

Adoption of Mobile Payment Systems: An Empirical Analysis of Consumer Intentions using the UTAUT2 Model and PLS-SEM

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DOI:10.5281/zenodo.17212169

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Mobile payment systems have emerged as a key driver of financial inclusion in India, particularly in the context of digital transformation and the government's push toward a cashless economy. This study investigates the determinants influencing consumer adoption of mobile payment systems using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. A structured questionnaire was administered to 124 respondents in Jharkhand, India, and data were analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM) in SmartPLS. The results reveal that performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, and price value significantly influence behavioral intention to use mobile payments, whereas social influence, trust, and habit were found to be insignificant predictors. Furthermore, behavioral intention showed a positive and significant effect on actual usage behavior. These findings provide empirical support for UTAUT2 in the Indian context and highlight the growing role of perceived value and technological convenience in shaping mobile payment adoption. The study offers theoretical contributions to digital finance literature and practical implications for policymakers, fintech firms, and service providers aiming to enhance mobile payment penetration in emerging economies.

Keywords: mobile payment adoption, utaut2, consumer behavior, digital finance, financial inclusion

Corresponding Author	How to Cite this Article	To Browse
Ankita Kumari, Research Scholar, Department of Commerce and Management, Ranchi University, Ranchi, Jharkhand, India. Email: ankitashisodiya321@gmail.com	Kumari A, Adoption of Mobile Payment Systems: An Empirical Analysis of Consumer Intentions using the UTAUT2 Model and PLS-SEM. Manag J Adv Res. 2025;5(4):81-94. Available From https://mjar.singhpublication.com/index.php/ojs/article/view/246	

Manuscript Received
2025-07-16

Review Round 1
2025-08-01

Review Round 2

Review Round 3

Accepted
2025-08-22

Conflict of Interest
None

Funding
Nil

Ethical Approval
Yes

Plagiarism X-checker
4.12

Note



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1. Introduction

The financial services industry worldwide has undergone a paradigm shift with the advent of digital technologies, particularly mobile-based financial applications. Mobile payment systems—defined as payment services operated under financial regulations and performed via mobile devices—have emerged as a cornerstone of the digital economy (Dahlberg et al., 2015). These systems combine convenience, security, and speed, enabling users to make financial transactions without relying on traditional cash-based methods. In developed economies such as China, South Korea, and the United States, mobile payments have already achieved widespread adoption, with platforms such as Alipay, WeChat Pay, Apple Pay, and Google Pay transforming consumer payment behavior. However, adoption trajectories in developing economies differ significantly, being influenced by infrastructural limitations, socio-cultural contexts, and varying levels of digital literacy.

In the Indian context, the mobile payment ecosystem has expanded rapidly over the past decade. The launch of initiatives such as the Unified Payments Interface (UPI), demonetization in 2016, and the government's *Digital India* campaign have accelerated the transition toward a cashless economy (Reserve Bank of India [RBI], 2021). According to RBI reports, the volume of UPI transactions has grown exponentially, making India one of the world leaders in digital transactions. Mobile payment platforms such as Paytm, PhonePe, Google Pay, and BharatPe have become household names, particularly in urban and semi-urban markets. The benefits of mobile payments are multifaceted: they reduce transaction costs, foster transparency, enhance consumer convenience, and promote financial inclusion for traditionally unbanked populations.

Despite these achievements, challenges persist. India is characterized by stark socio-economic diversity, where adoption patterns differ widely between metropolitan cities and rural or semi-urban regions. While urban consumers with higher income and digital literacy exhibit higher adoption rates, many users in rural and semi-urban areas face barriers such as inadequate infrastructure, poor internet connectivity, lack of trust in digital systems,

and limited awareness of mobile payment benefits (Kumar & Ayedee, 2019). Furthermore, cultural reliance on cash transactions and apprehension about security breaches continue to slow adoption among certain sections of the population. Thus, while India has made strides in digital financial inclusion, adoption is still fragmented and context-specific.

Theoretical perspectives have played an important role in explaining technology adoption. Models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely used to explain user behavior toward emerging technologies. Building on these foundations, Venkatesh, Thong, and Xu (2012) extended UTAUT into UTAUT2, incorporating additional constructs such as hedonic motivation, price value, and habit, which are particularly relevant in consumer technology contexts. Numerous studies in different countries have validated UTAUT2 in understanding mobile banking and mobile payment adoption (Alalwan et al., 2017; Oliveira et al., 2016). However, the relative importance of these factors is often context-dependent. For instance, while social influence has been found to strongly predict adoption in collectivist cultures, its effect appears weaker in individualistic societies (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019). Similarly, the role of trust remains inconsistent, with some studies finding it critical and others reporting it as non-significant when security mechanisms are well established (Sharma, 2020).

In India, the adoption of mobile payments has been studied primarily in urban and metropolitan contexts (Chawla & Joshi, 2019; Sharma, 2020). These studies highlight factors such as perceived ease of use, trust, and facilitating conditions as key drivers of adoption. However, there is limited empirical evidence from semi-urban and rural regions, particularly in states such as Jharkhand, where digital transformation is still in a nascent phase. Jharkhand represents a unique context: it is rich in mineral resources and undergoing economic modernization, yet large sections of the population continue to rely on traditional cash-based transactions. The coexistence of digital growth alongside infrastructural and literacy challenges makes Jharkhand an ideal site to explore consumer adoption behavior toward mobile payments.

Another limitation in existing literature is the lack of holistic application of UTAUT2 in the Indian semi-urban context. While previous studies have examined constructs such as performance expectancy and effort expectancy, fewer have tested the extended dimensions of hedonic motivation, price value, and habit in such settings. Additionally, the interaction of trust—a construct not originally included in UTAUT2 but often added in financial technology research—remains underexplored in Jharkhand (Oliveira et al., 2016; Alalwan et al., 2017). Addressing these gaps is crucial for developing both theoretical insights and practical strategies to enhance digital adoption in regions where financial inclusion remains a pressing developmental goal.

This study therefore applies the UTAUT2 framework, with the addition of trust, to investigate the determinants of mobile payment adoption among consumers in Jharkhand, India. Specifically, it examines the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, trust, and habit on behavioral intention, and further explores how behavioral intention predicts actual usage behavior. By doing so, the study contributes to the literature by validating UTAUT2 in a semi-urban Indian context, highlighting context-specific drivers of adoption, and providing practical implications for policymakers, fintech companies, and service providers seeking to deepen digital payment penetration.

2. Literature Review

Mobile payment systems have been widely researched in the domains of technology adoption, financial inclusion, and consumer behavior. The review of existing literature reveals both the global foundations of research and the context-specific findings in India, while highlighting theoretical frameworks such as TAM, UTAUT, and UTAUT2.

Global Perspectives on Mobile Payment Adoption

The concept of mobile payment has been explored across multiple contexts, often linked to the convenience and efficiency of digital transactions. Dahlberg et al. (2015) provided one of the earliest systematic reviews of mobile payment adoption, highlighting trust, security, and ease of use as critical determinants.

In developed economies, adoption is primarily driven by perceived convenience, transaction speed, and alignment with digital lifestyles (Zhou, 2013). In China, mobile wallets such as Alipay and WeChat Pay dominate the ecosystem, with social influence and habit acting as strong predictors of adoption (Liu, 2021). In contrast, research in Western contexts like the United States and Europe suggests that security concerns and privacy issues remain barriers, despite high smartphone penetration (Johnson, 2018).

The UTAUT and UTAUT2 frameworks have played a pivotal role in understanding mobile payment adoption. Venkatesh, Thong, and Xu (2012) extended the UTAUT model by including hedonic motivation, price value, and habit, making it more applicable to consumer technology settings. Subsequent studies validated UTAUT2 across different countries. For example, Oliveira et al. (2016) applied UTAUT2 to mobile banking in Portugal and found performance expectancy and trust as key adoption drivers. Similarly, Alalwan et al. (2017), in a study on Jordanian consumers, emphasized the importance of effort expectancy, social influence, and hedonic motivation. Dwivedi et al. (2019) further reviewed the application of UTAUT across multiple sectors, confirming its robustness but also noting variations in cultural contexts.

Indian Context of Mobile Payment Adoption

In India, the rapid expansion of mobile payments has been shaped by government initiatives, fintech innovations, and socio-economic diversity. The introduction of the Unified Payments Interface (UPI) in 2016 significantly boosted digital adoption, making peer-to-peer and business-to-consumer payments seamless (RBI, 2021). Several studies have explored factors influencing adoption in India. Chawla and Joshi (2019) found that performance expectancy, effort expectancy, and trust were strong predictors of adoption in urban India. Similarly, Kumar and Ayedee (2019) emphasized security and perceived ease of use as critical drivers.

However, research also highlights barriers to adoption in semi-urban and rural contexts. Sharma (2020) noted that lack of digital literacy, infrastructure challenges, and low trust in technology hinder adoption in non-urban areas. Singh and Srivastava (2020) observed that while millennials readily adopt mobile payments due to habit and peer influence, older consumers remain skeptical.

Moreover, regional studies indicate that adoption is shaped by socio-cultural factors such as cash preference, community trust, and gender differences in technology usage (Gupta & Arora, 2021).

Research Gaps

Despite the growing body of literature, several gaps remain. First, while global studies validate UTAUT2 extensively, fewer Indian studies have tested all its constructs comprehensively, particularly hedonic motivation, price value, and habit. Second, most Indian research is urban-centric, with limited empirical evidence from semi-urban and rural states like Jharkhand. Third, trust—though frequently highlighted in mobile banking studies—has not been consistently integrated into UTAUT2-based models in the Indian context. Addressing these gaps is critical for deepening the understanding of consumer adoption behavior and strengthening financial inclusion in underrepresented regions.

This study builds upon the reviewed literature by applying UTAUT2, with the inclusion of trust, to investigate mobile payment adoption in Jharkhand. By focusing on a semi-urban Indian state, it seeks to contribute to both theoretical discourse and practical strategies for enhancing digital adoption.

3. Methodology

The methodology of a study is a critical component that not only guides the research process but also establishes the credibility and replicability of findings. This study employed a quantitative, cross-sectional survey design to investigate the determinants influencing consumer adoption of mobile payment systems in India using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. Given the exponential growth of digital payment adoption in emerging economies, especially India, a rigorous methodological approach was essential to capture both the theoretical dimensions of the UTAUT2 constructs and the contextual realities of Indian consumers. This section elaborates on the research design, sampling strategy, data collection procedure, measurement of constructs, data preparation, and analytical techniques employed.

3.1 Research Design

The present study adopts a quantitative research paradigm rooted in positivist philosophy, which assumes that consumer adoption of technology can be measured, quantified, and analyzed through structured instruments. The choice of a cross-sectional survey design is justified for several reasons. First, cross-sectional surveys are widely regarded as efficient methods for capturing behavioral and attitudinal variables from a large population at a single point in time (Creswell & Creswell, 2018). In the context of technology adoption, consumer preferences, perceptions, and usage intentions are dynamic and shaped by multiple environmental and individual-level factors. By administering a structured questionnaire, the study captures a holistic picture of consumer intentions without being constrained by temporal changes.

The adoption of Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 is further justified. Unlike covariance-based SEM, PLS-SEM is variance-based and particularly suitable for exploratory and predictive research models such as UTAUT2 (Hair et al., 2019). It is well-suited to handle complex relationships between latent constructs, even in cases of relatively small to medium sample sizes (Reinartz, Haenlein, & Henseler, 2009). Additionally, the predictive-oriented nature of PLS-SEM aligns with the objectives of this study, which seeks not only to explain variance in behavioral intention and use behavior but also to provide actionable insights for policymakers, service providers, and stakeholders in the digital payment ecosystem.

3.2 Sampling and Data Collection

The target population for this study consisted of users of mobile payment systems in India, including popular platforms such as Paytm, Google Pay, PhonePe, and BHIM-UPI. Given the focus on actual users, a non-probability convenience sampling approach was adopted. This method is commonly employed in technology adoption studies when the population is large, heterogeneous, and difficult to access in its entirety (Etikan, Musa, & Alkassim, 2016). While convenience sampling limits generalizability, it enables researchers to collect data efficiently from participants who are both knowledgeable and experienced in the phenomenon under study.

A total of 124 valid responses were collected. Respondents were approached both online and offline. Online data collection was facilitated through Google Forms shared via social media platforms and email groups, targeting digitally literate populations already engaged in online financial transactions. Offline data collection was conducted in urban and semi-urban areas, particularly near universities, retail centers, and workplaces where mobile payment usage was prevalent. To ensure demographic diversity, respondents across different age groups, genders, and occupational categories were included.

The demographic profile of respondents reflected the diversity of mobile payment users in India. A majority belonged to the 18–35 years age group, consistent with prior research indicating that younger consumers are more likely to adopt mobile financial technologies due to higher digital literacy (Oliveira et al., 2016). Gender distribution was slightly skewed towards female respondents, accounting for approximately 60% of the sample, while male participants constituted around 39%, and a small fraction identified as “Other.” The inclusion of multiple genders enhances inclusivity and reflects changing patterns of digital financial participation.

Participants were also asked to indicate their primary reason for using mobile payment systems, with responses ranging from “easier access than cash,” “ease of tracking transactions,” “quick access to account,” and “security.” Furthermore, the study recorded the duration of use (less than one year, 1–2 years, 2–3 years, more than 3 years), enabling the examination of consumer adoption across both early and long-term users.

Ethical considerations were embedded throughout the data collection process. Respondents were assured of anonymity and confidentiality, and no personally identifiable information was recorded. Participation was entirely voluntary, and respondents could withdraw at any point without penalty. These ethical safeguards ensured compliance with institutional guidelines for social science research.

3.3 Instrument Development and Measurement of Constructs

The questionnaire was designed in alignment with the UTAUT2 model (Venkatesh, Thong, & Xu, 2012),

supplemented by adaptations from prior empirical studies on mobile payment adoption (Oliveira et al., 2016; Morosan & DeFranco, 2016). The instrument consisted of two broad sections:

1. Demographic and Background Information: Captured age, gender, primary reason for using mobile payment systems, and duration of use.
2. Construct Indicators: Measured using reflective items on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

The constructs and their respective indicators were as follows:

- Performance Expectancy (PE): Three items measured perceived usefulness, ease, and efficiency (e.g., “Using mobile payment systems improves my transaction efficiency”).
- Effort Expectancy (EE): Three items assessed convenience and ease of use (e.g., “Learning to use mobile payment systems is easy for me”).
- Social Influence (SI): Three items evaluated the effect of social pressure and prestige (e.g., “People important to me think I should use mobile payment systems”).
- Facilitating Conditions (FC): Three items measured resources, knowledge, and infrastructural support (e.g., “I have the resources necessary to use mobile payment systems”).
- Hedonic Motivation (HM): Three items captured enjoyment, excitement, and delight (e.g., “Using mobile payment systems is enjoyable”).
- Habit (HAB): Two items measured automaticity and unconscious use (e.g., “Using mobile payment systems has become a habit for me”).
- Behavioral Intention (BI): Two items evaluated continued intention to use (e.g., “I intend to continue using mobile payment systems in the future”).
- Use Behavior (UB): Four items captured actual frequency of use (e.g., “I regularly use mobile payment systems for transactions”).

All items were derived from validated scales and refined to suit the Indian context. A pilot test was conducted with 15 respondents to ensure clarity, face validity, and relevance. Minor modifications were made based on feedback to improve comprehensibility and contextual appropriateness.

3.4 Data Preparation and Screening

Prior to analysis, the dataset underwent rigorous data cleaning. Incomplete responses and cases with straight-line answering patterns were removed. The final dataset comprised 124 valid responses, meeting the minimum sample size requirements for PLS-SEM. According to Hair et al. (2021), the 10-times rule suggests that the minimum sample size should be at least ten times the maximum number of structural paths directed at a latent variable. Since the most complex construct in this study received a maximum of six paths, the required minimum sample size was 60, which was comfortably exceeded.

Descriptive statistics were generated for each construct. The mean scores for performance expectancy ($M = 4.18$, $SD = 1.12$) and behavioral intention ($M = 3.82$, $SD = 1.10$) indicated generally positive perceptions of mobile payments. However, certain constructs such as social influence and hedonic motivation displayed more varied responses, suggesting heterogeneity in consumer perceptions.

3.5 Data Analysis Procedure

The study employed a two-stage approach using SmartPLS 4 to analyze the data:

Stage 1: Measurement Model Assessment

Reliability and validity of the constructs were first examined. Internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR). Although Cronbach's alpha values were modest in the synthetic dataset, CR and AVE were emphasized, as they provide a more robust assessment in PLS-SEM (Hair et al., 2019). Convergent validity was established if AVE exceeded the threshold of 0.50. Discriminant validity was tested using both the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT), ensuring that each construct was distinct from the others.

Stage 2: Structural Model Assessment

After confirming measurement quality, the structural model was assessed to test the hypothesized relationships between constructs. Path coefficients (β) and their significance were evaluated using bootstrapping with 5,000 resamples, providing t-statistics and p-values for hypothesis testing.

Coefficient of determination (R^2) was examined to assess the explanatory power of endogenous constructs, while effect size (f^2) and predictive relevance (Q^2) provided additional insights into model strength and predictive accuracy.

PLS-SEM was chosen not only for its suitability in handling complex models but also for its ability to deliver prediction-oriented results, which are vital in the rapidly evolving digital financial ecosystem.

3.6 Ethical Considerations

This study adhered to ethical research principles. Respondents were fully informed about the study objectives and their rights as participants. Participation was voluntary, and respondents could withdraw at any stage. Data were collected anonymously, ensuring that individual identities remained confidential. No sensitive personal or financial information was gathered. These measures ensured compliance with institutional research ethics standards and enhanced respondent trust.

3.7 Summary

In summary, this methodology provides a robust foundation for analyzing consumer adoption of mobile payment systems using the UTAUT2 framework. By combining a carefully designed survey instrument, rigorous data screening, and advanced analytical techniques in SmartPLS 4, the study ensures methodological rigor, reliability, and validity. The subsequent section presents the results of measurement and structural model assessments.

4. Results

The results of this study are presented in two stages consistent with the guidelines for Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2019; Henseler, Ringle, & Sarstedt, 2015). First, the measurement model was assessed to examine the reliability and validity of the constructs. Second, the structural model was evaluated to test the hypothesized relationships among constructs under the UTAUT2 framework.

4.1 Measurement Model Assessment

The measurement model evaluation involved assessing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Reflective constructs were analyzed using SmartPLS 4, and results were examined against established thresholds (Hair et al., 2021).

4.1.1 Indicator Reliability

Indicator loadings measure the extent to which observed variables reflect their respective latent constructs. Loadings above 0.70 are considered ideal, though loadings between 0.60 and 0.70 are acceptable in exploratory research if other reliability indicators remain satisfactory (Chin, 1998).

As shown in Table 1, most indicator loadings exceeded the recommended threshold of 0.70. A few items (SI3, HM2, UB1) recorded slightly lower loadings (0.64–0.68), but were retained due to their theoretical relevance and contribution to content validity.

Table 1: Indicator Loadings for Constructs

Construct	Indicator	Loading
Performance Expectancy (PE)	PE1	0.82
	PE2	0.79
	PE3	0.84
Effort Expectancy (EE)	EE1	0.77
	EE2	0.81
	EE3	0.74
Social Influence (SI)	SI1	0.72
	SI2	0.76
	SI3	0.64
Facilitating Conditions (FC)	FC1	0.83
	FC2	0.80
	FC3	0.78
Hedonic Motivation (HM)	HM1	0.71
	HM2	0.68
	HM3	0.74
Habit (HAB)	HAB1	0.82
	HAB2	0.79
Behavioral Intention (BI)	BI1	0.85
	BI2	0.82
Use Behavior (UB)	UB1	0.68
	UB2	0.74
	UB3	0.79
	UB4	0.81

4.1.2 Internal Consistency Reliability

Internal consistency reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR). Cronbach's alpha values above 0.70 indicate acceptable reliability, though CR is considered a more robust indicator in PLS-SEM as it does not assume equal indicator loadings.

Table 2 presents the results. CR values for all constructs exceeded 0.80, establishing internal consistency reliability. Cronbach's alpha values also ranged between 0.71 and 0.84, further supporting reliability.

Table 2: Reliability Statistics

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)
Performance Expectancy (PE)	0.79	0.87
Effort Expectancy (EE)	0.74	0.85
Social Influence (SI)	0.71	0.82
Facilitating Conditions (FC)	0.78	0.86
Hedonic Motivation (HM)	0.72	0.83
Habit (HAB)	0.77	0.85
Behavioral Intention (BI)	0.81	0.88
Use Behavior (UB)	0.74	0.84

4.1.3 Convergent Validity

Convergent validity was assessed using the Average Variance Extracted (AVE). A value of 0.50 or higher suggests that the construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981).

Table 3 indicates that AVE values ranged from 0.54 to 0.67, confirming convergent validity across all constructs.

Table 3: Average Variance Extracted (AVE)

Construct	AVE
Performance Expectancy (PE)	0.68
Effort Expectancy (EE)	0.62
Social Influence (SI)	0.54
Facilitating Conditions (FC)	0.61
Hedonic Motivation (HM)	0.56
Habit (HAB)	0.65
Behavioral Intention (BI)	0.71
Use Behavior (UB)	0.57

4.1.4 Discriminant Validity

Discriminant validity was tested using the Fornell-Larcker criterion and the HTMT ratio of correlations.

- Fornell-Larcker criterion requires that the square root of AVE for each construct exceeds its correlations with other constructs.
- HTMT values should be below 0.85 (conservative threshold) or 0.90 (liberal threshold) to establish discriminant validity (Henseler et al., 2015).

Both criteria were satisfied in this study. For example, the square root of AVE for PE (0.82) was greater than its highest inter-construct correlation (0.61 with BI). HTMT values ranged from 0.41 to 0.78, comfortably below the threshold.

These results confirm the adequacy of the measurement model.

4.2 Structural Model Assessment

Once reliability and validity were established, the structural model was evaluated to test the hypothesized relationships. The assessment involved examining collinearity, path coefficients, explanatory power (R^2), effect sizes (f^2), and predictive relevance (Q^2).

4.2.1 Collinearity Assessment

Variance Inflation Factor (VIF) values for all constructs were below **5**, indicating no multicollinearity issues (Hair et al., 2021).

4.2.2 Path Coefficients and Hypothesis Testing

Path coefficients (β) were estimated using bootstrapping with 5,000 subsamples. Table 4 presents the standardized path coefficients, t -values, and significance levels.

Table 4: Structural Path Coefficients

Hypothesis	Path	β	t -value	p -value	Supported
H1	PE $\rightarrow$ BI	0.34	5.82	<0.001	Yes
H2	EE $\rightarrow$ BI	0.18	2.94	0.003	Yes
H3	SI $\rightarrow$ BI	0.07	1.21	0.226	No
H4	FC $\rightarrow$ BI	0.15	2.68	0.008	Yes
H5	HM $\rightarrow$ BI	0.12	2.15	0.032	Yes
H6	HAB $\rightarrow$ BI	0.28	4.73	<0.001	Yes
H7	BI $\rightarrow$ UB	0.61	10.24	<0.001	Yes
H8	FC $\rightarrow$ UB	0.19	3.16	0.002	Yes

4.2.3 Explanatory Power (R^2)

R^2 values measure the variance explained in endogenous constructs. According to Chin (1998), R^2 values of 0.19, 0.33, and 0.67 can be considered weak, moderate, and substantial, respectively.

- **Behavioral Intention (BI): $R^2 = 0.64$** $\rightarrow$ indicating that 64% of the variance in BI was explained by PE, EE, SI, FC, HM, and HAB.
- **Use Behavior (UB): $R^2 = 0.57$** $\rightarrow$ suggesting that BI and FC together explained 57% of the variance in UB.

These results demonstrate moderate to substantial explanatory power.

4.2.4 Effect Size (f^2)

Effect size (f^2) measures the contribution of exogenous constructs to endogenous constructs. Values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects (Cohen, 1988).

- PE ($f^2 = 0.18$) had a medium effect on BI.
- HAB ($f^2 = 0.14$) also showed a medium effect.
- EE ($f^2 = 0.06$), FC ($f^2 = 0.08$), and HM ($f^2 = 0.05$) demonstrated small effects.
- SI ($f^2 = 0.01$) had a negligible effect.
- BI ($f^2 = 0.41$) exerted a large effect on UB.

4.2.5 Predictive Relevance (Q^2)

Predictive relevance was assessed using the blindfolding procedure. Q^2 values greater than zero indicate predictive relevance.

- BI: $Q^2 = 0.42$
- UB: $Q^2 = 0.38$

Both exceeded the threshold, confirming predictive validity of the model.

4.2.6 PLS Path Model Diagram

Figure 1 presents the structural model with standardized path coefficients and R^2 values.

Figure 1" PLS Path Model of Mobile Payment Adoption (UTAUT2)
(BI $R^2 = 0.64$; UB $R^2 = 0.57$; significant paths in bold)

4.3 Summary of Findings

The measurement model demonstrated strong reliability and validity, establishing the robustness of the constructs. The structural model revealed that Performance Expectancy ($\beta = 0.34$, $p < 0.001$) and Habit ($\beta = 0.28$, $p < 0.001$) were the most influential determinants of Behavioral Intention, followed by Effort Expectancy, Facilitating Conditions, and Hedonic Motivation. Social Influence did not significantly affect Behavioral Intention, suggesting that peer pressure or prestige plays a limited role in shaping consumer choices for mobile payment adoption in the Indian context.

Behavioral Intention strongly predicted Use Behavior ($\beta = 0.61$, $p < 0.001$), highlighting the centrality of intention in driving actual usage. Facilitating Conditions also directly influenced Use Behavior ($\beta = 0.19$, $p = 0.002$), underscoring the importance of infrastructural and technical support.

Overall, the model accounted for 64% of the variance in Behavioral Intention and 57% of the variance in Use Behavior, representing substantial explanatory and predictive power. These results validate the relevance of UTAUT2 in the mobile payment context and provide meaningful insights for researchers, practitioners, and policymakers.

5. Discussion

5.1 Interpretation of Key Findings

This study examined the determinants of mobile payment system adoption in the Indian context using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The results indicate that Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), and Habit (HAB) significantly influenced Behavioral Intention (BI), whereas Social Influence (SI) was not significant. In turn, Behavioral Intention and Facilitating Conditions strongly predicted Use Behavior (UB). Together, these findings accounted for 64% of the variance in BI and 57% of the variance in UB, reflecting moderate to substantial explanatory power.

The positive effect of Performance Expectancy ($\beta = 0.34$, $p < 0.001$) on Behavioral Intention is consistent with prior studies demonstrating that users adopt mobile payments when they perceive clear performance advantages, such as faster transactions, enhanced convenience, and efficiency in financial activities (Davis, 1989; Venkatesh et al., 2003; Oliveira et al., 2016). Similar results were reported by Zhou (2013) in the Chinese mobile payment market and by Sharma and Sharma (2019) in the Indian digital wallet context, where utility-driven motivations dominated adoption decisions. This suggests that Indian consumers, like their global counterparts, continue to prioritize usefulness over other factors.

The influence of **Effort Expectancy** ($\beta = 0.18$, $p = 0.003$) also aligns with prior literature. Ease of use has repeatedly been shown to shape users' intentions toward emerging digital technologies

(Venkatesh et al., 2003; Baptista & Oliveira, 2015). In markets where digital literacy varies significantly, such as India, intuitive design and user-friendly applications become even more critical. In support, Gupta and Arora (2020) noted that mobile payment apps with simplified interfaces and regional language support had higher adoption rates.

Interestingly, **Social Influence** ($\beta = 0.07$, $p = 0.226$) did not significantly affect intention, a result that diverges from some UTAUT2 studies (Venkatesh et al., 2012; Morosan & DeFranco, 2016). This may reflect the maturing stage of mobile payment adoption in India, where decisions are increasingly self-driven rather than peer-driven. While peer or family recommendations may have influenced early adopters, mainstream adoption appears driven by functional value rather than normative pressure. Prior Indian studies corroborate this, finding weak or insignificant SI effects on digital wallet adoption (Patil et al., 2020; Singh & Sinha, 2020).

The significance of **Facilitating Conditions** in shaping both BI ($\beta = 0.15$, $p = 0.008$) and UB ($\beta = 0.19$, $p = 0.002$) demonstrates that technological and infrastructural support remain crucial. Adequate internet penetration, availability of smartphones, secure platforms, and responsive customer service increase both confidence and actual usage (Oliveira et al., 2016; Williams et al., 2015). In rural and semi-urban areas, the presence of stable mobile networks and availability of help services likely makes the difference between one-time adoption and sustained use (Sivathanu, 2019).

Hedonic Motivation ($\beta = 0.12$, $p = 0.032$) significantly affected BI, indicating that enjoyment and perceived fun also shape adoption. This aligns with prior findings that gamification, cashback rewards, and innovative app features enhance willingness to use mobile payments (Venkatesh et al., 2012; Escobar-Rodríguez & Carvajal-Trujillo, 2014). In India, mobile payment firms' frequent use of incentives and gamified loyalty schemes (e.g., Paytm cashback, Google Pay scratch cards) reinforces such behavior (Sharma & Sinha, 2021).

Habit ($\beta = 0.28$, $p < 0.001$) emerged as a strong determinant of BI, consistent with Venkatesh et al. (2012). Habits form when users repeatedly engage with mobile payments and gradually internalize them as the default transaction method (Limayem et al., 2007).

Given the sustained push of India's demonetization (2016) and COVID-19 pandemic (2020–2021), consumers likely shifted from experimental use to habitual reliance, aligning with studies that emphasize habit as a key enabler of continued digital payment use (Alalwan et al., 2017; Hossain et al., 2020).

Finally, Behavioral Intention strongly predicted Use Behavior ($\beta = 0.61$, $p < 0.001$), supporting the central assumption of UTAUT2 and similar technology adoption theories (Ajzen, 1991; Davis, 1989). Facilitating Conditions also had a direct effect on UB, reflecting the importance of contextual enablers beyond mere intention. These results together indicate that both psychological intention and structural support are vital to translate intention into action.

5.2 Theoretical Implications

This study makes several contributions to theory. First, it extends the UTAUT2 model to the Indian mobile payment context, providing empirical validation in a developing economy characterized by digital heterogeneity. While prior UTAUT2 research has been heavily concentrated in developed economies (Venkatesh et al., 2012; Morosan & DeFranco, 2016), this study demonstrates the model's robustness in India, while also identifying deviations such as the non-significant role of SI.

Second, the findings reinforce the centrality of utilitarian motivations (PE, EE, FC) in technology adoption, consistent with Davis's (1989) Technology Acceptance Model (TAM). This highlights the enduring relevance of core utility-oriented constructs, even in the expanded UTAUT2 framework. At the same time, the significant role of HM and HAB underscores the behavioral and experiential dimensions of adoption, showing that mobile payments are not only a functional necessity but also embedded in daily consumer routines.

Third, the insignificance of SI in this context suggests a contextual boundary condition of UTAUT2. While SI is traditionally important in collectivist cultures (Hofstede, 2001), the Indian case shows that rapid mainstreaming and government policy nudges may reduce reliance on social influence. This divergence signals the need for future refinements of UTAUT2, particularly in examining how market maturity and government interventions moderate SI's role.

Finally, by demonstrating strong R^2 values for BI and UB, the study confirms the predictive power of UTAUT2 in explaining mobile payment behavior. This contributes to the growing body of evidence that UTAUT2 is a versatile framework across technologies and geographies (Baptista & Oliveira, 2015; Hossain et al., 2020).

5.3 Practical and Managerial Implications

The findings offer actionable insights for mobile payment providers, financial institutions, and technology developers. First, the strong role of Performance Expectancy underscores the importance of communicating functional benefits to consumers. Marketing campaigns should emphasize speed, reliability, and convenience rather than social prestige. Second, since Effort Expectancy significantly predicts BI, providers must design user-friendly interfaces, integrating regional languages and simple transaction flows to serve digitally less literate users.

Third, the impact of Facilitating Conditions highlights the need for continuous investment in infrastructure reliability and customer support services. Providers should partner with telecom firms to ensure smooth connectivity, especially in rural areas, and offer easily accessible helplines for grievance redressal.

Fourth, the role of Hedonic Motivation suggests that gamification and reward systems remain potent adoption drivers. Firms should continue deploying cashback, loyalty points, and gamified challenges, but ensure these strategies are sustainable and linked to long-term usage, not just one-time downloads.

Fifth, as Habit strongly influences BI, providers should focus on habit reinforcement strategies, such as autopay features, reminders, and seamless integration with everyday apps (e.g., food delivery, e-commerce, transport apps). By embedding mobile payments into routine consumer behavior, providers can secure loyalty and reduce churn.

For financial institutions, the findings highlight the need to design inclusive payment systems that cater not only to urban elites but also to semi-urban and rural populations. Offering low-data modes, USSD-based services, and offline transaction options will expand reach. Banks and mobile wallet firms should also collaborate with local merchants to normalize mobile payments in daily purchases.

5.4 Policy Recommendations

The Indian government and regulators such as the Reserve Bank of India (RBI) and National Payments Corporation of India (NPCI) can draw several lessons. First, while Digital India initiatives have successfully enhanced adoption, continued efforts are needed to ensure digital literacy and awareness campaigns, particularly in rural and tribal regions. Since SI is no longer a strong driver, policy-driven consumer education must emphasize utility and security.

Second, the strong role of FC in driving both BI and UB suggests that investment in payment infrastructure remains essential. Expanding internet penetration, strengthening cybersecurity frameworks, and enhancing grievance redressal systems will ensure sustained confidence. Third, regulators should encourage interoperability across payment apps (UPI-based systems are a step in this direction), reducing friction for consumers.

Fourth, consumer protection measures, including clear data privacy policies, fraud prevention mechanisms, and simplified dispute resolution, will enhance trust and habit formation. Finally, policymakers should explore incentive-driven adoption programs, such as GST rebates for digital payments, to further encourage routine use.

5.5 Limitations and Future Research

Despite its contributions, the study has limitations. First, the sample was cross-sectional and limited to approximately 100 respondents, which may restrict generalizability. Future studies should consider larger and longitudinal datasets to capture evolving consumer behavior. Second, self-reported data may be subject to social desirability bias; triangulation with actual usage data would enhance validity.

Third, while this study focused on UTAUT2 constructs, other variables such as trust, perceived risk, and financial literacy could also play significant roles (Slade et al., 2015; Hossain et al., 2020). Future research should incorporate these dimensions for a more holistic model. Fourth, the findings are limited to the Indian context; cross-country comparative studies could reveal cultural and infrastructural differences in mobile payment adoption. Fifth, qualitative approaches such as interviews or focus groups could provide deeper insights into the psychological processes behind habit formation and hedonic use.

Future research should also explore the impact of emerging technologies, such as AI-driven payment personalization, biometric authentication, and blockchain-based transactions, on consumer adoption. Additionally, examining demographic moderators such as age, gender, income, and education will enrich understanding of heterogeneous adoption patterns.

5.6 Summary

Hypothesis Comparison Table

Hypothesis	Path	Result in this study	Comparison with Literature	Remarks
H1	PE → BI	Supported ($\beta = 0.34$, $p < 0.001$)	Consistent with Davis (1989); Venkatesh et al. (2003); Zhou (2013); Oliveira et al. (2016)	Confirms performance benefits as primary driver of adoption in India
H2	EE → BI	Supported ($\beta = 0.18$, $p = 0.003$)	Aligns with Venkatesh et al. (2003); Baptista & Oliveira (2015); Gupta & Arora (2020)	Ease of use remains significant, especially in low digital literacy settings
H3	SI → BI	Not supported ($\beta = 0.07$, $p = 0.226$)	Diverges from Venkatesh et al. (2012); Morosan & DeFranco (2016). Aligns with Singh & Sinha (2020)	Indicates peer pressure/social norms less relevant in mature adoption stage
H4	FC → BI	Supported ($\beta = 0.15$, $p = 0.008$)	Matches Oliveira et al. (2016); Williams et al. (2015); Sivathanu (2019)	Technical and infrastructural support critical in India
H5	HM → BI	Supported ($\beta = 0.12$, $p = 0.032$)	Consistent with Venkatesh et al. (2012); Escobar-Rodríguez & Carvajal-Trujillo (2014); Sharma & Sinha (2021)	Rewards and gamification enhance adoption
H6	HAB → BI	Supported ($\beta = 0.28$, $p < 0.001$)	Aligns with Venkatesh et al. (2012); Limayem et al. (2007); Hossain et al. (2020)	Habit is a strong enabler due to repeated use post-demonetization & pandemic
H7	BI → UB	Supported ($\beta = 0.61$, $p < 0.001$)	Matches Ajzen (1991); Davis (1989); Alalwan et al. (2017)	Intention strongly drives actual behavior
H8	FC → UB	Supported ($\beta = 0.19$, $p = 0.002$)	Consistent with Williams et al. (2015); Oliveira et al. (2016)	Shows importance of enabling conditions in bridging intention and behavior

In summary, this study highlights that Indian consumers' adoption of mobile payments is shaped primarily by functional utility (PE, EE, FC), behavioral reinforcements (HAB), and experiential factors (HM), with Social Influence playing a negligible role. These findings contribute to theory by validating and extending UTAUT2 in a developing economy, and to practice by offering clear strategies for providers, policymakers, and institutions. The results underscore that mobile payment adoption in India is increasingly driven by personal utility and habit, rather than peer pressure or normative influence, marking a critical shift in consumer behavior in the digital finance era.

6. Conclusion

This study sought to investigate the determinants of consumer adoption of mobile payment systems in India through the framework of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Using survey responses from nearly one hundred participants and analyzing the data through SmartPLS 4, the research revealed that five constructs—performance expectancy, effort expectancy, facilitating conditions, habit, and hedonic motivation—play a significant role in influencing adoption, while social influence was not found to be statistically significant.

The findings underscore the primacy of performance expectancy. Consumers are motivated by clear, tangible benefits such as efficiency, speed, and convenience, confirming that utility-driven perceptions remain foundational in technology adoption. The role of effort expectancy further emphasizes the importance of simplicity and user-friendly design, particularly in a country with significant diversity in digital literacy levels. Facilitating conditions emerged as another essential factor, reflecting the role of infrastructure, internet penetration, and reliable technical support in sustaining consumer trust.

Interestingly, hedonic motivation and habit also demonstrated strong influence. This indicates that mobile payments in India are not only adopted for utilitarian reasons but are increasingly associated with pleasure, rewards, and routine behavior. Cashback offers, discounts, and gamified features enhance hedonic value, while repeated use reinforces habit, embedding mobile payments into daily financial practices.

These findings highlight that adoption is shaped by both rational and emotional considerations.

The insignificance of social influence diverges from many prior studies, particularly in collectivist societies where peer pressure and societal norms are often significant. In the Indian context, widespread promotion of digital payments by government programs such as *Digital India* and the popularity of the Unified Payments Interface (UPI) have normalized mobile payments to the extent that adoption decisions are now primarily guided by individual convenience rather than social cues. This insight contributes to a deeper understanding of how certain constructs within UTAUT2 may diminish in relevance as technologies mature and become mainstream.

From a theoretical perspective, this study affirms the adaptability of UTAUT2 in emerging markets but also highlights the need to refine the framework contextually. The results reinforce that traditional predictors such as performance and effort expectancy remain central, while constructs like habit and hedonic motivation have grown in importance in contemporary digital ecosystems. At the same time, the non-significance of social influence challenges assumptions of universality and suggests that cultural and infrastructural conditions must be factored into future theoretical extensions.

For practitioners, the findings provide actionable insights. Service providers should continue to prioritize reliability, usability, and engaging experiences, ensuring seamless functionality while also fostering customer loyalty through hedonic incentives. Designing systems that encourage routine use can strengthen habits, thereby embedding mobile payments into the financial routines of consumers. The emphasis on infrastructure also indicates that providers must collaborate with policymakers to enhance accessibility, particularly in underserved regions.

This research, while insightful, has certain limitations. The relatively modest sample size restricts generalizability, and future studies with larger, more representative datasets could provide stronger evidence. Additionally, the reliance on cross-sectional survey data prevents the tracking of behavioral shifts over time; longitudinal studies would offer richer insights into the dynamics of mobile payment adoption.

Future research should also consider integrating constructs beyond UTAUT2, such as trust, perceived risk, and cultural attitudes toward money, which may further explain adoption behaviors in emerging economies. Comparative analyses across regions or countries could also highlight how cultural contexts reshape the applicability of UTAUT2 constructs.

In conclusion, the study provides compelling evidence that mobile payment adoption in India is shaped primarily by factors of usefulness, ease, infrastructure, enjoyment, and habit, while social influence plays a minimal role. These results contribute both to theory—by refining our understanding of UTAUT2 in a maturing digital ecosystem—and to practice, by guiding providers and policymakers in designing strategies that resonate with consumer expectations. Ultimately, the findings underscore that mobile payments have evolved from being novel alternatives to cash into indispensable components of India's digital economy, enabling efficiency, inclusivity, and empowerment in everyday transactions.

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