# Understanding Factors Affecting UPI Adoption among Low-Income Consumers in India

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## Abstract

**Purpose :** The study investigated the factors influencing the behavioral intention to use Unified Payment Interface (UPI) apps among low-income Indian consumers. It examined how consumers' behavioral intention to use UPI apps was influenced by their perceptions of the technology's performance (performance expectancy), ease of use (effort expectancy), presence of facilitating conditions (FC), social influence (SI), and perceived risks (PR).

**Design/Methodology/Approach :** An empirical study using a causal research design was conducted. The sampling unit consisted of Indian citizens with monthly household incomes below ₹ 20,000. Data were collected using questionnaires from 351 respondents and analyzed using structural equation modeling with AMOS 21.

**Findings :** The findings demonstrated that performance expectancy, effort expectancy, and facilitating conditions positively impacted the behavioral intention to use UPI apps. A negative relationship was found between PR and behavioral intention. SI showed no impact on the usage intention among low-income consumers.

**Practical Implications :** Understanding the adoption of UPI apps among low-income consumers can help policymakers and app developers promote financial inclusion by developing strategies to bridge the digital divide in India.

**Originality/Value :** The study is unique as it extended the unified theory of acceptance and use of the technology model by including the PR construct in the context of UPI app adoption among the low-income population of India. Understanding this demographic is important to attaining financial inclusion.

*Keywords :* behavioral intention to use UPI, unified payment interface (UPI), perceived risk, facilitating conditions

JEL Classification Codes : G2, G5, G59, O30

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Digital payments in India are experiencing rapid growth, fuelled by factors like the introduction of innovative payment products, increasing smartphone adoption, a growing demand for faster payment methods, and a concerted effort from the Government and regulators to promote digital channels. In 2016, the Government of India introduced the Unified Payment Interface (UPI), heralding a transformative initiative aimed at democratizing digital payment services nationwide (Rastogi et al., 2021). UPI is a digital

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innovation with an instant payment option, developed indigenously in India. Facilitated by the National Payments Corporation of India (NPCI), UPI enables real-time fund transfers between bank accounts through mobile devices, garnering widespread adoption as a secure and convenient payment method.

India has emerged as a frontrunner in digital transactions, surpassing other leading nations in real-time payments, with India accounting for a remarkable 89.5 million digital transactions, constituting nearly 46% of global real-time payments, a figure surpassing the combined total of the other four countries ("India leads global digital payments," 2023). Additionally, the India Digital Payments Report by Worldline highlights a significant growth trajectory, with person-to-merchant (P2M) transactions surging from 18.62 billion in the first half of 2022 to 22.75 billion in the corresponding period of 2023, reflecting a notable 22% increase (Kothari, 2023).

However, the challenge of financial exclusion remains a significant impediment to achieving equitable development in digital payments despite the growth in FinTech and Digital payments in India (Amnas et al., 2024; Kapoor & Mohandas, 2023). There is a concern that this trend may further exacerbate the existing divide between individuals who already have access to digital financial services and those who may be unable to do so, such as rural populations, women, the ultra-poor, migrants and refugees, indigenous communities, the elderly, and those with limited literacy skills (Vaghela et al., 2023), commonly known as the Bottom of the Pyramid (BoP). The BoP concept refers to the social and economic grouping of the world's four billion world's people, who represent a sizable but underserved market hampered by significant barriers that limit their ability to realize their own personal, familial, and societal benefits.

An NPCI research states that 57% of India's lowest-income households own a smartphone. However, only 24% use them for digital payments ("India leads global digital payments," 2023). Given the huge market penetration and the relatively high affordability of smartphones among the lower income consumers and their low usage of digital payments, there arises a need to understand the factors influencing UPI adoption within this demographic. This has to be one of the major components in building such a shared understanding of digital payment as we drive financial innovation inclusively. This understanding is crucial for the inclusive adoption of digital payment systems. It is significant to examine the variables that influence UPI adoption among low-income consumers, who represent a sizeable portion of the population and typically struggle with technology access and usage. This study aims to address this gap in the body of knowledge by exploring the factors that influence the intention to use UPI among individuals with a monthly household income below ₹ 20,000. It analyses the behavioral determinants of UPI adoption by poor consumers. The study introduces five factors based on the technology acceptance model, consolidating the factors into performance expectancy (PE), which refers to the extent of consumer belief in how the UPI that they use will help to be more productive in performing certain tasks, effort expectancy (EE), that is the consumer functionality perception on use to UPI, facilitating conditions (FC), that refers to consumer perception on the availability of organizational or technological facilities called the success system, perceived risk (PR), which is consumer perception of the potential negative impacts of UPI, and social influence (SI), that is considering the influence of friends, family, or social networks on consumers' decisions to adopt UPI. This, in turn, will be effective in understanding the motivations and barriers for low-income consumers to adopt UPI, thus providing insights into the existing literature related to behavior intent to adopt digital payments among low-income consumers.

FinTech such as UPI not only provides convenience in transactions but also eliminates many of the charges associated with traditional banking, thus reducing the overall cost and making financial services more accessible and affordable for low-income consumers (Joseph et al., 2023). This accessibility is crucial as it allows individuals who were earlier excluded from formal financial systems to participate and be integrated with the financial mainstream (Demir et al., 2022). By understanding the perceptions and attitudes of low-income consumers toward UPI adoption, the study tries to provide insights to inform application developers, designers, and marketers on strategies to augment the accessibility and usability of UPI apps.

## Research Questions

- How do consumers' perceptions of the advantages offered by UPI influence their behavioral intention to use (BIU) UPI apps among low-income consumers?
- What is the impact of consumers' perception of the ease of use associated with utilizing UPI on the behavioral intention to use UPI apps among low-income consumers?
- How does the SI of friends, family, or social networks affect the BIU of UPI apps among low-income consumers?
- What role do consumers' perceptions regarding the availability of organizational or technical support aiding in the effective use of UPI play in influencing the BIU of UPI apps among low-income consumers?
- How do consumers' perceptions of the potential risks associated with using UPI influence the BIU of UPI apps among low-income consumers?

## Literature Review

### *Unified Payment Interface (UPI)*

UPI is a platform that integrates multiple bank accounts into a single mobile application, regardless of the participating bank. It combines various banking functionalities, such as fund transfer and merchant payments (National Payments Corporation of India, NPCI, n.d.). This indigenous innovation was designed with the vision of universalizing digital payments and achieving financial inclusion and economic development (Rastogi et al., 2021). UPIs are well-liked by the general public due to their lower transaction costs, perceived value, add-on benefits, and lack of need to exchange sensitive banking information (Gupta et al., 2019). Lower financial literacy (Vaghela et al., 2023), security concerns like data breaches, fraud, cyberattacks, lack of basic infrastructure, and PR (Gupta et al., 2019) are major concerns among low-income consumers. The review of extant literature reveals a dearth of research in the area of UPI adoption in general, particularly in the adoption of UPI among low-income consumers.

### *Unified Theory of Acceptance and Use of Technology*

Multiple theories with distinct determinants have been developed in the technology adoption research domain. The technology adoption model, as proposed by Venkatesh et al. (2003), called the unified theory of acceptance and use of technology (UTAUT), is adopted as the theoretical framework for this study. Elements from the eight other models, including the theory of planned behavior (TPB), theory of reasoned action (TRA), social cognitive theory (SCT), technology acceptance model (TAM/TAM2), motivational model (MM), C-TAM-TPB model, innovation diffusion theory (IDT), and model of PC Usage (MPCU) are also integrated into the model adopted for this study. Many studies have employed this framework to conduct technology adoption research, while others have integrated previous models or introduced new constructs to enhance their investigations further. According to the UTAUT model, as proposed by Venkatesh et al. (2003), PE, EE, SI, and FC influence behavioral intention to use a technology and/or use of technology. This study develops an enhanced model (de Sena Abrahão et al., 2016) by introducing the concept of PR (Williams et al., 2011) into the UTAUT model, as established by Venkatesh et al. (2003), to analyze the adoption of UPI by low-income customers. The theoretical model of extended UTAUT, which has been used in this study to investigate the uptake of UPI among low-income end users, is the subject of the literature review that follows.

### *Performance Expectancy (PE)*

PE is the degree to which a person believes that using a particular information system or technology system will help him or her perform or improve specific tasks (Venkatesh et al., 2003; Venkatesh et al., 2012). People tend to use any technology when they perceive it will enhance their performance efficiency (Gupta et al., 2023). Conversely, the perception of no benefits or improvements negatively influences their attitude toward embracing technology (Bhat & Chauhan, 2023). PE is one of the key constructs in the UTAUT model. In the context of UPI adoption, PE can be understood as to what extent a user trusts that using UPI will make their job of completing the intended activities easier. UPI payment apps offer a wide range of useful features for their users. These services include accelerating payments for necessary low-value transactions and timely notification of the status of transactions, which makes UPI highly valuable as a service to consumers. Most of the past studies on the mobile payments domain have suggested that the perceived usefulness (or PE) of the technology has a significant positive impact on consumer's behavioral intention to use (BIU) the technology (Kumar et al., 2018). Based on these, the first hypothesis is proposed:

- **Ha1 :** The level of PE significantly influences the BIU of UPI apps.

### *Effort Expectancy (EE)*

EE is another significant element within the UTAUT model. EE is the consumers' perception of the ease of utilizing a technology (Venkatesh et al., 2003; Venkatesh et al., 2012). A positive relationship between EE and technology adoption has been observed in previous research on mobile wallets (Singh, Sinha, et al., 2020), mobile banking, and mobile payments (Pal et al., 2015; Su et al., 2018). Hence, based on the existing body of literature, it is reasonable to posit that:

- **Ha2 :** EE has a significant influence on the BIU of UPI apps.

### *Social Influence (SI)*

Consumers frequently rely on peer-to-peer information when deciding to adopt a technology (Kalinic et al., 2019). SI is a major construct in the UTUAT model. It refers to how much individuals perceive that their social network, comprising family, friends, and peer groups, believes they should use and adopt certain technology (Venkatesh et al., 2003). SI can lead individuals to modify their perception of technology or adjust their behavioral intention to comply with social pressure and thus adopt it. This positive relationship has been confirmed by previous research on technologies such as digital payments (Sivathanu, 2019) and QR code payment systems (de Luna et al., 2019). Payment apps, such as Paytm, Google Pay, Amazon Pay, PhonePe, etc., have been using promotional strategies of a referral system by rewarding users for recommending the app. In order to increase SI, this encourages users to recommend the app to friends and family. Based on the above, we propose the following hypothesis:

- **Ha3 :** SI has a significant influence on BIU and the UPI apps.

### *Facilitating Conditions (FC)*

FC refers to the perception of individuals regarding the existence of organizational or technical support that would help the consumers in the effective use of any specific technology (Venkatesh et al., 2003). Factors such as the availability and affordability of mobile devices, access to an internet connection, and ease of obtaining technical knowledge to effectively understand the use of the app are some of the FCs that shape the user's intention to use UPI apps (Chawla & Joshi, 2019). While some of the previous studies on mobile wallets have affirmed the significance of FCs on BIU technology (Madan & Yadav, 2016), others have not found any significant impact of FCs on BIU (Oliveira et al., 2016). This research targets a section of the population with low socio-economic backgrounds, considering their higher vulnerability to the lack of FCs while using payment applications. Based on these considerations, the fourth hypothesis is formulated:

↳ **Ha4 :** FC has a significant influence on BIU and the UPI apps.

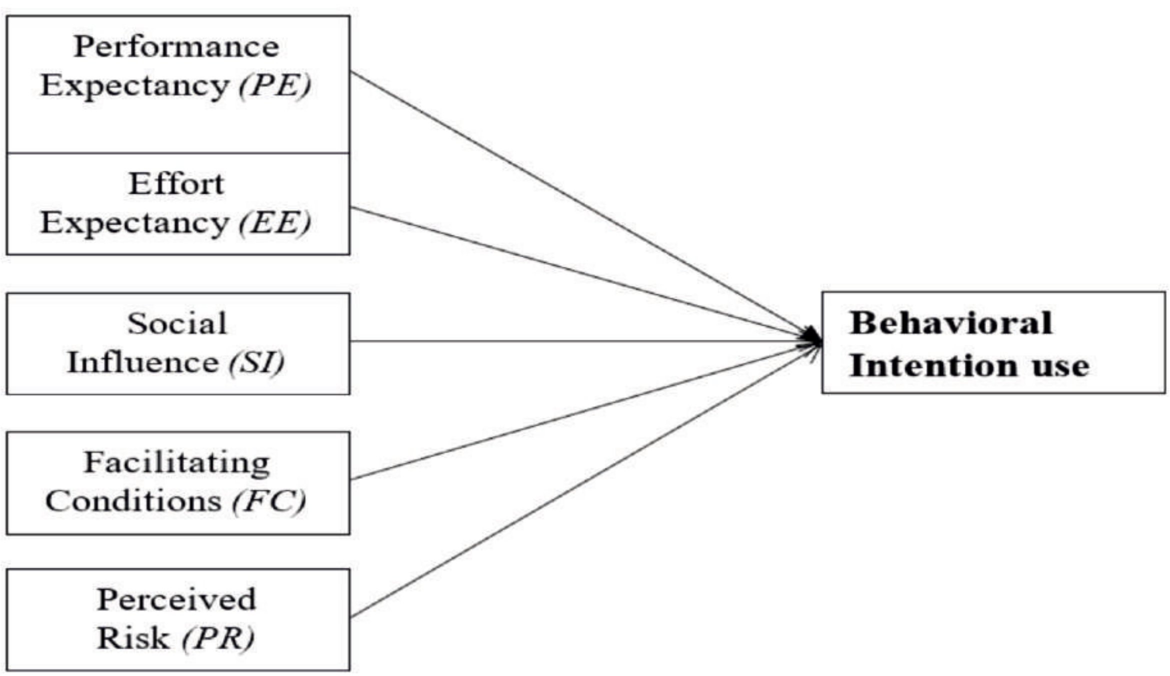
### *Perceived Risk (PR)*

A crucial factor that shapes users' BIU technology is PR, which is the perceived potential uncertainties and negative consequences associated with engaging in a particular activity (Liébana-Cabanillas et al., 2019). It encompasses the subjective perception of uncertainty and the associated potential adverse outcomes resulting from using a particular product or service. These opinions affect users' impressions of UPI adoption in terms of trust, dependability, and confidence. The perception of risk can reduce consumers' intention to use any technology (Demir et al., 2022). For example, users may be concerned about unauthorized parties obtaining their personal information or transaction particulars from the UPI apps. The perception of these risks may discourage them from adopting such payment methods (Pal et al., 2021). Based on these observations, the following hypothesis is proposed:

↳ **Ha5 :** PR has a significant negative influence on the BIU UPI app.

The proposed model is diagrammatically represented in Figure 1.

**Figure 1.** ***Hypothesized Model***



## Research Methodology

### *Type of Research*

The study was conducted using empirical research. The study's informal design aided in the analysis of the variables' relationship. The responses from the participants were collected using a structured questionnaire. The questionnaire was divided into two sections, one collecting demographic data of the respondents and another with items measuring the study variables. A 5-point Likert scale using responses ranging between "*strongly disagree*" and "*strongly agree*" was used for the latter. A pretest was conducted to ensure the reliability of the constructs. The data were then analyzed using structured equation modeling using IBM SPSS and AMOS version 21.

### *Sampling Unit*

The sampling unit consisted of respondents from the Indian state of Kerala, belonging to the low-income category with a monthly income of less than ₹ 20,000. The sample was filtered to include only respondents with prior experience using UPI for money transfers or financial transactions.

### *Measurement Development*

The measurement items for the constructs of PE, EE, SI, FC, and BIU were adopted and adapted from the study of Venkatesh et al. (2012). The items to measure the construct of PR were adopted from Featherman and Pavlou (2003).

### *Data Collection*

The questionnaire was translated into the respondents' native tongue as soon as it was decided it was appropriate for the study in order to improve understanding. Non-probabilistic sampling was employed to obtain the data. The data were collected between December 2022 and February 2023. The focus of this study was specifically on the low-income category of consumers. To confirm that a respondent belonged to the low-income category, their monthly household income was confirmed to be less than ₹ 20,000 before they were given the questionnaire. The fact that every respondent has previously used UPI for financial transactions or money transfers was also confirmed. Customer surveys totaling 475 were distributed, and 351 of the replies were taken into account for the research. The reliability and correctness of the results were ensured by not using incomplete responses in the analysis. Table 1 highlights the major demographic profiles of the respondents.

**Table 1.** ***Demographic Profile of the Respondents***

| **Demographics** | | **Frequency** | **Percentage** |
|---|---|---|---|
| **Gender** | Female | 176 | 50.1 |
| | Male | 175 | 49.9 |
| **Age** | 18–34 years | 150 | 42.7 |
| | 35–44 years | 94 | 26.8 |
| | 44–55 years | 67 | 19.1 |
| | Above 55 years | 40 | 11.4 |
| **Sector of Employment** | Security persons | 46 | 13.1 |

| | | | |
|---|---|---|---|
| | Private car divers | 123 | 35 |
| | Salespersons | 94 | 26.8 |
| | Maidservants | 51 | 14.5 |
| | Fish vendors | 13 | 3.7 |
| | Others | 24 | 6.8 |
| **Highest Education** | PG | 2 | 0.56 |
| | UG/Diploma | 70 | 19.9 |
| | Plus Two | 183 | 52.1 |
| | High School/Tenth | 96 | 27.3 |

## Data Analysis and Results

### *Exploratory Factor Analysis*

The analysis began with an exploratory factor analysis (EFA) to assess the items and factors. A suitable degree of correlation with the underlying components was indicated by factor loadings greater than 0.55 for every item. To ensure sampling adequacy, the Kaiser–Meyer–Olkin (KMO) was employed and yielded a value of 0.918, which exceeded the suggested threshold of 0.70. Additionally, Bartlett's test of Bartlett's with $p < 0.001$ indicated that the correlations between the items were sufficient for further analysis (Bartlett, 1954).

Harman's single-factor test was employed to examine the potential presence of common method bias (CMB). For this, EFA with unrotated PCA factor analysis was applied to all the items included in the study. The purpose was to examine if any one factor dominates the results. The items were forced to load into a single factor, which showed 46.159% of the total variance. Since the factor explained below the accepted threshold of 50% variance, it suggests that any potential common method bias in the study is minimal and unlikely to have a substantial impact on results (Tehseen et al., 2017).

### *Results of Measurement Model and Validity of Constructs*

The proposed model for the study was analyzed and validated using structural equation modeling (SEM). First, the measurement model is assessed using model fit indices, as provided in Table 2. The results indicate a good fit between the proposed model and the data. The chi-square statistic was 741.159 with a *df* of 235. The acceptable range is indicated by the CMIN/*DF* ratio of 3.154, indicating a fair fit.

The reliability of the latent variables assessed using the measure of Cronbach's alpha coefficient ranged between 0.938 and 0.960 (Table 3). These coefficients were higher than the 0.70 acceptable cutoff. Analyses of

**Table 2.** ***CFA Model Fit Measures***

| **Measure** | **Estimate** |
|---|---|
| CMIN | 741.159 |
| *DF* | 235.000 |
| CMIN/*DF* | 3.154 |
| CFI | 0.951 |
| SRMR | 0.036 |
| RMSEA | 0.078 |

Table 3. *Measures of Construct Validity and Reliability*

| Constructs | Cronbach's Alpha | Average Variance Extracted | Critical Ration | MSV | ASV | FL Range |
|---|---|---|---|---|---|---|
| *PR* | 0.951 | 0.835 | 0.953 | 0.291 | 0.197 | 0.85–0.96 |
| *SI* | 0.956 | 0.814 | 0.956 | 0.282 | 0.18 | 0.85–0.94 |
| *PE* | 0.938 | 0.791 | 0.938 | 0.213 | 0.12 | 0.86–0.91 |
| *FC* | 0.946 | 0.814 | 0.946 | 0.540 | 0.32 | 0.85–0.94 |
| *EE* | 0.960 | 0.835 | 0.953 | 0.578 | 0.37 | 0.90–0.92 |
| *BI* | 0.956 | 0.884 | 0.958 | 0.578 | 0.36 | 0.88–0.97 |

Table 4. *Correlation Matrix of Constructs and Square Root of AVE*

| | *EE* | *SI* | *PR* | *FC* | *PE* | *BIU* |
|---|---|---|---|---|---|---|
| *EE* | **0.914** | | | | | |
| *SI* | 0.502 | **0.902** | | | | |
| *PR* | –0.533 | –0.316 | **0.914** | | | |
| *FC* | 0.735 | 0.531 | –0.431 | **0.902** | | |
| *PE* | 0.461 | 0.177 | –0.356 | 0.280 | **0.890** | |
| *BIU* | 0.760 | 0.488 | –0.539 | 0.725 | 0.441 | **0.940** |

***Note.*** * The AVE values are provided in bold.

convergent and discriminant validity determine if the metrics employed to evaluate various conceptions are unique and effectively capture distinctive features of the phenomenon. Convergent validity confirms that the items within each construct are strongly related to each other, while discriminant validity ensures that the study variables are distinct from one another. The composite reliability (CR) values exceed the threshold of 0.70 (Table 3). The average variance extracted (AVE) values, representing convergent validity, are also above the recommended value of 0.5 (Table 3). Additionally, the MSV and ASV values were lesser than the AVE measures, indicating good discriminant validity (Table 3).

Table 4 demonstrates that the square root of the AVE for each construct is greater than the correlation coefficients with other variables, suggesting strong discriminant validity. These results are consistent with the established criteria outlined by Fornell and Larcker (1981) and Hair et al. (2010).

### *Results of the Structural Model*

The structural model fit is assessed next (Table 5). The goodness of fit indicators for the structural model is as follows: The chi-square to degrees of freedom ratio (chi-square/*df*) is 3.485, which falls below the recommended threshold of 5, indicating an acceptable fit (Bentler & Dudgeon, 1996). The adjusted goodness of fit index (AGFI) value of 0.8, as proposed by Hu and Bentler (1999), denotes a satisfactory fit because it is equivalent to the indicated value of 0.8. The comparative fit index (CFI) value of 0.943 exceeds the recommended threshold of 0.9, indicating a good fit (Bentler & Dudgeon, 1996). The normed fit index (NFI) value of 0.922 is above the threshold of 0.9, further supporting a good fit (Bentler & Dudgeon, 1996). The Tucker–Lewis index (TLI) of 0.933 also exceeds the recommended threshold of 0.9, which suggests a good fit (Bentler & Dudgeon, 1996). The root mean square error of approximation (RMSEA) value of 0.084 is less than the recommended threshold of 0.08, indicating

Table 5. *The Structural Model Fit Indicators*

| Fit indices | Values |
|---|---|
| $X^2/df$ | 3.485 |
| AGFI | 0.8 |
| CFI | 0.943 |
| TLI | 0.933 |
| NFI | 0.922 |
| RMSEA | 0.084 |

a reasonable fit (Hu & Bentler, 1999). These findings indicate that the structural model fits the data well according to various goodness of fit criteria.

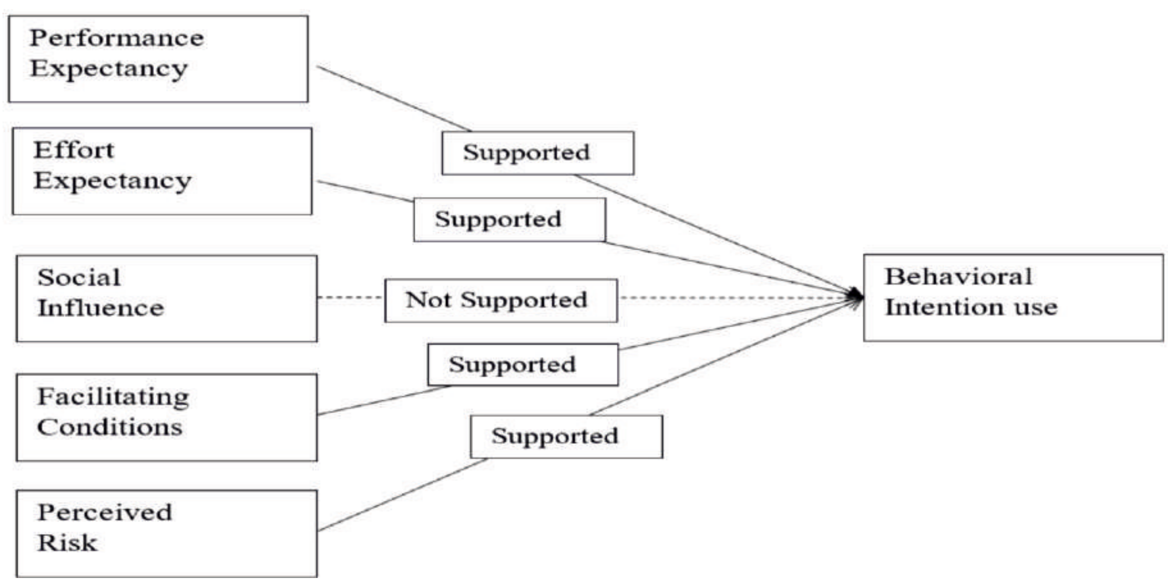
### *Hypotheses Testing*

The research hypotheses were tested by analyzing the standardized estimates of each path in the SEM model (Table 6).

Table 6. *Path Analysis Results*

| Number | Hypotheses | Unstandardized Estimate | Standardized Estimate | *p*-value | Supported |
|---|---|---|---|---|---|
| Ha1 | $PE \rightarrow BIU$ | 0.121 | 0.138 | <0.05 | Yes |
| Ha2 | $EE \rightarrow BIU$ | 0.286 | 0.305 | <0.05 | Yes |
| Ha3 | $SI \rightarrow BIU$ | 0.052 | 0.073 | >0.05 | No |
| Ha4 | $FC \rightarrow BIU$ | 0.384 | 0.360 | <0.05 | Yes |
| Ha5 | $PR \rightarrow BIU$ | –0.145 | –0.152 | <0.05 | Yes |

Figure 2. *Structural Model*



The standardized estimates show the degree and direction of the paths between the independent variables and the BIU. Hypotheses Ha1 ($\beta = 0.138$, $p < 0.05$), Ha2 ($\beta = 0.305$, $p < 0.05$), Ha4 ($\beta = 0.360$, $p < 0.05$), and Ha5 ($\beta = -0.145$, $p < 0.05$), are supported as their $p$-values are less than 0.05 and their standardized estimates are statistically significant. However, hypothesis Ha3 is not supported because its $p$-value exceeds 0.05, revealing that there is no significant association between SI and the BIU. The conclusions drawn from the hypotheses testing are visually presented in Figure 2.

## Discussion

The study is conducted to examine the behavioral factors that influence consumers to use UPI among low-income consumers. The study focused on factors that measured the consumers' perception that employing a technology provides advantages in carrying out specific tasks (called PE), consumers' perception of the ease associated with utilizing technology (EE), their perception regarding the existence of organizational or technical support that helps in the effective use of a specific technology FC, PR and the perception of the social cycle SI. The findings revealed that FC emerged as the most significant antecedent, indicating its strong influence on BIU and the UPI apps. The intention of low-income consumers to use UPI was found to be influenced by EE, PR, and PE in that order. Thus, the study's conclusions aligned with those of earlier investigations by Alalwan et al. (2017), Madan and Yadav (2016), Shaikh et al. (2018), and Venkatesh et al. (2012).

As per the findings of this study, FC is found to be the most significant indicator of intention to use UPI as it enables individuals to overcome the challenges faced and help them use the UPI system effectively. This result is consistent with previous studies conducted by Thakur and Srivastava (2014) and Venkatesh et al. (2012). This establishes that people pay specific attention to the presence of resources, assistance, skills and other facilities to use UPI effectively. The availability and accessibility of smartphones, constant internet connectivity, technical assistance, customer services, and having the required knowledge about technology are just a few examples of FCs that have a significant impact on a person's behavioral intention to embrace UPI (Pahari et al., 2023).

The findings of this study have supported a significant association between EE and BIU of UPI services ($\beta = 0.305$, $p < 0.001$), as opposed to the results of Madan and Yadav (2016). This suggests that the consumers' perception regarding the difficulty level in using UPI apps determines their adoption of the technology, which is consistent with the findings of other researchers (Alalwan et al., 2017; Kalinic et al., 2019; Pahari et al., 2023; Shaikh et al., 2018; Venkatesh et al., 2012). Thus, the usability of the technology and the ease with which consumers can learn to use the technology are pivotal factors, especially among the lower-income population.

Ha1, which suggests a positive relationship between the PE of UPI apps and the intention to use UPI, is found to be significant in this study ($\beta = 0.138$, $p < 0.001$). This result suggests the significance of functional utilities in deciding whether to adopt UPI for low-income consumers. UPI has simplified consumers' daily payment and receipt processes, such as utility bill payments, cab fares, and purchases of goods and services. Compared to mobile banking, which requires additional information such as account number, IFSC code, bank details, etc., the UPI system enables payments by simply entering the recipient's virtual payment address or phone number. A monthly report on income and expenses like rewards earned, amount sent to family and friends, payment to utilities, etc., would add functional utilities to the system. This could also prevent consumers from switching to alternate methods of payment. These utilities may positively affect the low-income consumers' attitudes toward the adoption and usage intention of the system.

In alignment with the research conducted by Madan and Yadav (2016), this study suggests that the perception of potential risks significantly and negatively influences the behavioral intention to utilize UPI. This suggests that consumers may be concerned about personal information and transaction history being disclosed or misused or the possibility of the UPI system malfunctioning and not performing as intended. A further factor that could heighten the risk perception of the low-income population is the concern of feeding false information or utilizing UPI wrongly. Further customer risk issues include viruses on mobile devices, inadequate data protection, and user behavior profiling. These factors play a significant role in shaping consumers' BIU of UPI apps. These observations emphasize the importance of addressing security measures and reassurances to enhance user trust and confidence in the system.

The result of the study also suggested that SI has no significant impact on the BIU of UPI apps for low-income consumers. Their intents may be shaped more by other elements like system usability, favorable settings, personal experience, or cognitive attitudes about the system; therefore, SI is probably not given much weight by them. Singh, Sahni, et al. (2020) claimed that when determining their intentions to use UPI, consumers give weight to their prior experiences.

## Implications

### *Theoretical Implications*

The UTUAT model has been thoroughly examined for studying the adoption of mobile payments technology (de Luna et al., 2019; Eriksson et al., 2021; Gupta et al., 2020; Hussain et al., 2019; Ligon et al., 2019; Sharma et al., 2022). However, limited research has been conducted on UPI, an Indian innovation (Bhat & Chauhan, 2023; Gochhwal, 2017; Gupta et al., 2023; Joseph et al., 2023; Rastogi et al., 2021), especially among the low-income group. This study contributes to the body of knowledge by examining the factors influencing the BIU to adopt UPI among Indian low-income consumers using an extended UTAUT model. The findings of the study also contribute significantly to the existing literature by introducing the construct of PR and extending the UTAUT.

### *Managerial Implications*

Identifying the determinants of UPI adoption can help in framing the policies with the aim of financial inclusion and reducing the gap among the masses in using the digital payment system. There are various implications stemming from the results of this study for application developers, designers, marketers, policymakers, and financial institutions that aim to improve UPI adoption among low-income consumers. The study's focus on low-income consumers is especially important as the Indian government regards UPI as a critical tool for promoting financial inclusion. For example, a wider adoption of the UPI can lead to innovations.

The study emphasizes the significance of FCs to drive UPI adoption among low-income consumers. Ensuring the availability of necessary resources, technical support, and access to reliable networks is crucial for enabling individuals to use UPI effectively (Saikia & Jacob, 2021). Therefore, Policymakers may focus on addressing infrastructure gaps, if any, and providing all essential support to enhance the overall UPI experience. EE also emerged as a significant factor influencing UPI adoption. To encourage low-income consumers to adopt UPI, app developers may prioritize user-friendly interfaces, an intuitive navigation system, and options for operating the app in local languages. Simplifying the UPI app's usability can contribute to higher adoption rates among individuals with lower levels of education and digital literacy. Addressing security and privacy concerns will build trust and confidence among low-income consumers. Clear communication about data protection measures and proactive measures to prevent system malfunctions can help alleviate PRs associated with UPI usage.

UPI service providers should prioritize technology security to address any sense of insecurity among users. Investments in robust technical infrastructure are essential to reduce failed transactions and prevent fraudulent activities. Measures should also be implemented to enhance user education on reporting and avoiding fraudulent transactions, as well as providing adequate redress mechanisms for affected consumers. Once individuals realize the usefulness, ease of use, and risk-free nature of UPI, their likelihood of adoption increases, especially when they have access to the necessary FCs. Collectively, these efforts can drive the adoption of UPI among low-income consumers and contribute to financial inclusion.

## Limitations of the Study and Scope for Future Research

The study has the following limitations. The present study employed a non-probability convenience sampling method to collect data via a self-administered questionnaire. Data collection was limited to participants residing in the state of Kerala.

Future research can build upon this study by exploring additional factors that may influence UPI adoption among low-income consumers. Factors such as trust, perceived value, and personal innovativeness could be examined to gain a more comprehensive understanding of the adoption process. Moreover, qualitative research methods, such as interviews or focus groups, can offer more insights into the experiences and perceptions of low-income consumers regarding UPI adoption. Additionally, conducting comparative studies across different regions and socioeconomic backgrounds can shed light on the contextual variations in UPI adoption.

## Authors' Contribution

The manuscript is the combined effort of the authors. Rosin C. Jacob proposed the area of research and the initial conceptual model. Johney Johnson also supervised the entire work and provided valuable suggestions. Literature was extracted from scholarly journals by Rosin C. Jacob and Mishel Elizabeth Jacob. All the authors together developed the hypothesis and the instrument for measuring the construct. Rosin C. Jacob collected the data. Rosin C. Jacob and Mishel Elizabeth Jacob analyzed the data. Rosin C. Jacob, Mishel Elizabeth Jacob, and Johney Johnson contributed to the drafting, reviewing, and editing of the manuscript and wrote the interpretations, implications, and conclusion.

## Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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