

Evaluating the Actual Usage of UPI Payment Services in North-East India through the Lens of UTAUT 2 Framework

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Abstract

Business in India witnessed many significant changes after the COVID-19 pandemic, one of them being the increasing use of digital money instead of hard cash. This use of digital money is facilitated by UPI (Unified Payment Interface) services, whereby payments can be easily made via easily accessible device like mobile phones. Though many players have created their own UPI services, only a few have the major market share and are able to provide requisite customer satisfaction. This research is done to understand the factors influencing the behavior intention and actual usage of UPI payment services. The identified factors may help the providers with sufficient knowledge to address the customer needs.

The relationship between latent variables with behavioral intention and actual usage of UPI Payment services is tested with structural model UTAUT2 proposed by Venkatesh et al. (2012) along with defining relation between behavioral intention and actual usage. The UTAUT2 questionnaire (adapted version) was utilized to collect data from 456 UPI users to understand the proposed model using variable based SmartPLS v4.0. The proposed structural model was moderate in predicting actual usage and behavioral intention to use UPI payment services through Q-Square predictive relevance calculations. In the study, it was proved that behavioral intention played a mediating role between the exogenous variables and actual usage. It was also verified that age and use experience plays a moderator role in the relationship between behavioral intention and actual usage. The study concludes that the proposed model is fit, reliable, and valid using various statistical analysis and can be considered as an addition to the existing literature on UTAUT2 and UPI usage.

Keywords: UPI payment services, Extended UTAUT2, PLS-SEM, SmartPLS, Predictive relevance, R-square, mediating variable, moderating variable.

1. Introduction

In April 2016, the National Payment Corporation of India introduced a novel public payment system known as the ‘Unified Payments Interface’ (UPI), conceived with the vision of establishing a green, secure, efficient, accessible, inclusive, authorized, free, and one-click retail payment settlement mechanism in India. The widespread availability of smart- phones and internet access, coupled with factors such as the demonetization of large currency denominations in 2016 and COVID – 19 – related restrictions, has propelled the increasing prominence of digital payment applications. UPI, specifically, has played a pivotal role in enabling wide-spread digital micro-payments, reaching a substantial volume of 21.7 billion transactions in January, 2025 alone and holding an 84.8% share of retail digital payments volume. Despite this explosive growth – from 18 million transactions in 2016.

The Unified Payments Interface (UPI), launched by the National Payments Corporation of India (NPCI) in 2016, has revolutionized digital payments in India, achieving over 21.7 billion transactions in January 2025 alone and holding an 84.8% share of retail digital payments volume. Despite this explosive growth – from 18 million transactions in 2016-17 to 186 billion in 2024-25 – gaps persist between user’s behavioral intentions to adopt UPI and their actual sustained usage, particularly influenced by demographics, risks, and infrastructure. This paper examines these dynamics using the UTAUT2 framework to bridge intention – usage disparities and inform policy for broader inclusion.

As mobile phones and internet access, prerequisites for UPI, become more affordable and accessible, a favorable environment is emerging for UPI to establish itself as a preferred digital platform in India, thereby contributing to the ongoing sustainable financial inclusion process. However, it is noteworthy that UPI has predominantly found acceptance among the urban population in India (Padaki, 2022). Given that the majority of the population in India and other developing countries belongs to the bottom of the pyramid (BOP), it becomes crucial to delve into the adoption process of UPI among BOP users. Exploring the factors influencing UPI adoption in the BOP population is particularly intriguing in light of these dynamics.

2. Literature review

The implementation of the Unified Payment Interface (UPI) as a technological innovation in banking is a recent development for its stakeholders. It is imperative to understand the adoption process of UPI among consumers from the perspective of researchers, the banking ecosystem,

and governmental institutions.

Understanding customer requirements and preferences is utmost important considering the increased growth and use of UPI payment services. The study was undertaken to understand the behavioral intention and actual usage of UPI payment services. UTAUT 2 model proposed by Venkatesh et al. (2012) was utilized for understanding the relationship between the defined variables and constructs. The observations of the study is relevant to the readers as there is no such study undertaken addressing the North-East Indian customers and their preferences. The outcome of the study will definitely add to the existing knowledge and provide a new perspective in understanding customer of UPI payment services.

Partial least square – structural equation modeling framework was utilized to establish the relationships between the variables and constructs. Literature review and author's own interpretation was utilized to propose a study model. The questionnaire for data collection was created after doing literature review. The data obtained from survey was utilized to analyze the proposed model using SmartPLS v.4.0. The results are discussed in details along with other observations in the results and conclusion section.

UTAUT2 as a model for understanding adoption of technology has been applied in many research areas, including health and fitness apps (Yuan et al., 2015); M-learning (Yang, 2013); Travel apps (Gupta et al., 2018); Smartphone fitness apps (Dhiman et al., 2019); Mobile food ordering apps (Alalwan, 2020); mobile health adoption (Duarte and Pinho, 2019).

Unified Theory of Acceptance and Use of Technology (UTAUT) was proposed by Venkatesh, Morris, Davis and Davis (2003). The concept of UTAUT was drawn from eight different technology adoption models including Theory of Reasoned Action, Technology Acceptance model 2, Theory of Planned Behavior, Motivational Model, Combine TAM and TPB, Model of PC Utilization, Innovation Diffusion, and Social Cognitive theory (Venkatesh et al., 2003). With the combination of these models, the UTAUT model was able to explain and describe the acceptance of new technology by the consumer in a uniform way. UTAUT used our constructs: performance expectancy, social influence, effort expectancy, and facilitating conditions to define the user behavior and behavioral intentions (Venkatesh et al., 2003). UTAUT 2 was suggested by Venkatesh et al. (2012) as a modification to the earlier model by including new constructs, namely, hedonic motivation, price value, and habit. Age, gender, and Use experience were

included as moderating variables.

Performance Expectancy (PE) is the user's perception that technology will improve their performance (Venkatesh et al., 2012). Performance expectancy is found to significantly influence behavior intention in many studies (Oliveira et al., 2016; Jambulingam, 2013; Nair et al., 2015; Sair & Danish, 2018; Chua et al., 2018). Effort Expectancy (EE), the ease of using a technology or the effort required to use a technology is found to significantly influence behavior intention by many studies (Teo & Noyes, 2012; Tan et al., 2011). Social Influence (SI), is the influence of people close to the consumer (social circle) on using a technology is also found to significantly influence behavioral intention by many studies (Venkatesh et al., 2003; Latif & Zakaria, 2020; Oliveira et al., 2016; Farooq et al., 2017). Similarly, Facilitating Condition (FC) is the user perception that required infrastructure exists for using the technology (Venkatesh et al., 2003). FC is found to significantly influence behavioral intention in many studies (Foon & Fah, 2011; Wu et al., 2008). Hedonic Motivation (HM) is the pleasure derived from using a technology (Brown & Venkatesh, 2005). HM is found to influence behavioral intention by many studies (Alalwan, 2020; Tak & Panwar, 2017; Farooq et al., 2017). Price Value (PV) is the difference in the cost and benefit of using a technology and is found to significantly influence behavioral intention by many studies (Kwateng et al., 2018; Farooq et al., 2017). However, since UPI payment interface in India is free of cost and hence the Price value factor does not apply in this particular study as done in many studies (Tamilmani et al., 2018). Automatic or continuous behavior due to learning is termed as Habit (HT) (Limayem et al., 2007). Habit is found to influence behavioral intention in many studies (Alalwan, 2020; Tak & Panwar, 2017; Duarte & Pinho, 2019).

Behavioral Intention (BI) is the intention to consume that influences the behavior of a consumer (Ajzen, 1991). Behavioral intention in the study is the intention to use the UPI payment services. It denotes how much the consumer has planned to perform a future behavior (Huang & Kao, 2015). Actual Usage (AU) is the final outcome, it is the behavioral intention converted to actual use of a technology as posited by many studies (Tao, D., 2009; Febrianto et al., 2018).

There is a recognized need for research that measure actual usage (AU) as an outcome variable directly, rather than solely focusing on behavioral intention, to bridge the intention-behavior gap (Razi et al., 2024).

Thus, the following hypotheses are framed for analysis

- H1: PE influences BI for using UPI payment services.
- H2: EE influences BI for using UPI payment services
- H3: SI influences BI for using UPI payment services
- H4: FC influences BI for using UPI payment services
- H5: HM influences BI for using UPI payment services
- H6: HT influences BI for using UPI payment services.
- H7: BI influences AU for using UPI payment services.

Moderating effect of age, gender, and use experience has been studied in adoption of new technology (Venkatesh et al., 2012). In this study, age, gender, use experience, and occupation are proposed as moderating variables. Outcome of the study will help in understanding their impact and significance.

Hence, the additional hypotheses are proposed as:

- H8a: Gender has a moderating effect on the relationship between BI and AU
- H8b: Age has a moderating effect on the relationship between BI and AU
- H8c: Use experience has a moderating effect on the relationship between BI and AU
- H8d: Occupation has a moderating effect on the relationship between BI and AU.

In summary, the UTAUT2 model and its various extensions have provided a strong foundation for understanding the factors influencing behavioral intention and actual usage. Including UPI, in India. However, existing literature indicates a continued need for research that delves deeper into specific demographic segments, the moderating roles of contextual factors, the long-term sustainability of adoption, and the precise mechanisms translating intention to sustained usage, especially for a transformative platform like UPI.

3. Research Methodology

3.1 Research Objective

- Utilize the modified UTAUT 2 model to study the influence of defined variables on the Behavioral Intention and Actual Usage of UPI Payment Services.

- Validate the influence of exogenous variables defined as UTAUT2 model variables on the endogenous variables (Behavioral Intention and Actual Usage).
- Estimate the explanatory and predictive power of the proposed model on consumer behavior of UPI payment services.

3.2 Research Design

With UTAUT 2 framework as the base model and on detailed literature review, the proposed model is created as shown in Fig. 1.

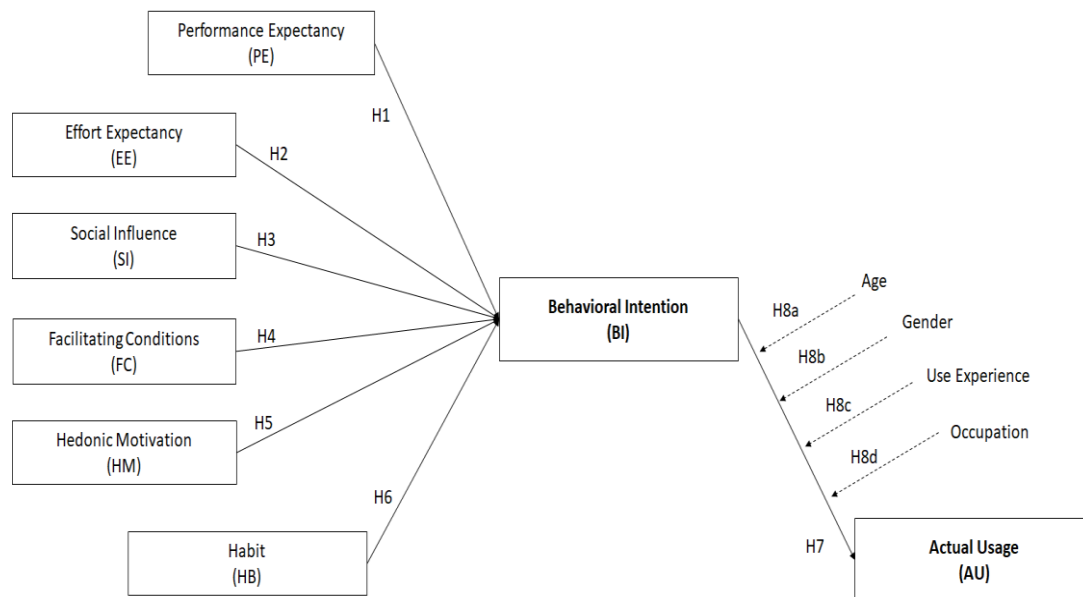


Figure 1: Proposed Conceptual model for the study

3.3 Measurement Instrument

A questionnaire was adapted from Razi et al. (2024) & Venkatesh et al. (2012). The items were adapted based on literature review. The questionnaire was adapted by dividing it into two section. Section – I was designed to collect the demographic information of the respondent. Section II was designed to address the different constructs of the study.

A pilot survey was undertaken with 50 samples to verify the framing of the questions, its relevance and suitability. The questionnaire as finalized by the researcher is enclosed in Table 2. Likert – type scale representing ‘strongly agree’ to ‘strongly disagree’ with scores varying from 5 to 1 respectively is used to gather users viewpoint.

Table 1: Scale and Construct

Construct	Number of Items	Source (s)
Performance Expectancy	5	Razi et al. (2024) & Venkatesh et al. (2012) (4 item); Authors own wording verified through pilot survey (1 item)
Effort Expectancy	5	Razi et al. (2024) & Venkatesh et al. (2012) (4 item); Venkatesh et al. (2003) (1 item)
Social Influence	5	Razi et al. (2024) & Venkatesh et al. (2012) (3 item); Yang (2013) (1 item); Authors own wording verified through pilot survey (1 item)
Facilitating Conditions	5	Razi et al. (2024) & Venkatesh et al. (2012) (4 item); Venkatesh et al. (2003) (1 item)
Hedonic Motivation	7	Venkatesh et al. (2012)(3 item); Yang (2013) (2 item); Authors own wording verified through pilot survey (2 item)
Habit	5	Venkatesh et al. (2012) (4 item); Authors own wording verified through pilot survey (1 item)
Behavioral Intention	5	Razi et al. (2024) & Venkatesh et al. (2012) (3 item); Authors own wording verified through pilot survey (2 item)
Actual usage	3	Razi et al. (2024). (3 item)

3.4 Data Collection

The final questionnaire was circulated to around 520 prospects through online and offline methods. The respondents were selected using non-probability, purposive sample and snowballing was involved to gather adequate responses from active users of UPI services. The data was collected during the period of October 2025 to December 2025 in North-Eastern states of India. 26 respondents didn't respond to the questionnaire, 20 responses were rejected because of missing information, and 18 responses were found to be ineligible because of multiple attempts to some questions. Thus, finally 456 responses were found to be suitable for further calculations and analysis.

3.5 Data Analysis Technique

Partial least square SEM, i.e. a variance based SEM has greater statistical power at all sample size and uses all kinds of variance from the independent variable to predict the variance in dependent variable. (Sarstedt et al., 2017). Since the study is exploratory in nature, PLS-Structural Equation Modelling is found suitable as it is based on variance than a covariance based SEM.

Smart PLS v4.0 is used for analysis of the data collected. Structural Equation Modelling is used to estimate the relationship between the measured variable and latent constructs.

A two stage process is followed for assessing the measurement model and structural model (Anderson and Gerbin, 1988) using Smart PLS v4.0. The reflective model (Measurement model) is evaluated using indicator reliability (factor loading), internal consistency reliability, convergent reliability, and discriminant validity. The formative model is evaluated using collinearity, predictive relevance, explanatory powers, and significance and relevance of path through path coefficient (Ringle et al., 2020; Benitez et al., 2020). Moderating and mediating role of the variables are being assessed through β value, t-statistics and p-values.

3.6 Descriptive analysis

The demographic profile of the respondents is presented below. Attempt is made to ensure that no bias is generated due to saturation of respondents in any single category.

Table 2: Descriptive Analysis

Demographic Variable	Category	No. of respondents	Percentage
Gender	Male	289	63.38%
	Female	167	36.62%
Age (in years)	Below 25	114	46.40%
	25 – 35	102	17.20%
	35 – 45	154	19.20%
	Above 45	86	17.20%
UPI use experience	Less than 3 years	302	47.80%
	3 years and above	154	52.20%
Occupation	Student	125	45.40%
	Working Professional	104	17.10%
	Business	94	19.80%
	Not employed	133	17.70%

Source : Author's calculation

4. Analysis and Results

4.1 Measurement Model

4.1.1 Item reliability, Composite reliability and Convergent validity

In order to check the reliability of the items in measurement model, factor loading were estimated and analyzed. The item loadings are more than 0.70, hence items may be considered as reliable (Hair et al., 2011). The below table shows the Dillion-Goldstein's rho (ρ_a) is above 0.70. The composite reliability, CR values are > 0.70 , suggesting internal consistency reliability of the measures. The Cronbach's alpha value are > 0.70 for all the constructs and may be considered as reliable (Hair et al., 2011). All the Average Variance Extracted (AVE) meets the minimum criteria of 0.70.

Table 4: Construct reliability and validity (Connecting two SmartPLS v.4.0 outputs)

	Items	Factor Loadings	Cronbach's alpha	CR(ρ_a)	CR(ρ_c)	AVE
AU	AU1	0.878	0.814	0.817	0.905	0.789
	AU2	0.916				
	AU3	0.887				
BI	BI1	0.899	0.931	0.926	0.934	0.793
	BI2	0.885				
	BI3	0.878				
	BI4	0.894				
	BI5	0.882				
PE	PE1	0.924	0.924	0.931	0.932	0.795
	PE2	0.927				
	PE3	0.902				
	PE4	0.852				
	PE5	0.876				
EE	EE1	0.865	0.916	0.926	0.941	0.776
	EE2	0.884				
	EE3	0.933				
	EE4	0.886				
	EE5	0.912				
SI	SI1	0.844	0.924	0.937	0.943	0.814

	SI2	0.926				
	SI3	0.873				
	SI4	0.845				
	SI5	0.914				
FC	FC1	0.897	0.942	0.925	0.946	0.798
	FC2	0.914				
	FC3	0.789				
	FC4	0.924				
	FC5	0.945				
HM	HM1	0.901	0.921	0.935	0.948	0.747
	HM2	0.898				
	HM3	0.843				
	HM4	0.856				
	HM5	0.814				
	HM6	0.842				
	HM7	0.874				
HT	HT1	0.872	0.903	0.914	0.933	0.745
	HT2	0.827				
	HT3	0.865				
	HT4	0.856				
	HT5	0.876				

4.1.2 Discriminant Validity

Fornell-Larcker criterion table is generated to check the correlation between the measures. It is evident that square root of AVE is greater than the correlation with other constructs. This proves discriminant validity (Fornell-Larcker, 1981).

Table 5: Fornell-Larcker criterion

	AU	BI	PE	EE	SI	FC	HM	HT	PV
AU	0.888								
BI	0.57	0.891							
PE	0.658	0.576	0.892						
EE	0.453	0.375	0.345	0.881					

SI	0.375	0.675	0.578	0.248	0.902				
FC	0.276	0.565	0.697	0.578	0.574	0.893			
HM	0.564	0.589	0.713	0.354	0.246	0.275	0.864		
HT	0.487	0.453	0.475	0.292	0.473	0.576	0.538	0.863	

Further, Heterotrait-Monotrait Ratio (HTMT) test shows that all correlations are below 0.85, further confirming discriminant validity (Henseler et al., 2015; Hair et al., 2011).

Table 6: Heterotrait monotrait ratio (Matrix)

	AU	BI	PE	EE	SI	FC	HM	HT	PV
AU									
BI	0.567								
PE	0.646	0.566							
EE	0.433	0.414	0.378						
SI	0.315	0.578	0.579	0.286					
FC	0.345	0.615	0.704	0.595	0.594				
HM	0.547	0.591	0.725	0.314	0.324	0.475			
HT	0.417	0.458	0.496	0.442	0.413	0.376	0.524		

Validity is further confirmed by cross-loading of individual items in the constructs. Table 4 shows the values are within the acceptable range >0.70 . Conclusion may be drawn that there is no cross loading and the measures are independent (Hair et al., 2011).

The tests mentioned above confirms the reliability, convergent validity and divergent validity of the measurement model. Hence, further analysis is performed.

4.2 Structural Model Assessment

4.2.1 Collinearity Assessment

The Variance Inflation Factor (VIF) values are less than 5 and hence no collinearity within the data (Hair et al., 2011).

Table 7: VIF inner model values (Output from Smart PLS)

	AU	BI
AU		
BI	3.246	
PE		1.294

EE		1.568
SI		1.976
FC		1.456
HM		1.759
HT		2.574

4.2.2 Estimating Path Coefficients

PLS-SEM algorithm is run in SmartPLS to estimate the path coefficients. These path coefficient represents the hypothesized relationship among the constructs. The output coefficients will not only identify significant path but also suggest the relevant effects of the constructs. The figure below is generated from SmartPLS highlighting the coefficients.

Figure 2: Path analysis of the proposed structural model (Bootstrapping output from SmartPLS)

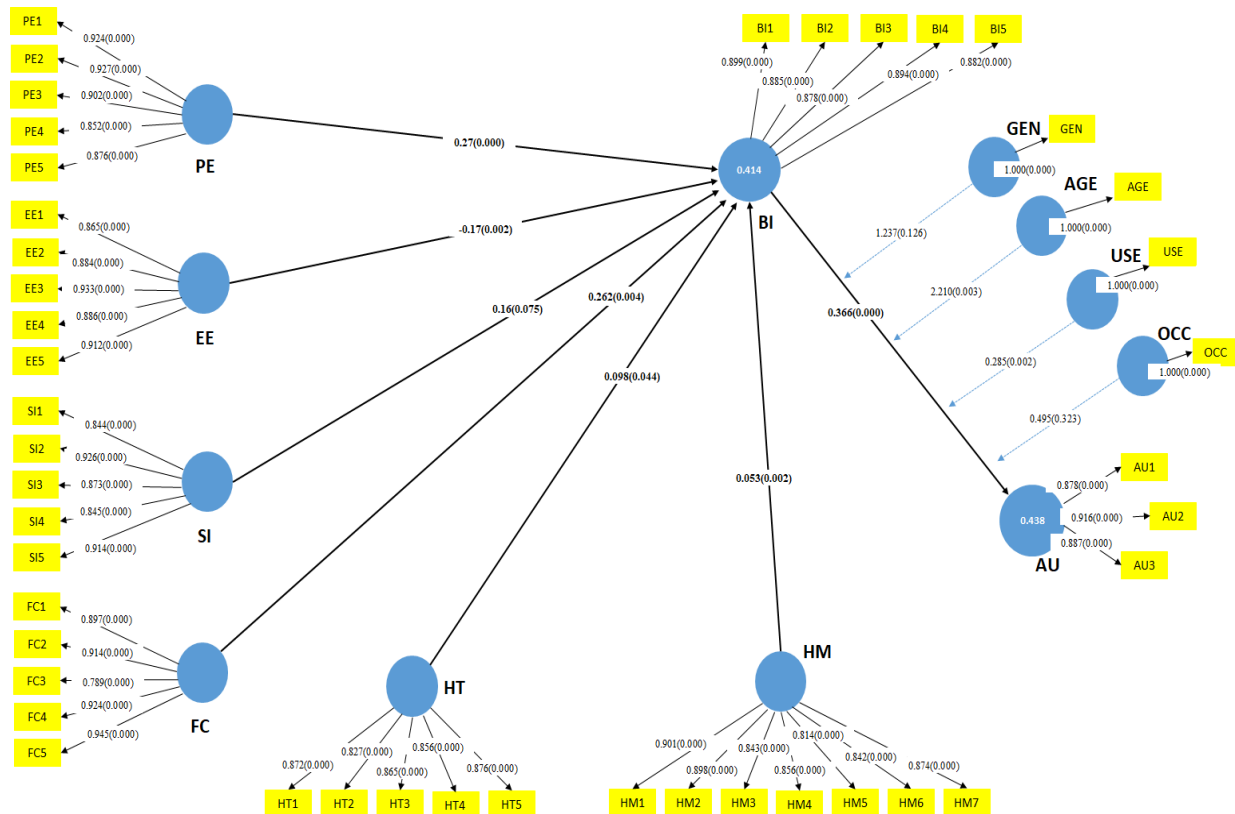


Table 8: Path Coefficients – Mean, STDEV, T values, P values (Output from SmartPLS)

	Original Sample (O)	Sample mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P values
BI → AU	0.366	0.366	0.064	5.719	0
PE → BI	0.27	0.67	0.069	3.913	0
EE → BI	-0.17	1.35	0.045	3.778	0.002
SI → BI	0.16	0.16	0.087	1.839	0.075
FC → BI	0.262	0.462	0.043	6.093	0.004
HM → BI	0.353	0.353	0.054	6.537	0.002
HT → BI	0.098	0.1	0.034	2.882	0.044

With T statistics greater than 1.96 and p-value less than 0.05, the path BI – AU, PE – BI, EE – BI, SI – BI, FC – BI, HM – BI, and HT – BI are found significant. The path connecting EE & FC to BI are not significant.

In the path coefficients – confidence interval bias corrected, it is checked whether zero (0) falls between 2.50% and 97.5% (95% confidence interval). From the table 9, we observe that path from EE to BI and FC to BI has zero (0) in between 2.50% to 97.5% confidence interval, making it an insignificant relationship.

Table 9: Path Coefficients – Confidence Interval bias corrected

	Original Sample (O)	Sample mean (M)	Bias	2.50%	97.50%
BI -> AU	0.366	0.366	0	0.126	0.463
PE ->BI	0.27	0.67	0	0.275	0.542
EE ->BI	-0.17	1.35	0	-0.124	0.162
SI -> BI	0.16	0.16	0	0.054	0.264
FC -> BI	0.262	0.462	0	0.154	0.034
HM ->BI	0.353	0.353	0.001	0.064	0.254
HT -> BI	0.098	0.1	0.001	0.135	0.252

4.2.3 Mediation Analysis

A variable acting as an intermediate variable between a dependent variable and an independent variable is called as Mediating Variable. Its effect helps us to understand the nature and strength of the relationship between dependent and independent variables.

In this study, Behavioral Intention (BI) is proposed as a mediating variable connecting the independent variables to dependent variable (Actual Usage). The mediation effect size can be evaluated to estimate the proportion of the total effect mediated by the mediator variable. Total effect is the overall effect of the independent variable on the dependent variable including both direct effect and indirect effect through the mediator (Baron and Kenny, 1986; Shrout & Bolger, 2002; Preacher & Hayes, 2008).

The table 10 shows the specific indirect effects (mean, STDEV, T-Value and P-value) to find out the significant effects.

Table 10: Specific Indirect effect (Mean, STDEV, T value, P value) (Output from SmartPLS)

	Original Sample (O)	Sample mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P values
BI -> AU	0.028	0.034	0.021	1.333	0
PE -> BI	0.037	0.039	0.024	1.542	0.029
EE -> BI	-0.032	-0.032	0.022	1.455	0.26
SI -> BI	0.049	0.048	0.022	2.227	0.003
FC -> BI	0.042	0.042	0.026	1.615	0
HM -> BI	0.112	0.112	0.032	3.500	0.002
HT -> BI	0.131	0.133	0.038	3.447	0.002

From the output generated by SmartPLS, it may be observed that except EE, all other constructs (HM, HT, PE, FC, and SI) have significant indirect effect on the actual usage mediated through behavioral intention.

4.2.4 Estimation of coefficient of determination (R^2)

Coefficient of Determination (R^2) reflects the amount of variance in the endogenous construct explained by all the exogenous constructs linked to it. Table 11 shows the output of the PLS-SEM results generated from SmartPLS v.4.0. 40.8% of the variance in Behavioral Intention (BI) and 42.4% of the variance in Actual Usage (AU) is explained by the exogenous variables linked to it respectively. Hair et al. (2011) posited that 0.75, 0.50, and 0.25 as substantial, moderate, and weak R –square values. Chin (1998) posited 0.67, 0.33, and 0.19 as substantial, moderate, and weak R-square values. And hence, R-square values for BI and AU can be considered in the moderate range.

Table 11: R^2 values

	R-square	R-square adjusted
AU	0.438	0.424
BI	0.414	0.408

4.2.5 Effect size (f^2)

The strength of each measure in explaining the variance in the dependent variables is denoted by Effect Size (f^2). The f-square output generated from SmartPLS is tabulated below. F-square values of 0.02 to 0.15, 0.15 to 0.35, and greater than 0.35 can be considered to have small, moderate, and large effect in the dependent variables (Hair et al., 2011; Cohen, 1992). And hence, it may be concluded that BI has significant moderate effect on AU. HM, PV and PE have large significant effect on BI and SI has moderate significant effect on BI.

Table 12: f-square matrix

	AU	BI	Effect Size	Significance
AU				
BI	0.18		Moderate	Significant
EE		0.006		
FC		0.004		
HM		0.043	Large	Significant
HT		0.004		
PE		0.038	Large	Significant
SI		0.03	Moderate	Significant

4.2.6 Predictive Relevance (Q²)

For Predictive Relevance, Stone – Geisser (Q²) value is calculated using Smart PLS predict feature. It measures whether a model has predictive relevance of the endogenous construct. A value greater than 0 (zero) indicates that values are well re-constructed and that the model has predictive relevance. Q-square values are benchmarked at $0.02 < Q^2 < 0.15$, $0.15 < Q^2 < 0.35$ and $Q^2 > 0.35$ for weak, moderate and strong degree of predictive relevance of each effect (Hair et al., 2019). The results obtain after running predictive analysis in SmartPLS is shown below in Table 13:

Table 13: Predictive Relevance Q-Square (Output from SmartPLS)

	Q ² predict	RMSE	MAE
AU	0.334	0.786	0.654
BI	0.421	0.678	0.604

4.2.7 Goodness of Fit

For Goodness of Fit, the value of SRMS (Standardized Root Mean Square Residual) is analyzed. A value of 0 of SRMR is considered as a perfect fit, a value less than 0.08 is considered as a good fit (Hu & Bentler, 1998). Normed Fit Index (NFI) ranges between 0 to 1, and a value closer to 1 is a good fit (Bentler & Bonett, 1980). From the model fit data of SmartPLS, it can be observed that SRMS value is 0.05 (Good fit) and NFI value is 0.823 (Good fit). Hence, the proposed model may be considered as a good fit.

Table 14 : Model Fit (Output from SmartPLS)

	Saturated model	Estimated model
SRMR	0.042	0.05
d_ULS	2.874	3.023
d_G	1.862	1.954
Chi-square	4676.812	4897.234
NFI	0.856	0.823

4.3 Moderating role of gender, age, occupation and use experience

Moderating effect exists when a third variables influences relationship between the dependent and independent variables. The strength or direction of relationship between independent variable and dependent variables is influenced by moderating variable. A positive moderating effect strengthens the relationship and a negative moderating effect weakens the relationship between the variables. Variables, namely, age, gender and years of using UPI payments services (Use experience) are considered as moderating variables in the study to understand their influence over the relationship between the behavioral intention and actual usage of UPI payment services. To determine the influence of the moderating variables, the path coefficients are determined using SmartPLS as shown in table 15.

Table 15: Moderating path coefficients (Output from SmartPLS)

	Original sample (O)	Sample mean (N)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
GEN X BI -> AU	0.176	0.104	0.062	1.267	0.123
AGE X BI -> AU	0.104	0.11	0.023	3.002	0.003
USE X BI -> AU	0.086	0.094	0.068	1.308	0.003
OCC X BI -> AU	0.012	0.016	0.035	0.776	0.574

	Original sample (O)	Sample mean (N)	Bias	2.50%	97.50%
GEN X BI -> AU	0.176	0.104	-0.002	-0.038	0.356
AGE X BI -> AU	0.104	0.11	0	0.024	0.146
USE X BI -> AU	0.086	0.094	0	0.032	0.125
OCC X BI -> AU	0.012	0.016	-0.001	-0.044	0.086

As can be observed from the data gathered in the output as shown in the table 15, two relationships, namely age and use experience have moderating influence over relationship between BI and AU. Since the influence is positive, we may conclude that age and use experience strengthens the relationship between Behavioral Intention and Actual Usage of UPI payment service (Du Plessis & De Witte, 2020, Moradi et al., 2021).

4.4 Hypotheses testing

Bootstrapping method with 5000 samples was run in SmartPLS v.4.0 to verify the posited hypotheses of the proposed paths. The detailed t-statistics and p-value generated with significance tallied at 95% level are tabled in Table 16. It can be concluded that performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, and habit have significant influence on behavioral intention to use UPI payment services. The results shows that age and use experience positively moderates the relationship between BI and AU. Other variable, gender and occupation have no significant moderating effects on the relationship between BI and AU.

Table 16: Hypotheses testing (SmarPLS output and Author Interpretations)

Hypotheses	Paths	T statistics	P values	Result
H1	Performance expectancy – Behavioral intention	3.913	0.000**	Supported
H2	Effort expectancy – Behavioral intention	3.778	0.002**	Supported
H3	Social influence – Behavioral intention	1.839	0.075	Not-supported
H4	Facilitating condition – Behavioral intention	6.093	0.004**	Supported
H5	Hedonic motivation – Behavioral intention	6.537	0.002**	Supported
H7	Habit - Behavioral intention	2.882	0.044**	Supported
H9a	Gender moderates BI -> AU	1.304	0.321	Not supported
H9b	Age moderates BI -> AU	4.282	0.002**	Supported
H9c	Use Experience moderates BI -> AU	1.232	0.002**	Supported
H9d	Occupation moderates BI -> AU	2.242	0.112	Not supported

** Statistically significant with 95 percent confidence

5. Conclusion

This study was conducted to propose a working model for understanding the behavioral intention and actual usage of UPI payment services in India primarily utilizing UTAUT 2 framework. The proposed model was based on UTAUT 2 framework. Statistical test were performed utilizing SmartPLS v4.0 to test the accuracy of the proposed model. After confirming indicator reliability and internal consistency reliability, the convergent validity between the items within the construct and divergent validity between the constructs were found to be within prescribed limits and hence

concluded as reliable and valid. The proposed SEM model was examined via path coefficients, explanatory power and predictive power obtained from the variance based SmartPLS v4.0.

The path coefficients and p-value indicated that all paths are significant except Social Influence (SI) connecting to Behavioral Intention (BI). The R-Square value that provides the explanatory power of the structural model was found to be at moderate level (AU – 0.438; BI – 0.414). The Q-square value used to assess the predictive power of the proposed model was found to be moderate in predicting actual usage (AU – 0.334; BI – 0.421).

The study concludes that performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, and habit have significant indirect effect on actual usage mediated through behavioral intention, whereas social influence do not have significant indirect effect. The study also observed that Age and Use Experience were found to have moderating effect on the relationship between behavioral intention and actual usage of UPI payment services, whereas gender and occupation were found to have no effect on this relationship.

6. Theoretical Implications

The validity of the theoretical model was established to analyze the behavioral intention and actual usage of UPI payment services. The model provides moderate predictive relevance for actual usage and strong predictive relevance for behavioral intention. Hence, the study results may summarized that extended UTAUT2 model is effective in predicting consumer behavior in using UPI payment services. The results of the study are in alignment to similar studies such as mobile payment in Portugal (Oliveira et al., 2016), travel apps in India (Gupta et al., 2018), health & fitness apps in the US (Yuan et al., 2015). The analysis and outcomes provides an important contribution to the existing knowledge on UPI payment services and in supporting the UTAUT 2 model for understanding consumer behavior.

7. Limitations

The scope of the research may be broaden by incorporating other variables in addition to other variables identified by UTAUT 2 model such as inclusion of regional languages, effect of promotional schemes, etc. Advanced analytical tools like MCDM may be utilized to perform a more comprehensive analysis assigning importance of each variable. The geographical spread utilized in the study was also a limitation as it was restricted to one geographical area. A detailed analysis may be performed including a more diverse population.

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