Behavioural Determinants of UPI Adoption: An Extended UTAUT Model Using PLS-SEM

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Abstract: *Despite UPI's revolutionary impact of the Unified Payments Interface (UPI) on cashless payments in India, little is known about the behavioural factors that encourage widespread adoption. Drawing on UTAUT and extending it with perceived security and hedonic motivation, and introducing trust as a moderator, this study employs PLS-SEM on cross-sectional survey data from 408 UPI users across Goa, collected between December 2025 and April 2026. The findings confirm performance expectancy, facilitating conditions, social influence, perceived security, and effort expectancy as significant determinants of behavioural intention. Trust amplifies the influence of perceived security on intention, and behavioural intention partially mediates the effect of performance expectancy on usage behaviour. Hedonic motivation was not significant, reflecting the utilitarian orientation of Goan UPI users.*

Keywords: UTAUT, Behavioural Intention, Perceived Security, Trust; Digital Payments

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1. INTRODUCTION

Worldwide digital payment transactions totalled $9.46 trillion in 2023 and are expected to rise to $14.78 trillion by 2027 (Statista, 2024). Launched by the NPCI in 2016, UPI processed more than 15 billion monthly transactions valued at ¹ 21.55 lakh crore by December 2024, positioning India as the leading real-time payments market (NPCI, 2025). The UPI's zero-cost architecture and alignment with the Jan Dhan–Aadhaar–Mobile initiative have advanced financial inclusion, while COVID-19 normalised contactless payments across demographic groups (S. K. Sharma & Sharma, 2019). Goa, with its high per capita income and tourism-driven economy, presents an under-researched context for such enquiries.

Sustaining adoption requires an understanding of behavioural antecedents. UTAUT (Venkatesh et al., 2003) (Uunified Theory of Acceptance and use of Technology) provides the most integrative theoretical base, yet fintech extensions incorporating perceived security and trust are necessary (Baptista & Oliveira, 2015; Kim et al., 2010). Prior literature inadequately addresses the moderating role of trust in the security intention relationship, hedonic adoption dimensions, and the indirect performance expectancy–usage behaviour pathway in Indian state-level contexts (Joshi, 2024; Malhotra, 2025). This study addresses these gaps through an extended UTAUT model tested via PLS-SEM on Goan data. The objectives are as follows: (i) identify direct predictors of behavioural intention; (ii) assess the effect of intention on usage behaviour; (iii) test trust as a security–intention moderator; and (iv) confirm the mediation of the effect of performance expectancy through behavioural intention.

2. LITERATURE REVIEW

2.1 Theoretical Foundation: UTAUT

(Venkatesh et al., 2003), established the UTAUT by integrating eight earlier theoretical frameworks, which identified social influence, enabling circumstances, performance expectation, and effort expectancy as the key factors influencing technology adoption, which together explained almost 70% of the variation in adoption intent. Then, UTAUT2 (Venkatesh et al., 2012) expanded consumer settings to include hedonic incentives, habits, and price values. While demonstrating the need for security- and trust-related enhancements in fintech contexts, applications in mobile banking validate UTAUT's resilience. (Baptista & Oliveira, 2015; Lin et al., 2022).

2.2 Construct Definitions and Hypothesis Development

Performance expectancy refers to the perceived performance gains from technology use(Venkatesh et al., 2003). In digital payments, this encompasses transaction speed, reliability, and utilities. PE is consistently the dominant adoption driver (Padma Kiran & Vedala, 2025) and exerts a direct influence on usage behaviour (Venkatesh & Morris, 2000).

H1: Behavioural intention positively influences usage behaviour.

H2: Performance expectancy positively influences behavioural intention.

H3: Behavioural changes in use are positively impacted by performance expectations.

H4: Performance expectation and use behaviour are affected by behavioural intention.

According to Venkatesh et al. (2003), the term "effort expectancy" refers to how easy one thinks a technology system would be to use. The linguistically diverse population of Goa places a premium on an easy-to-navigate interface. A study by Jacob et al. (2024) in India's UPI settings suggests that EE is a strong predictor.

H5: Effort expectancy positively predicts behavioural intention.

Within UPI adoption, social influence captures how peer opinions push individuals toward a decision(Venkatesh et al., 2003). In India's collectivistic society, peer endorsements critically shape digital adoption (Chatterjee & Bolar, 2018; Joshi, 2024), further amplified by UPI referral programs.

H6: Greater social influence is associated with stronger behavioural intention.

Facilitating conditions measure whether users feel adequately supported by infrastructure, devices, and merchant networks to use UPI without friction(Venkatesh et al., 2003).The important enabling factors in Goa include merchant readiness, smartphone accessibility, and network availability. Jacob et al. (2024) found that these characteristics had a disproportionate impact on users with lower incomes, which reflects the different economic profiles of the areas.

H7: Facilitating conditions positively influence behavioural intention.

A person's hedonic motivation stems from the pleasure they derive from using technology, while enabling circumstances indicate the strength of their behavioural intention. (Venkatesh et al., 2012). Hedonic motivation refers to the pleasure one derives from using technology, whereas more conducive situations result in higher behavioural intention.: (Lin et al., 2022; Malhotra, 2025) report significance, whereas (S. Sharma & Chauhan, 2024) find no effect for Generation Z.

H8: Hedonic motivation positively influences behavioural intention.

Perceived Security captures beliefs regarding protection from fraud and unauthorised access (Kim et al., 2010). Security concerns remain a persistent global barrier (Ramos de Luna et al., 2019), and UPI fraud incidents have heightened Indian consumer apprehension.

H9: Perceived security positively influences behavioural intention.

Trust reflects confidence in a digital platform based on favourable expectations (Gefen et al., 2003). It moderates the effect of security on intention: users who trust the platform respond more strongly to security assurances (Lin et al., 2022; McKnight et al., 2002) pertinent in Goa's tourism-facing merchant environment.

H10: Trust acts as a moderator between the link between one's perception of safety and their decision to act.

3. RESEARCH METHODOLOGY

According to Saunders et al. (2019), this study used a positivist quantitative survey approach. Between December 2025 and April 2026, researchers in Goa, India conducted a cross-sectional study.

3.1 Survey Instrument

The reliability and content validity of the items were ensured by drawing on well-established peer-reviewed scales. The following statements were taken from the study by Venkatesh et al. (2003): performance expectation, effort expectancy, social influence, enabling factors, behavioural intention, and use behaviour. We used three questions from McKnight et al. (2002) to measure trust and three from Venkatesh et al. (2012) to measure hedonic motivation. Five questions based on those of (Kim et al., 2010) were used to gauge the level of perceived safety. Everyone could choose where they stood on a five-point agreement continuum: 1 for very disagree and 5 for very agree.

3.2 Sample Size Justification and Data Collection

To determine whether the sample size was sufficient, we used the 10:1 subject-to-indicator ratio for PLS-SEM, as described by Hair et al. (2017). Here, the indicator count is the maximum number of routes directed toward a single latent construct. Seven direct routes (PE, EE, SI, FC, HM, PS, and the TR interaction) influence behavioural intention, and at least 70 responses are required. With 408 participants, the sample size was much higher than the minimum required to draw valid conclusions using route estimation and bootstrapping (58:1) (Hair et al., 2017).

We utilised a non-probabilistic convenience sample to find people in Goa who were at least 18 years old and had used a UPI app in the three months before the survey. In Goa, the poll was disseminated via online chat rooms, professional networks and alumni associations. N = 408 is the final, acceptable sample size after 33 replies were removed because of systematic response patterns or incomplete submissions out of 441.

3.3 Demographic Profile

Table 1 summarises the characteristics of the sample.

Table 1: Demographic Profile (N = 408)

Variable	Category	n	%
Gender	Male	188	46.08
	Female	220	53.92
	Total	408	100
Age	18–25	131	32.11
	26–45	147	36.03
	46–65	57	13.97
	66–75	41	10.05
	>75	32	7.84
	Total	408	100
Occupation	Student	73	17.89
	Private Emp.	126	30.88
	Self-emp.	90	22.06
	Govt. Emp.	53	12.99
	Other	66	16.17
	Total	408	100
Income (₹)	<25,000	159	38.97
	25–50K	126	30.88
	50–75K	94	23.04
	>75K	29	7.11
	Total	408	100
UPI Apps	One	184	45.1
	Two	139	34.07
	Three	57	13.97
	>Three	28	6.86
	Total	408	100

Note: Female respondents constitute 53.92% of the sample; the 18–45 age cohort accounts for 68.14% of the sample. Private employees (30.88%) dominate occupationally, and 38.97% report a monthly income below ¹ 25,000, confirming UPI's penetration into lower-income segments. Approximately 79% of the participants used one or two applications concurrently.

4. RESULTS

4.1 Measurement Model

PLS-SEM analysis was performed using SmartPLS 4. According to Hair et al. (2017), convergent validity was established by assessing outer loadings (threshold > 0.70), Cronbach's alpha (α > 0.70), composite reliability (CR > 0.70), and average variance extracted (AVE > 0.50). As shown in Table 2, all the structures satisfied these requirements.

Table 2: Measurement Model - Convergent Validity

Construct / Item	Loading	α	CR	AVE
Behavioural Intention		**0.817**	**0.891**	**0.732**
BI1 / BI2 / BI3	0.845–0.861			
Effort Expectancy		**0.786**	**0.874**	**0.698**
EE1 / EE2 / EE3	0.795–0.858			
Facilitating Conditions		**0.795**	**0.868**	**0.688**
FC1 / FC2 / FC3	0.778–0.868			
Hedonic Motivation		**0.797**	**0.873**	**0.696**
HM1 / HM2 / HM3	0.786–0.862			
Perf. Expectancy		**0.892**	**0.908**	**0.665**
PE1 / PE2 / PE3	0.814–0.858			
Perceived Security		**0.892**	**0.908**	**0.665**
PS1–PS5	0.769–0.845			
Social Influence		**0.796**	**0.874**	**0.699**
SI1 / SI2 / SI3	0.808–0.886			
Trust		**0.793**	**0.857**	**0.667**
TR1 / TR2 / TR3	0.733–0.856			
Usage Behaviour		**0.84**	**0.901**	**0.753**
UB1 / UB2 / UB3	0.844–0.888			

According to Fornell and Larcker, to conduct a discriminant validity test, the square root of each construct's AVE (diagonal) must be greater than all inter-construct correlations. Table 3 verifies this for every pair of constructs.

Table 3: Discriminant Validity - Fornell-Larcker Criterion

	BI	EE	FC	HM	PS	PE	SI	TR	UB
BI	**0.86**								
EE	0.31	**0.84**							
FC	0.38	0.13	**0.83**						
HM	0.28	0.16	0.22	**0.83**					
PS	0.32	0.21	0.22	0.12	**0.82**				
PE	0.46	0.21	0.15	0.23	0.16	**0.83**			
SI	0.34	0.21	0.12	0.17	0.17	0.19	**0.84**		
TR	0.23	0.13	0.18	0.21	0.16	0.21	0.23	**0.82**	
UB	0.52	0.23	0.29	0.19	0.25	0.36	0.21	0.18	**0.87**

Note: The diagonal elements represent "AVE; the off-diagonal elements are inter-construct correlations.

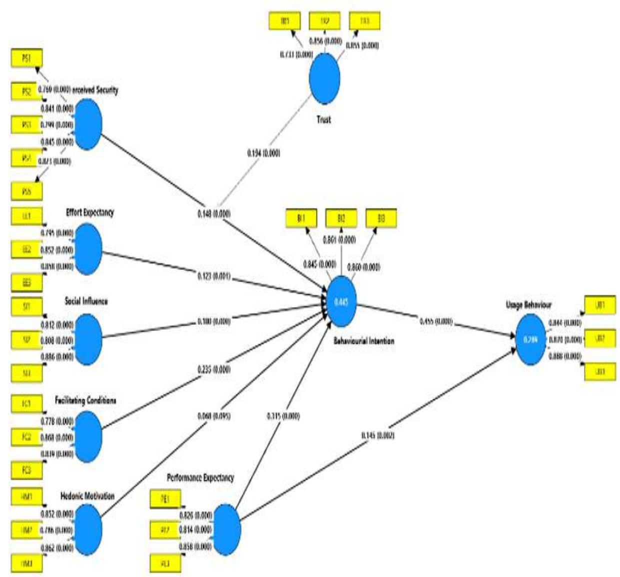

Figure 1: Structural Model of Factors Influencing Behavioural Intention and Usage Behaviour towards UPI-Based Mobile Payment Systems

4.2 Predictive Accuracy

Table 4: Predictive Accuracy of Endogenous Constructs

Construct	R^2	Q^2	Verdict
Behavioural Intention	0.445	0.418	Substantial
Usage Behaviour	0.289	0.213	Substantial

For behavioural intention, the model explained 44.5% of the variation, and for use behaviour, it explained 28.9%. Both conceptions had Q^2 values greater than zero, which means they were predictively relevant according to the Stone-Geisser criteria. (Hair et al., 2017).

4.3 Structural Model and Hypothesis Testing

Path coefficients were estimated using bootstrapping with 5,000 resamples (Hair et al. 2017). Table 5 presents all the results.

Table 5: Structural Model - Hypothesis Testing

H	Path	β	SD	t	p
H1	BI → UB	0.46	0.04	10.77	0
H2	PE → BI	0.32	0.04	8.19	0
H3	PE → UB	0.15	0.05	3.08	0
H4	PE→BI→UB	0.14	0.02	6.34	0
H5	EE → BI	0.12	0.04	3.23	0
H6	SI → BI	0.18	0.04	4.43	0
H7	FC → BI	0.24	0.04	5.96	0
H8	HM → BI	0.07	0.04	1.67	0.1
H9	PS → BI	0.15	0.04	3.88	0
H10	TR×PS→BI	0.19	0.04	4.9	0

Nine of the ten hypotheses were supported. H8 is rejected because hedonic motivation does not significantly predict behavioural intention.

5. DISCUSSION

Consistent with Kiran and Sailaja (2025), performance expectation is the most powerful predictor of behavioural intention ($\beta = 0.315$, $p < 0.001$). This confirms that transactional efficiency is the primary motivation for adoption, even in a high-income state such as Goa. Its direct effect on usage behaviour (H3: $\beta = 0.145$) and confirmed mediation (H4: $\beta = 0.143$) indicate that performance value shapes adoption through both intentional and habitual mechanisms.

For the approximately 39% of respondents with monthly incomes below [1] 25,000, facilitating circumstances significantly impact adoption trends in Goa. Merchant onboarding and improving rural connections are two of the most pressing policy concerns. The semi-urban, tourist-based economy of Goa also shows that social influence, as shown by referral incentives and peer recommendations, is still strong.

H10: $\beta = 0.194$ suggests that institutional trust boosts the adoption impact of perceived security, which is in agreement with McKnight et al. (2002), who found that perceived security ($\beta = 0.148$) is an independent predictor of intention. This is of paramount importance in the tourist industry in Goa because of the high prevalence of merchant-side fraud. Although older users still experience some friction, the decreasing effect of effort expectation ($\beta = 0.123$) indicates that UPI interfaces are becoming more standardised.

Contrary to earlier research by Malhotra (2025) (Lin et al. (2022), as well as (S. Sharma and Chauhan (2024) found that hedonic motivation was not significant ($\beta = 0.068$, $p = 0.095$). This could be because the Goan sample is more pragmatic and financially restricted, emphasising transactional efficiency rather than emotional satisfaction.

6. THEORETICAL CONTRIBUTIONS

The authors highlight three important contributions of this study. First, this study builds on previous work by tailoring the UTAUT model to the fintech industry in Goa and showing that improvements in trust and security greatly increase the model's explanatory power. Second, in the context of fintech acceptance, where these aspects are often examined independently, trust has a moderating role in the link between security and intention. Third, it supports the idea that behavioural intention partially mediates performance expectation, which gives a more nuanced picture of adoption dynamics than the traditional UTAUT and is in line with requests for more robust mediating structures in the realm.

7. MANAGERIAL IMPLICATIONS

The results show that gamification or rewards programs do not work as well in Goa as they do in cities; therefore, we should consider investing in making transactions more trustworthy. Merchant onboarding and offline solutions to assist areas with poor access should be top priorities for fintech companies. Along with technological improvements, trust and security measures should include communication to avoid fraud, verified merchant labelling, and open dispute settlement. By actively engaging with rural communities and drawing on peer networks as the main source of information, policymakers may increase their social impact.

8. LIMITATIONS AND FUTURE SCOPE

Limitations on regional applicability and causation claims are imposed by non-probabilistic sampling and the single time-point approach. We may need more all-encompassing emotional tools, as the hedonic motivation finding was not statistically significant. A crucial UTAUT2 construct, the lack of habit, was acknowledged. Future research should examine subgroups in Goa, such as rural-urban and tourist-resident, using longitudinal designs. It should also incorporate measures of innovativeness, perceived risk, habits, and comparative studies across other Indian states.

9. CONCLUSION

This study confirms, using 408 users in Goa, that an expanded UTAUT model of UPI adoption is correct. Perceived security, social influence, enabling circumstances, performance expectations, and effort expectancy are important determinants of behavioural intention. Behavioural intention partly mediates the influence of performance anticipation on use behaviour, and trust improves the effect of perceived security on intention. The study's findings underscore the utilitarian character of UPI adoption, as the hedonic incentive was shown to be non-significant. These results provide insight into the current level of UPI adoption in India's smaller state economies and add to the growing body of literature on UTAUT theory in developing fintech markets.

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