastava, S. (2020). Mobile banking service quality and mobile wallet adoption: The role of network externalities. International Journal of Bank Marketing, 38(4), 841–862.

[31] Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness and trust. Psychology & Marketing, 32(8), 860–873.

[32] Srivastava, S. C., Chandra, S., & Theng, Y. L. (2019). Evaluating the role of knowledge management in influencing customer satisfaction with mobile commerce. Journal of Global Information Management, 18(3), 21–40.

[33] Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. MIS Quarterly, 15(1), 125–143.

[34] Triandis, H. C. (1977). Interpersonal Behavior. Brooks/Cole.

[35] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

[36] Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178.