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The Role of Perceived Trust and Social Influence in Digital Payment Adoption: Evidence from Rural Haryana

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Abstract:

India is leading the world in e-wallet adoption. While urban adoption has been impressive, there are significant sections of society that have not been penetrated by this innovation. Surprisingly, while urban adoption has been extensively studied and is well understood using established theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT), there remains an empirical void regarding the theory's applicability in agrarian states such as Haryana. The existing literature often overlooks the complex interplay between trust and social influence, moderated by important factors such as age. This study extends the UTAUT framework with Perceived Trust as a context-specific construct. Data were collected from 220 respondents across select villages using a questionnaire and analyzed using Structured Equation Modeling with software applications named IBM SPSS and AMOS. The results indicate that Perceived Trust, Social Influence & Performance Expectancy significantly affect behavioral intention. According to a multigroup analysis, it was revealed that age is a strong moderator, social influence is a strong driver for young users, and it was found that perceived trust and effort expectancy were critical for older users. This information can help shape the policies of companies and policymakers who wish to close the urban-rural adoption gap and reduce reliance on cash in India's economy.

Keywords: e-wallets, rural Haryana, behavioral intention, effort expectancy, performance expectancy, perceived trust.

INTRODUCTION

Technology enables people across the world to transact money in different and distinctive ways. India is a World Leader in E-Wallets – along with China, the digital payment ecosystem in India experienced a great transformation after the launch of the Digital India project and demonetization in 2016. The demonetization caused citizens to shift towards cashless payment systems (Reserve Bank of India [RBI] 2017). E-wallets have become most common since they make financial transactions hassle free. E-wallets are software on mobile devices that allow users to make payments without cash. Because e-wallets gave a chance to make payments without moving cash physically, payment activities have evolved. You can now pay the bills, shop online, and transfer funds all at the cost of just a few clicks. All you need is a smartphone and a simple Internet connectivity (Dahlberg et al. 2008). Major e-wallet providers are Indian companies like Paytm, BharatPay and PhonePe leading the e-wallet system. International players like Google, Samsung and Apple are also trying to capture the Indian e-wallet industry.

The rise of digital services in India has accelerated due to a combination of factors. After the start of Jio telecom in September 2016, heavy competition between telecom providers resulted in affordable and widespread availability of cheap high-speed Internet. Furthermore, several innovations began taking place with business process reengineering, management developmental business modules and systems management plans, which resulted in the launch of UPI (Unified Payments Interface) (NPCI 2023). Though digital payments have seen impressive penetration in India, a large section of society is still deprived of its benefits. Some northern states of India which have always been agrarian and cash-dominated, like Haryana, have still not become a part of this impressive digital payments evolution. For rural users, trust and social influence appear to be two key drivers of new technology adoption, in addition to other more obvious factors, such as perceived ease of use and usefulness (Venkatesh et al., 2003). Low digital literacy and varying levels of awareness significantly impact how rural users perceive and accept e-wallets (Rai and Sharma, 2019; Balasundaram et al.,2025). Haryana is consistently ranked as one of the richest agrarian states in India based on the average monthly income per agricultural household and has huge untapped potential hidden in rural settings.

While existing studies have extensively explored adoption in urban settings, empirical evidence for rural adoption remains scarce (Singh et al., 2020). Although cities in Haryana have recorded major improvements in digital financial inclusion, sections of the rural population are lagging behind, primarily due to perception (Government of Haryana, 2022). This study aims to understand the role of perceived trust in addition to well-established constructs of UTAUT, such as social influence. The study also goes into depth by understanding various age groups and what affects them by applying a multigroup analysis. Oftentimes treating the rural population as one group does not indicate the true picture. This study aims to deeply understand what affects the adoption of young vs. old people separately (Kusairi, 2025). The results should help policymakers and wallet providers design their approach for the inclusive upliftment of the digital payments ecosystem and the inclusive growth of the country. No section of society should be deprived of the benefits and productivity gains that e-wallets provide.

LITERATURE REVIEW

Technology adoption models: TAM/UTAUT

User acceptance of technology has long been at the core of Information Systems Research. One of the most well-known and used frameworks for understanding why people accept or reject technologies is Davis' Technology Acceptance Model (TAM). According to TAM, two major components, perceived usefulness and perceived ease of use, affect an individual's intention to use a new technology (Davis, 1989).

Although Davis' TAM has shown itself to be very effective and has been used extensively across many different contexts, researchers have sought to extend TAM by incorporating additional social and contextual factors that may impact whether individuals will choose to use a specific technology.The Unified Theory of Acceptance and Use of Technology (UTAUT) extends the work of prior models including TAM; this theory draws upon multiple theoretical perspectives to understand how and why individuals adopt new technologies (Venkatesh et al., 2003). Additionally, UTAUT proposes four primary antecedents to an individual's intention to use technology: Performance Expectancy; Effort Expectancy; Social Influence; Facilitating Conditions. Further, UTAUT includes moderating variables to account for differences among individuals who may be affected differently based on characteristics such as Age, Gender, Experience etc.While UTAUT provides a very robust explanation of how and why individuals accept or reject technologies, recent research studies have incorporated additional constructs into the framework with respect to Trust -- especially within digital and online environments where there are high levels of uncertainty and perceived risk.

Perceived Trust

Perceived trust has emerged as a critical factor in technology adoption, particularly in online environments. Trust refers to the belief that a system is reliable, secure, and capable of protecting users' interests (Gefen et al., 2003).

In contexts involving uncertainty, such as e-commerce, fintech, and online services, trust plays a pivotal role in reducing perceived risk and increasing user confidence (Pavlou, 2003; Amnas et al., 2023). Studies have shown that trust significantly influences behavioral intention, often acting as a mediator or direct predictor alongside the traditional UTAUT constructs (Oliveira et al., 2016).

The inclusion of perceived trust in adoption models reflects the growing importance of security, privacy and transparency in shaping users decisions (Sonu et al., 2025).

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Age as a moderating variable

There is considerable evidence that age has an impact upon technology adoption behaviors. The UTAUT model posits that the degree to which the variables of interest -- particularly effort expectancy and social influence -- affect each other will be different depending upon the age group being studied (Venkatesh et al., 2003).Generally speaking, younger adults have a tendency to be affected by social influences and can adapt to use new technologies quickly, while older adults are generally more influenced by the perceived usefulness of the technology and facilitating conditions (Morris and Venkatesh, 2000). Older adults also appear to experience greater degrees of risk aversion when evaluating whether or not to adopt a technology. These findings provide further support for the necessity of conducting multiple group comparisons to gain a greater understanding of how demographics can influence a user's likelihood of adopting a particular technology.

Research model and Hypothesis

Performance Expectancy (PE) is identified by Venkatesh et al. (2003) as the extent to which one believes that use of a particular technology will assist in achieving his/her goal faster or with greater success. Performance Expectancy is a major construct in the Unified Theory of Acceptance and Use of Technology (UTAUT). The authors indicate that it provides a basis for predicting a person's intention to utilize a new technology through perceptions of potential benefits from its adoption including but not limited to; increased efficiency, usefulness and speed. It has been reaffirmed with many previous studies (Kumar, 2024) that performance expectancy is a significant positive driver of a user's behavioral intention to adopt e-wallets (Oliveira et. al. 2016). Studies by Venkatesh et al. (2003) and Amoroso & Magnier-Watanabe (2012) found that if rural users can save a 10 km trip to a bank, this is considered a huge functional win, and their intention to adopt spikes dramatically. Based on these foundations, the following hypotheses are proposed:

H1: Performance expectancy has a significant positive effect on intention to use e-wallets in rural Haryana.

Effort Expectancy (EE) is another important construct that covers a critical gap left by PE. EE refers to the degree of ease associated with the use of a particular technology, in this case, e-wallets. It complements performance expectancy by covering usability gaps. In rural contexts, usefulness alone cannot drive adoption. While EE loses significance in tech-savvy urban consumers, studies focused on rural contexts (Salemink et al., 2017) have confirmed that ease of use makes a huge difference where digital literacy is low and technology adoption is in the initial stages. This leads to the following hypothesis:

H2: Effort Expectancy has a significant positive effect on the intention to use e-wallets in rural Haryana.

India has been a collectivist society, especially in rural areas. Word of mouth holds undeniable importance, and opinions are formed based on how influential people are (educated youth coming back from cities, politicians, or respected figures of the society) embracing a new technology. This naturally means that Social Influence (SI) is a huge driver of behavior intention, so much so that Baptista and Oliveira (2015) even highlighted that in early stage adoption markets, social validation can often outweigh individual utility. Hence, the following hypothesis is proposed:

H3: Social Influence has a significant positive effect on the intention to use e-wallets in rural Haryana.

Facilitating conditions were a significant factor in the past and are usually studied in combination with UTAUT constructs. According to Pandey & Kushwaha (2026) as well as Solanki & Fatima (2026), it is an important factor to consider . With affordable and high-speed Internet reaching most parts of Haryana in recent years, rapid smartphone adoption may have wiped the significance of this factor in recent years. This study aims to determine whether facilitating conditions have already been solved if it still matters in the current rural scenario of Haryana. The hypothesis is as follows:

H4: Facilitating conditions has a significant effect on the intention to use e-wallets in rural Haryana.

Rural users are very averse to the possibility of financial fraud or loss of money due to failed transactions. Being accustomed to an extremely reliable mode of cash payments and a physical ledger has the potential to keep them away from trying out new modes of payment. Change takes a long time in rural settings; hence, the adoption of new technology could suffer as a result. Studies on financial technology by Gefen et al. (2003) and Patil et al. (2020) suggest that trust is a prerequisite for intention in digital finance. This makes it very important to extend the well-understood constructs of UTAUT to understand the interplay with trust. Specifically, keeping the rural context in mind, the following hypothesis is expected to complete the puzzle:

H5: Perceived Trust has a significant positive effect on the intention to use e-wallets in rural Haryana.

Now, treating rural users as one group and generalizing based on that can only give us a vague picture. To obtain a more accurate understanding of how different demographic profiles may have different perspectives or requirements, we must look closer. For example, young people are likely more tech-savvy, and the urban versus rural lens may not highlight many differences worth studying, while older people may show an entirely different perspective or needs. Hence, we need to extend our study to look beyond just the rural dynamic; therefore, the following hypotheses are proposed:

H5a: The effect of Perceived Trust on the intention to use e-wallets vary greatly in young vs old people of rural Haryana.

Young people are usually very motivated or influenced by what their peers and others in society do. They want to try new things and challenge themselves. On the other hand, older people rarely mind getting accustomed to new technology if it is not easy to use, and this appears to be a make-or-break factor for the older population. Hence, it is reasonable to hypothesize that different demographic profiles may have their own variations in what matters more for them.

H5b: The effect of Social Influence on the intention to use e-wallets vary greatly in young vs old people in rural Haryana.

All the hypotheses in the proposed model are summarized in figure 1.

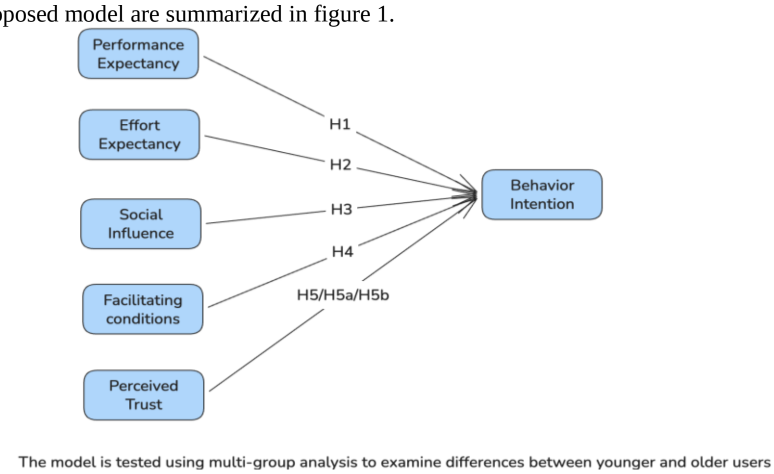

Figure 1: Proposed model

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METHODOLOGY

Research design

This study used a quantitative, cross-sectional research design to examine the determinants of behavior intention using the Structural Equation Modeling (SEM) approach. The model is grounded in an extended technology acceptance framework that incorporates performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived trust as predictors of behavioral intention.

Population and Sampling

The universe of the study is villages in Haryana state, and three villages were chosen from different districts of Haryana. One village from each of Sirsa, Hisar, and Rohtak provided a good distribution of data. Sirsa borders another wealthy state, Punjab, and has a thriving agriculture-based economy. Hisar borders Rajasthan, and the agricultural scenario varies significantly. Rohtak is on the inner side, and its villages show much less influence from neighboring states. In total, 220 samples were collected following the 10-times rule (Hair et al., 2019), with approximately 70 samples from each village.

Measurement and Instrument

The questionnaire used in this study was divided into two sections. Section 1 featured demographic statistics of the respondents, and the number of questions was kept minimal to avoid survey fatigue. Section 2 aimed to measure the key constructs for this study using a 5 point Likert scale to measure the intensity of responses. The scale for this study was mostly adopted from popular studies conducted in the past (Venkatesh et al., 2003; 2012; Gefen et al., 2003; Pavlou, 2003). Section 2 is further divided into six subsections with three items each, making it a very short questionnaire of <30 questions. Because of the quality of the scale, it was possible to show meaningful results with such a succinct one.

The details of each section is shown in table 1.

Table 1: Measurement items

Construct	Items	References
Performance expectancy	Using an e-wallet helps me manage my money and payments more quickly. Using an e-wallet makes it easier to send or receive money from family and friends. Overall, using an e-wallet is useful for my daily financial needs.	(Venkatesh et al., 2003; 2012) (Gefen et al., 2003; Pavlou, 2003)
Effort Expectancy	Learning how to use an e-wallet app is easy for me. The steps to make a payment using an e-wallet are clear and understandable. It does not take much mental effort to become skillful at using e-wallets.	
Social Influence	People who are important to me (family, friends) think I should use e-wallets. People in my village or community whose opinions I value use e-wallets. Local shopkeepers and merchants encourage me to pay using e-wallets.	
Facilitating Conditions	I have the necessary internet connection and smartphone to use e-wallets. E-wallet apps are available in a language (like Hindi) that I can easily understand. If I get stuck while using an e-wallet, there is someone around who can help me.	
Perceived Trust	I believe my money is safe when using well-known e-wallet apps. I trust that e-wallets will not charge me hidden fees without my knowledge. I am confident that if a transaction fails, my money will be refunded to my account.	
Behavioral Intention	I intend to use e-wallets for my future financial transactions. I plan to use e-wallets regularly in the next few months. I would recommend using e-wallets to others in my village.	

RESEARCH RESULTS

Validity and Reliability: Both Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA) have been undertaken to validate the measurement model. EFA has been performed on SPSS as a preliminary assessment to determine whether items can be used to measure their respective constructs. Since items were taken from established literature, it was expected that there would be little to observe. The results showed that each item was appropriate to its respective construct, with all items having factor loadings above 0.7; a comfortable threshold. Composite Reliability (CR) provided an additional means of validating the constructs through assessing construct validity. CR values for each construct were >0.8; further validation of the constructs. Subsequently, CFA was also undertaken using AMOS Version 23 as a means of assessing both convergent and discriminant validity. As evidence of support for convergent validity, results from average variance extracted (AVE) showed that AVE values were greater than 0.68 and less than 0.84 and hence were in the acceptable range given by Fornell and Larcker (1981). To provide additional support for discriminant validity Heterotrait-Monotrait Ratio (HTMT) values were calculated. Each of the HTMT values had a low ratio ranging from 0.34 to 0.70; lower than the suggested threshold of 0.85. The largest HTMT value of 0.70 occurred between Perceived Trust and Behavioral Intentions; still at a level that does not raise concern. Therefore, discriminant validity was established (Henseler et al., 2015).

Table 2 shows important parameters noted during this exercise.

Table 2: Convergent Validity

Relationship between constructs	Standard coefficient (SC)	Cronbach's alpha	Composite Reliability	Extracted variance
Performance expectancy -> PC1	0.844	0.870	0.87	0.69
-> PC2	0.825			
-> PC3	0.826			
Effort expectancy -> EE1	0.932	0.942	0.94	0.84
-> EE2	0.926			
-> EE3	0.896			
Social Influence -> SI1	0.856	0.895	0.91	0.77
-> SI2	0.872			
-> SI3	0.856			
Facilitating Conditions -> FC1	0.799	0.873	0.87	0.70
-> FC2	0.890			
-> FC3	0.813			
Perceived Trust -> PT1	0.852	0.877	0.88	0.71
-> PT2	0.814			
-> PT3	0.853			
Behavior intention -> BI1	0.904	0.923	0.92	0.80
-> BI2	0.896			
-> BI3	0.887			

Model Fit Assessment

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The structural model provided a good fit for the observed data. Overall fit indices indicated that the model fit was good. The Chi-Square statistic (chi square = 168.696, degrees of freedom = 130, p= .013) was statistically significant but this is sensitive to sample size. Therefore, alternative fit indices were used as well.

The Relative Chi-Square (CMIN/DF) was 1.298 which is below the suggested threshold of 3 therefore indicating a good fit. The Goodness-Of-Fit Index (GFI = .924), and the Adjusted Goodness-Of-Fit Index (AGFI = .899) are both in acceptable ranges.

Additionally, incremental fit indices indicate that the structural model has very high adequacy, with values at or above the recommended cutoff of .90 (CFI = .973), (TLI = .968), and (IFI = .973). Furthermore, the Root Mean Square Error Of Approximation (RMSEA) was approximately .037, and this is well below the threshold of .08 and indicates an excellent fit.

In summary, the findings provide support for the assertion that the structural model adequately models the data collected.

Analysis of the structural model

The standardized regression weights were used in order to evaluate the hypothesized relationships. Figure 2.0 shows the results that all proposed paths are positive and statistically significant. Results are shared below:

Performance Expectancy → Behavioral Intention ($\beta = 0.439$, $p < 0.001$)

Performance Expectancy has a significant positive effect on Behavioral Intention of the rural population of Haryana. This indicates that individuals are more likely to adopt the system when they perceive it as useful. This has been proved many times in the past and applies as is to the rural context of Haryana.

Effort Expectancy → Behavioral Intention ($\beta = 0.360$, $p < 0.001$)

Effort Expectancy shows the strongest influence on Behavioral Intention of rural Haryana. This suggests that ease of use is a critical determinant of user adoption. There is a significant learning curve to learning to use a smartphone and if e-wallet apps add to that burden, it may translate into lost users who won't try again for a long time.

Social Influence → Behavioral Intention ($\beta = 0.190$, $p < 0.001$)

Behavioral intention is heavily influenced by social influence; this shows that how other people view something can shape an individual's behavioral intention with respect to adopting new technologies in rural Haryana. The results show how important the views of the community are for influencing individuals' behaviors within a given community, such as when the collective consciousness or hive mind accepts a technology it will create a turning point in the process of acceptance.

Facilitating Conditions→ Behavioral Intention ($\beta = 0.118$, $p = 0.041$)

Facilitating Conditions have a positive but relatively weaker effect on Behavioral Intention, indicating that supporting infrastructure still contributes to user adoption in rural areas (Bagale and Srivastava 2023). This is likely explained by good facilitating conditions already in villages of Haryana. Most villages are covered by 4G high speed internet and most people now-a-days have a basic smartphone at a minimum. There is no lack of infrastructure at this point, it is just digital literacy and willingness, ease of use etc. The other factors are driving behavior intention to a much larger extent.

Perceived Trust→Behavioral Intention ($\beta = 0.396$, $p < 0.001$)

There is a very positive relationship between perceived trust and behavioral intent, indicating that building trust will have a large impact on how likely people from rural areas are to make use of mobile banking. A major concern for the implementation of digital services in rural India has been the fear of fraud online, which is consistent with our results in rural Haryana. With daily reports of various types of scam appearing in both the print and social media outlets in rural India, users can generally be considered as cautious. Building trust in the rural population is an important goal (and difficult to accomplish) and it has appeared to be one of the most influential factors when considering behavior intention.

Among all predictors, Performance Expectancy ($\beta = 0.439$) and Perceived Trust ($\beta = 0.396$) emerge as the most influential factors.

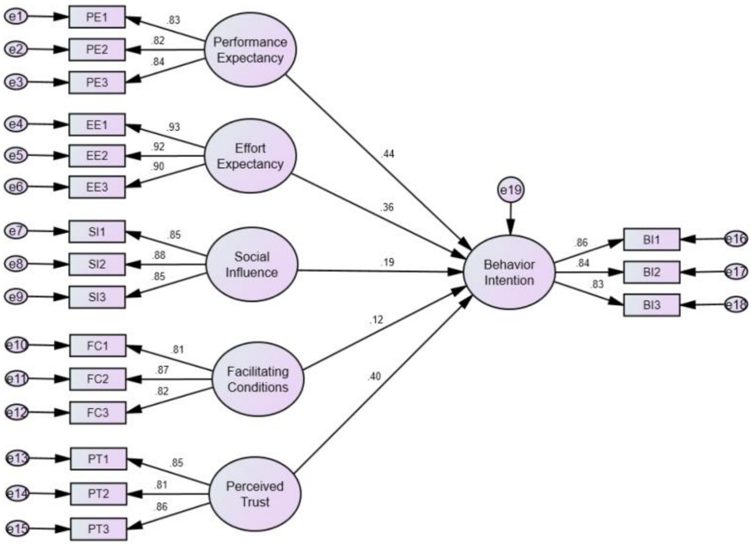

Figure 2.0: SEM results - combined

Multigroup analysis based on Age

Instead of looking at the rural population as one group, this study goes a step further and looks at different age groups. The sample was divided into young and old people. People with age > 38 were put into the old category. The results show a significant difference in factors influencing behavior intention.

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Old people

Social Influence → Behavioral Intention (β = 0.069, p < 0.001)
Effort Expectancy → Behavioral Intention (β = 0.439, p < 0.001)
Perceived Trust → Behavioral Intention (β = 0.548, p < 0.001)

As shown in figure 3 trust is a huge influencer for the old population. The ease of use also comes out as a make or break factor. They do not appear to respond so much to social influence. This shows the young population is more tech-savvy and understands digital ledgers more.

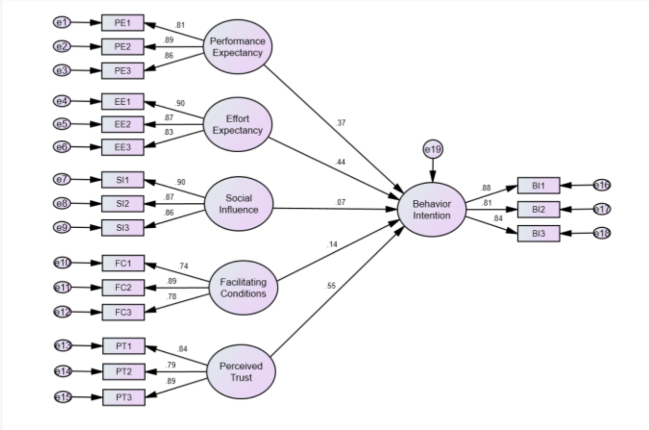

Figure 3: SEM results - old population group

Young people

Social Influence → Behavioral Intention (β = 0.380, p < 0.001)
Effort Expectancy → Behavioral Intention (β = 0.059, p < 0.001)

The younger generation, on the other hand, appears to have no problem getting their way around e-wallet apps. Figure 4 shows social Influence as a much significant factor for them. Performance expectancy is also a very heavy driver of behavior intention. This shows that if young people find the innovation worth their time, they will easily be able to use it.

This is a significant finding of the study and has implications both for policy makers and ewallet providers.

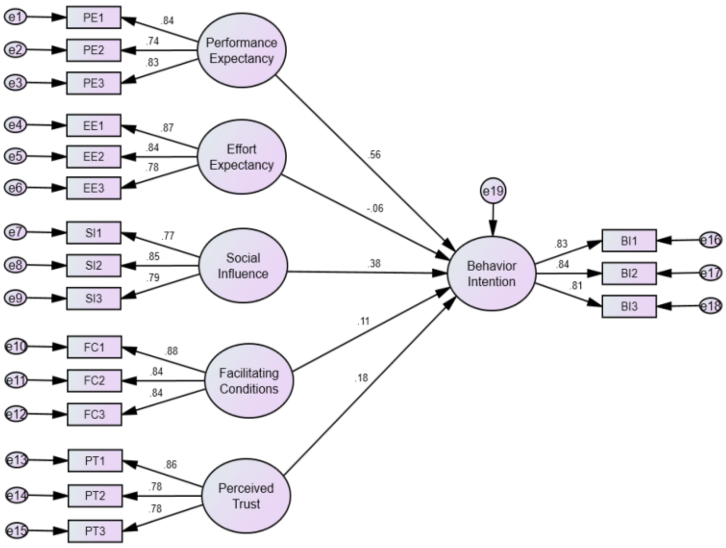

Figure 4 :SEM results - young population group

Table 3: Hypothesis testing

	Hypothesis	Result
H1	Performance expectancy has a significant positive effect on intention to use e-wallets in rural Haryana	Accepted
H2	Effort Expectancy has a significant positive effect on the intention to use e-wallets in rural Haryana	Accepted
H3	Social Influence has a significant positive effect on the intention to use e-wallets in rural Haryana	Accepted
H4	Facilitating conditions has a significant effect on the intention to use e-wallets in rural Haryana	Accepted
H5	Perceived Trust has a significant positive effect on the intention to use e-wallets in rural Haryana.	Accepted
H5a	The effect of Perceived Trust on the intention to use e-wallets vary greatly in young vs old people of rural Haryana.	Accepted
H5b	The effect of Social Influence on the intention to use e-wallets vary greatly in young vs old people in rural Haryana.	Accepted

DISCUSSION

The interactions between core constructs of UTAUT and extended variables were examined extensively within the context of rural Haryana. The primary goal of this research was to address the existing empirical gap in this area of investigation specifically focusing on agrarian and cash heavy rural economies. Unlike other studies which focus primarily on the broad array of factors affecting behavior, this study provided detailed insight into how generations differ in their behaviors. The implications of the findings have great significance for policymakers and service providers within the digital ecosystem.

The structural model indicated strong evidence supporting the hypothesized relationships affecting behavioral intent. Table 3 displays all five constructs identified in UTAUT2 – Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Perceived Trust - had statistically significant effects on behavioral intent for the total sample. Of these, both Performance Expectancy ($\beta = .439$) and Perceived Trust ($\beta = .396$) demonstrated the greatest predictive abilities as regards to forming behavioral intentions. This aligns with existing literature, Sivathanu (2018) found that performance expectancy is a key driver and Owusu et al. (2019) confirms that trust is a very significant factor in rural contexts. These two constructs were followed by Effort Expectancy ($\beta = .360$) and Social Influence ($\beta = .190$). While facilitating conditions ($\beta = .118$) had a significantly positive impact it showed less predictive ability compared to the four previously mentioned constructs.

The data collected from this research supports the concept that users will develop behavioral intentions based upon whether or not they believe a particular system is easy to use and/or can be trusted. The large impact of perceived trust is especially relevant since, in addition to perceived usability and usefulness, users' perception of the systems' credibility has been shown to be one of the most influential determinants of intention. This is consistent with recent trends in the development and deployment of technology. Users are increasingly concerned regarding issues related to the dependability, confidentiality and integrity of deployed technologies.

Further support for the prior conclusions derived from the Structural Model are supported through the multi-group analysis. One key finding from this analysis relates to age-specific differences in the structural relationship among the constructs of interest. A fundamental difference exists in how younger users respond to social influences versus older users. Younger users exhibited a greater propensity to respond to social pressures and peer opinions as opposed to older users who did not exhibit any statistically significant responses to social influences. The disparate response by younger vs. older users provides substantial support that social influence is not uniformly applied to various demographic groups; instead it is contingent upon specific user characteristics such as age.

In comparison to younger users, older users' formation of behavioral intention appears to be driven more so by their individual cognitive assessments (e.g., perceived usefulness /performance expectancy, trust) as opposed to those assessments resulting from social pressure. Additionally, young users are more likely to be influenced by their social environment, potentially because they are more engaged socially via social networking sites and also make decisions concerning product acquisition largely based on peer recommendations. This aligns with findings of Lian and Yen (2014). For experienced users in this sample the low importance of effort expectancy reflects the longitudinal transitions identified by Venkatesh et al. (2016).

Finally, additional support for the prior conclusions derived from the structural model are provided through comparisons of the magnitude of the relationships observed among the constructs of interest. For example, older users demonstrate larger path coefficient values for performance expectancy as well as smaller path coefficient values for social influence relative to younger users. Path coefficients representing effort expectancy demonstrated mixed results, including at least one instance wherein effort expectancy became statistically insignificant for a given group. The results imply that ease of use may not be equivalently important for all users once familiarity is achieved.

IMPLICATIONS

Theoretical Implications

The current study extends theoretical frameworks related to technology adoption models by including Perceived Trust as an important factor that influences Behavioral Intention. Therefore, the high and positive relationship found between Perceived Trust and Behavioral Intention confirms its status as a central construct in contemporary adoption contexts, in particular in digital environments.

Additionally, the Multi-Group Analysis has demonstrated that variables such as Age are significant Moderators of Technology Adoption. In fact, the lack of significance of Social Influence among older users contradicts the common belief that it is universally applicable and implies that Traditional Models of Technology Adoption (for example UTAUT) may benefit from being more explicit about Demographic Contingencies.

Moreover, the results confirm the Multidimensional Nature of Behavioral Intention demonstrating that Cognitive Factors (Usefulness; Ease of Use), Affective Factors (Trust), jointly determine User Decisions.

Practical Implications

From a managerial perspective, the implications of this research provide several practical guidelines:

- Design systems with simplicity and usability: Because effort expectancy is a major predictor, systems should be simple to understand and intuitive to use in order to minimize complexity.
- Develop and communicate trust: Organisations should prioritise features and methods which enhance users' perceived trust. It is very important to do so because of its high and positive relationship with behavioral intention.
- Segment your customers based on their age:
  - Younger customers will be most likely to respond positively to marketing strategies which leverage social influence such as peer reviews, testimonials, influencers endorsements and social media engagement.
  - Older customers will be most likely to respond positively to marketing strategies which emphasize functional value and trust. Examples include clear benefits, ease of use and assurances of safety and reliability.

Policy Implications

Institutions and policymakers who aim to promote technology adoption, should consider tailored approaches. Some examples include:

- Educational programs for older users, which focuses on building confidence and trust in technology.
- Awareness campaigns for younger users, can utilize social channels and peer influence to increase usage.

CONCLUSION OF DISCUSSION

Overall this study shows that Behavioral Intention can be influenced by a combination of performance factors (i.e. whether you are able to accomplish your desired outcome), effort factors (i.e. how much time/effort it takes to achieve the desired outcome), social factors (e.g. social norms, peer pressure) and trust based factors. The multi-group analysis also indicates user heterogeneity (for example; user demographics such as age) greatly influences the moderation relationship among these variables which reinforces the necessity for more personalized segmented approaches in both research and practice.

LIMITATIONS

Although this study has contributed to knowledge about digital payment adoption in rural Haryana, this study does have its limits. Haryana is ranked among the top agrarian rich states in the country; thus, the results from this study can not be generalized to all rural areas of India or for other developing countries. Further, even though there are many similarities in terms of socio-economic status and digital literacy in rural Haryana; the behavioral patterns identified in this study do not necessarily reflect the behavioral patterns found in other areas with different characteristics. Additionally, we captured user perception and behavioral intent at a single point in time; so we cannot identify trends in adoption behavior over time. Since the digital ecosystem continues to evolve quickly, it is particularly critical to observe how these trends will continue to develop. While using "Age" as a categorical moderating variable provides some insight into age-related variation in behavior, the interaction between age-related behavioral differences and other demographic (e.g., education, income) and psychographic variables (e.g., occupation, technology exposure), were explored only superficially in this study.

Lastly, this study focused primarily on behavioral intent instead of the actual use behavior. Although behavioral intent is a significant predictor of behavior, the difference between behavioral intent and actual adoption is another important area that was not investigated by this research.

FUTURE RESEARCH DIRECTION

There are many ways future studies will continue to expand on this study. In addition to extending the geographic area to evaluate rural and urban areas throughout the world, expanding the scope to evaluate rural and urban areas would increase the generalization of the results. Additionally, using measures of perceived risk, financial knowledge, cost factors, etc., could provide a better understanding of how users make decisions about adopting technology in rural settings. The study could also examine other types of trust (i.e., technological, institutional, and vendor) which could add more depth to the study.It is also suggested that by studying other moderators of behavior (e.g. age, gender, level of education, level of income, type of job), they can identify even more variability among users than was identified with respect to age alone. By gathering actual usage data or conducting mixed methods studies, researchers could identify barriers specific to particular contexts; thus, researchers can create recommendations for policy makers and developers of digital services.

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