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DRIVERS OF PASSIVE PAYMENT ADOPTION THROUGH WEARABLE DEVICES

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Abstract

The use of smart wearable devices offers a new dimension in digital finance providing consumers unprecedented convenience for passive contactless payments. However, despite the increasing usage of smart wearables and their integration with major financial institutions the usage of wearable payment systems is relatively limited in emerging markets like India. This disjunction between consumer adoption and technological capability emphasizes the importance of comprehending the elements that promote or impede wearable payment adoption. This study proposes an extended conceptual model that integrates Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework with Trust as an additional construct. Using data collected from 323 respondents in India, the proposed model was tested through Structural Equation Modeling. The findings reveal that Trust is a significant determinant in passive payments and psychological factors can surpass utilitarian factors. The findings indicate that Performance Expectancy, Price Value, and Habit positively influence behavioral intention. Results reveal that generational differences and contextual conditions moderate adoption. The finding empirically demonstrates that successful adoption of wearable payment systems is influenced by multidimensional relationship of psychological, functional, demographic and contextual factors. The study contributes to both theory and practice and offers actionable insights for fintech-developers, wearable manufacturers and policymakers aiming to improve user confidence and accelerate adoption in emerging economies.

Keywords

behavioural intention, emerging markets, passive payments, smart wearables, trust, wearable payment

1. Introduction

The digitalization of financial services has improved the convenience, speed and security of consumer transactions. Over the past decade payment methods have changed from physical currency to card payments followed by mobile and contactless payments (Aurazo et al., 2024). With the introduction of Unified Payment Interface (UPI) in 2016 mobile payments methods in India have gained widespread acceptance. In just a few years, mobile payment methods have gone from being a niche innovation to a mainstream transaction method. A more recent development is the emergence of wearable payment technologies using devices such as smartwatches, fitness trackers and smart rings (Verma & Sinha 2022). These devices once confined to health and lifestyle monitoring offer a promising option in digital payments. Wearable payment systems enable users to perform financial transactions using wearable smart devices to purchase goods or services (Bezhovski, 2016). Wearable payment are referred to as passive payment as the payment occurs with minimal user action using wearable technologies (Schmidt, 2000) . They facilitate contactless transactions either by tapping or bringing them close to payment terminals. They leverage technologies like Near Field Communication (NFC), Radio Frequency Identification (RFID) and tokenization (KPMG, 2023). As with any mobile payments, the challenge is not only about technological readiness but also user acceptance which is dependent on interrelated factors including perceived usefulness, usability, perceived risk, trust and social influence (Shin et al., 2019). However, the wearable payment technologies differ from conventional mobile payment systems due to interface limitations, shorter interaction time frame, lesser user input as well as transactional control (Verma & Sinha 2022). These could result in hesitancy among users as trust and perceived security are paramount in financial context. The prevailing research on wearable technologies has primarily focused on health and fitness applications there is a notable gap in the literature on wearable payments (Gimpel et al., 2019). Unlike mobile phones that require conscious user input for transactions, wearables typically operate more passively. Several researches have focused on mobile payments however, very few studies have explored wearable payment systems(Cao et al., 2021). There is increasing awareness about smart wearable devices but theoretical and empirical research on passive payment adoption in emerging markets like India is limited.

India has made large investments in programs such as Digital India and Bharat Interface for Money (BHIM). The Reserve Bank of India (RBI) and several commercial banks have introduced wearable payment solutions. Axis Bank's Wear N Pay, IndusInd Bank's Indus PayWear and State Bank of India's Titan Pay are a few examples of such programs (KPMG, 2023). However, in India, actual consumer adoption of wearable financial services is quite low, despite advancements and a discernible trend toward expansion. This disparity emphasizes the need for empirical knowledge about factors that impede user adoption. The study on adoption of new payment technologies is an important research area in information systems. One of the theoretical models which is widely recognized and empirically validated is the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2**)** introduced by Venkatesh et al. (2012). This framework includes several key determinants of technology adoption namely Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value and Habit. All these determinants collectively contribute to a substantial portion of the variance in user behavioral intention and actual usage. Nevertheless in domain like digital finance the framework has a significant limitation. The framework does not include trust which could be a determinant for wearable payment adoption as sensitive financial information are stored on the devices. In case of digital financial transactions users are concerned about data security, privacy, reliability of technology and perceived risks (Yousafzai, 2003). Many researchers have argued the need for trust, as a critical antecedent for technology acceptance particularly involving financial risk, privacy concerns and security expectations. The study addresses this gap. To provide a comprehensive understanding of wearable technology adoption the study proposes an UTAUT2 framework that incorporates the Trust construct.

2. Literature Review

The acceptance of wearable payment systems has increased globally, especially among the young and tech-savvy population. These payment methods are used for transactions in urban environments such as in retail, public transportation and campus ecosystems (Huang et al., 2005). The younger generation perceives wearable payment to be convenient, easy to use and compatible with modern lifestyle. However, the actual usage globally of this technology remains moderate suggesting a gap between adoption intention and continuous usage behavior (Al et al., 2023).

Research studies show that mobile payment cannot fully explain wearable payment behavior because the devices and procedures differ, and so do the drivers for adoption (Al Mamun et al., 2003). Wearable devices use embedded chips, tokenization, and biometric authentication, unlike mobile payments that rely on mobile applications. Wearable payments are also designed for passive transactions, where users simply tap a wearable device to make a seamless payment. Wearable payment systems support faster transactions with minimal user interaction, whereas mobile payments often require multiple steps, such as unlocking the device or scanning a code. Although both mobile and wearable payments use NFC technology, wearable payments face higher security challenges related to authentication. This is because there is no screen-based confirmation, and there are potential risks of device loss or unauthorized access (Onumadu, & Abroshan, 2024).

Studies on digital payment adoption have largely used the Technology Acceptance Model (TAM). TAM proposed by Davis (1989) explains technology adoption through perceived usefulness and perceived ease of use which influences behavioral intention and usage. TAM has widely been used in wearable payment research because of its simplicity and predictive power. However, several researchers have highlighted that TAM cannot capture the complexity of adoption of new payment technologies (Alkadi & Abed, 2023; Lee et al., 2003). Rabaai and Zhu (2021) extended TAM by including trust, security, cost and attractiveness of alternatives and found that these factors significantly affect behavioral intention to use wearable payments. The Diffusion of Innovation (DOI) theory explains adoption based on innovative characteristics like compatibility or relative advantage. DOI has been used to examine wearable technology adoption and studies indicate that compatibility and innovativeness are antecedents to perceived usefulness and ease of use which in turn influence adoption behavior (Veerisa & Donghee, 2022). Theory of Planned Behavior (TPB) focuses on attitude, subjective norms and perceived behavioral controls as predictors of behavioral intention. Research using TPB indicates that attitude toward technology and social pressure significantly affect adoption intention while perceived behavioral control indicates users confidence in usage of wearable payment systems (Berto et al., 2025).

In digital payment systems behavioral intention is a significant predictor and represents the likelihood that a user would use the system (Dahlberg et al., 2015). UTAUT framework has been widely validated to explain behavioral intention and usage in digital payments (Al et al., 2023; Hayat et al., 2022). Prior studies indicate functional, psychological and contextual factors influence the behavioral intention and actual usage. (Oliveria et al., 2016; Pal et al., 2019; Slade et al., 2015). Functional factors indicate the perceived performance, effort expectancy and facilitating conditions for using the system. Performance indicates faster transactions, improved efficiency and convenience. Effort expectancy refers to the ease of use or user friendliness of the system. Facilitating conditions include the availability of infrastructure and connectivity. Systems that provide reliable performance and require minimal effort are more likely to be accepted by users (Dennehy & Sammon, 2015). Psychological factors include trust, which indicates the reliability and security of transactions. Prior studies show that trust increases behavioral intention to use digital payment systems. Hedonic motivation and habit are psychological factors. Hedonic motivation refers to the gratification or pleasure of using technology while habit refers to prior experience. In digital payment system these factors are relevant as user experience may be a determinant for adoption (Marak et al., 2025). Contextual factors refer to social influence and environmental conditions. Social influence captures how people shape users decision to adopt a technology. UTAUT integrates multiple theories and incorporates four determinants of technology adoption performance expectancy, effort expectancy, social influence and facilitating conditions. UTAUT2 extended the UTAUT by including constructs on hedonic motivation, price value and habit making it suitable for mobile payments. Recent studies have increasingly used UTAUT2 to explain adoption of new technologies such as mobile payment, digital wallets and financial technology adoption (Martinez et al., 2022; Kanujiya et al., 2024). The framework does not include perceived risk, trust and security which could significantly improve the explanatory power of the model for digital technology payment. Amnas et al. (2023) used UTAUT2 model with trust and found that performance expectancy, facilitating conditions, price value habit and trust significantly influence fintech adoption intention.

2.1. Research Gap

The ecosystem in India for wearable payments is evolving with several banks launching wearable payment products. Despite these advancements empirical research on Indian consumer perception and adoption of these technologies is limited. Also wearable payment differ from traditional digital payments since they are passive transactions with minimal user interaction. This raises concerns of privacy, security and control making trust a critical determinant for adoption of wearable payment systems. However, prior studies have not sufficiently examined the role of trust in influencing the adoption of wearable system. Therefore there exists a research gap in understanding user’s behavioral intention to adopt wearable payment systems in India.

2.2. Research Objectives

1. To evaluate the effect of UTAUT2 drivers (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit) on Behavioral Intention to adopt passive payment.
2. To extend the UTAUT2 framework by integrating Trust and investigating its direct and indirect effects on Behavioral Intention and Use Behavior for wearable payment.
3. To examine the influence of age and gender as moderators in wearable payment systems.

2.3. Conceptual Framework and Hypotheses:

Based on the objectives of the research, the conceptual framework was developed as shown in Figure 1 and the following hypotheses were formed.

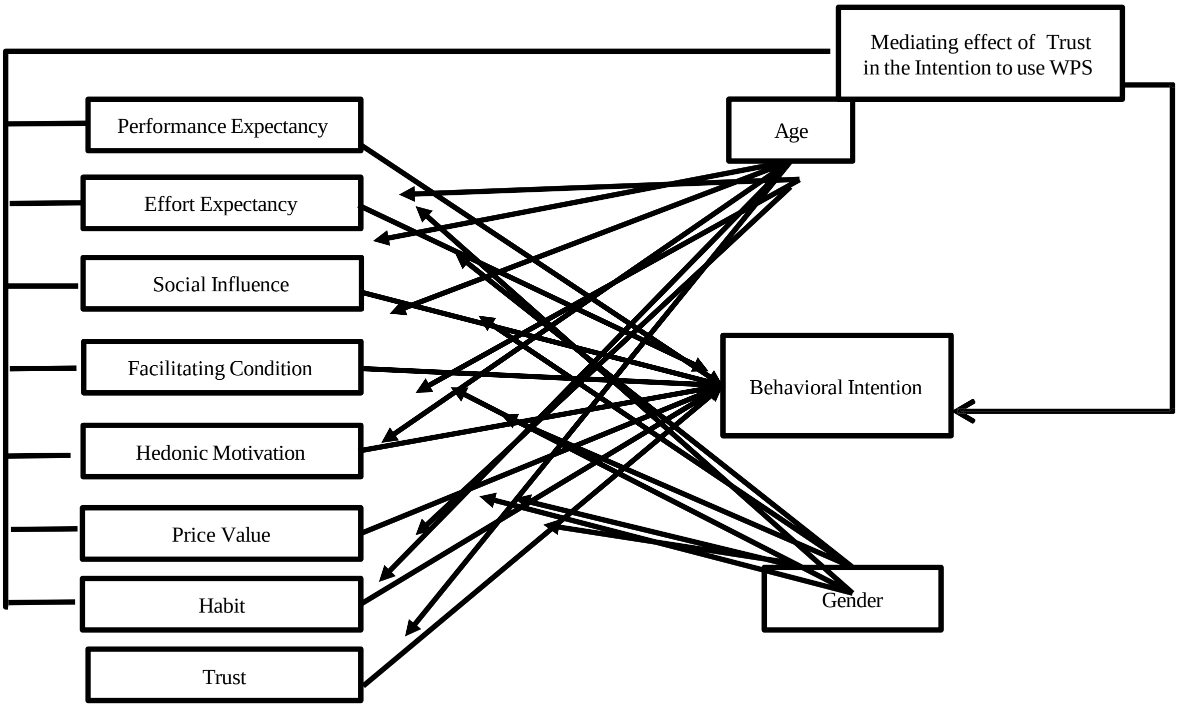

Figure 1: Conceptual Framework

H1: Performance Expectancy positively influences behavioral intention to use wearable payment systems.

H2: Effort Expectancy positively influences behavioral intention to use wearable payment systems.

H3: Social Influence positively influences behavioral intention to use wearable payment systems.

H4: Facilitating Conditions positively influence behavioral intention to use wearable payment systems.
H5: Hedonic Motivation positively influences behavioral intention to use wearable payment systems.
H6: Price Value positively influences behavioral intention to use wearable payment systems.
H7: Habit positively influences behavioral intention to use wearable payment systems.
H8: Trust positively influences behavioral intention to use wearable payment systems.
H9: Age moderates the effects of the constructs on the intention to use wearable payment systems.
H10: Gender moderates the effects of the constructs on the intention to use wearable payment systems.
H11: Trust mediates the effect of PE, EE, SI, FC, HM, PV and HB on the intention to use wearable payment systems.

3. Research Methodology

3.1. Research Design

This study uses a quantitative, cross-sectional research design to examine the driving factors influencing the behavioral intention of using wearable devices for passive payments. Structual Equation Modeling (SEM) was used as the analytical technique for finding the relationship between latent constructs. This study is based of UTAUT2, which is expanded by adding Trust as a crucial construct pertinent to passive payment systems.

3.2. Data Collection and Sampling

In this quantitative study, a purposive sampling technique is employed to select contextually relevant respondents. The data were collected through Google forms. Of the total responses, 323 responses are found to be complete and valid and used for analysis. The survey items were adapted from previously tested and validated instrument (Venkatesh et al.,2012), with minor changes made to cover the objectives of the study. The measurements factors were performance expectancy, effort expectancy, Social Influence, Facilitating conditions, Hedonic Motivation, Price Value, Habit, Trust and Behavioral Intention. All the Constructs are measured with 3 items. A five-point Likert scale was used for all the items, ranging from ‘1 - Strongly Disagree’ to ‘5 - Strongly

Agree'.

3.3. Data Analysis

Data analysis were conducted using Jamovi (Version 2.6.44) with the SEMlj Package for Structural Equation Modeling (SEM).
The descriptive characteristics of all items are shown in Table 1.

Table 1. Descriptive Statistics

	Mean	SD	Minimum	Maximum
Effort Expectancy (EE)	3.68	0.869	1.00	5.00
Performance Expectancy (PE)	3.55	0.865	1.00	5.00
Social Influence (SI)	3.35	0.972	1.00	5.00
Facilitating Condition (FC)	3.67	0.898	1.00	5.00
Hedonic Motivation (HM)	3.65	0.956	1.00	5.00
Price Value (PV)	3.55	0.882	1.00	5.00
Trust (TR)	3.15	0.979	1.00	5.00
Behavioural Intention (BI)	3.37	0.883	1.00	5.00

Harman's single-factor test was conducted to evaluate the common method bias. The test showed the single factor accounted for 24.3%, which is below the threshold value of 50%. The recorded Variance Inflation Factor (VIF) were less than 3.3 as presented in Table 2, which proves that the common method variance was not an issue for the study.

Table 2. VIF Score of Latent Constructs

	PE	EE	SI	FC	HM	PV	HB	TR
VIF	1.60	2.13	1.88	1.86	3.07	3.02	3.20	1.68

The correlation of latent factors indicated that the issue of CMV is not present, with the correlation among the constructs being lower than 0.90.

Table 3. Latent Constructs Correlation

	PE	EE	SI	FC	HM	PV	HB	TR	BI
PE	—								
EE	0.563	—							
SI	0.387	0.448	—						
FC	0.321	0.546	0.466	—					
HM	0.492	0.588	0.601	0.593	—				
PV	0.403	0.567	0.611	0.610	0.746	—			

PE EE SI FC HM PV HB TR BI

HB	0.428	0.588	0.617	0.530	0.728	0.730	—		
TR	0.333	0.360	0.474	0.405	0.506	0.498	0.615	—	
BI	0.498	0.625	0.618	0.526	0.717	0.697	0.746	0.603	—

The demographic characteristics including gender, age, location, and education are shown in Table 4. In terms of gender, the majority of the respondents were male (58.2%), while the female were only 41.8% of the sample. With respect to age, a significant proportion of the participants belonged to 18 – 24 years category, followed by 35 – 44 years and 25 – 34 years, while negligible percentage were aged 45 – 54 years and above 55 years. In term of place of residents, more than 50% were from metro / Tier 1 cities (54.8%), followed by urban/Tier 2 cities (30%) and semi-urban areas (13.9%), with a negligible participation from rural areas (1.2%). With respect to education qualification, the majority of the respondents were postgraduates (79.3%), followed by undergraduates (18.0%), while a small fraction had only completed high school (1.5%) or had doctoral degrees (1.2%). Overall, the sample is largely youth, educated, and urban-centric, which is appropriate for studying the adoption of emerging technologies such as wearable payment systems.

Table 4. Demographic Details

	N	**% of Total**		**N**	**% of Total**
Gender			**Place of Residence**		
Female	135	41.8%	Metro / Tier 1 City	177	54.8%
Male	188	58.2%	Rural	4	1.2%
Age			Semi-Urban / Town	45	13.9%
18 – 24 Years	162	50.2%	Urban / Tier 2 City	97	30.0%
25 – 34 Years	54	16.8%	**Education**		
35 – 44 Years	83	25.7%	Doctorate	4	1.2%
45 – 54 Years	23	7.1%	High School	5	1.5%
Above 55 Years	1	0.3%	Post Graduation	256	79.3%
			Under Graduation	58	18.0%

The reliability and validity of the construct were evaluated and is presented in Table 5. All the Cronbach’s alpha values are above the minimum threshold value of 0.7 with the minimum Cronbach’s alpha value being 0.820. Based on the values, all the factors were proven reliable. The composite reliability (CR) values range from 0.829 to 0.905, all values are higher than 0.7. (Hair et al.,2019). As per Fornell & Larcker (1981) suggestions, all the Average Variance Extracted (AVE) values are higher than the threshold value of 0.5 further proving convergent validity.

Table 5. Reliability and Validity

Variables	**Cronbach's α**	**McDonald's ω**	**AVE**
PE	0.869	0.870	0.693
EE	0.837	0.839	0.639
SI	0.866	0.868	0.690
FC	0.843	0.848	0.645
HM	0.904	0.905	0.761
PV	0.820	0.829	0.639
HB	0.872	0.873	0.696
TR	0.864	0.869	0.699
BI	0.870	0.875	0.697

Discriminant validity was established using Heterotrait-Monotrait (HTMT)). As shown Table 6 since the criterion value are less than 0.90, the study showed the evidence of lack of discriminant validity. These results confirm that the measurement model is robust and suitable for structural analysis.

Table 6. Discriminant Validity (HTMT)

	PE	EE	SI	FC	HM	PV	HB	TR	BI
PE	1.000								
EE	0.646	1.000							
SI	0.445	0.517	1.000						
FC	0.370	0.647	0.541	1.000					
HM	0.551	0.668	0.672	0.675	1.000				
PV	0.477	0.672	0.729	0.727	0.869	1.000			
HB	0.488	0.680	0.707	0.611	0.818	0.871	1.000		
TR	0.376	0.412	0.542	0.442	0.563	0.585	0.705	1.000	
BI	0.573	0.722	0.709	0.609	0.807	0.835	0.856	0.693	1.000

3.4. Confirmatory Factor Analysis (CFA)

The confirmatory factor analysis was conducted to evaluate the measurement model and examine the relationship between the latent constructs and observed variables. The model fit was assessed using multiple indices.

The chi-square statistic was significant with the following values χ^2 = 825, df =288, p<.001. The additional fit indices were considered due to sensitivity of the sample size. The Comparative Fit Index (CFI = 0.918) and Tucker-Lewis Index (TLI = 0.900) meet the recommended threshold of 0.90, indicating a satisfactory fit. The Standardized Root Mean Square Residual (SRMR = 0.060) is below the threshold of 0.08, suggesting a good fit. The Root Mean Square Error of Approximation (RMSEA = 0.076) is within the acceptable range, with a 90% confidence interval between 0.070 and 0.082.

The standardized factor loadings range from 0.672 to 0.896 as indicated in Table 7, exceeding the recommended value of 0.60, thereby confirming strong indicator reliability. These results indicate that the measurement model is adequate for further structural analysis.

Table 7. Measurement Model – Factor Loadings

Construct	Items	Factor Loading (β)
Performance Expectancy (PE)	PE1	0.780
	PE2	0.896
	PE3	0.814
Effort Expectancy (EE)	EE1	0.746
	EE2	0.755
	EE3	0.878
Social Influence (SI)	SI1	0.799
	SI2	0.817
	SI3	0.869
Facilitating Condition (FC)	FC1	0.811
	FC2	0.845
	FC3	0.763
Hedonic Motivation (HM)	HM1	0.855
	HM2	0.864
	HM3	0.894
Price Value (PV)	PV1	0.860
	PV2	0.672
	PV3	0.830
Habit (HB)	HB1	0.827
	HB2	0.864
	HB3	0.814
Trust (T)	TR1	0.895
	TR2	0.867
	TR3	0.731
Behavioral Intention (BI)	BI1	0.857
	BI2	0.772
	BI3	0.880

3.5. Structural Model Evaluation

After the confirmation of the measurement model, the structural model was evaluated to test the hypothesis. Here the relationship between the latent constructs were evaluated. The model demonstrated an acceptable overall fit. The chi-square statistic was significant as indicated in Table 8. As presented in Table 9, CFI (0.918) and TLI (0.900) indicate a satisfactory model fit. The SRMR (0.060) is below the recommended threshold of 0.08, while the RMSEA (0.058) falls within the acceptable range, further supporting the model fit.

The model also exhibits strong explanatory power, indicating 81.2% of the variance (R^2=0.812) in Behavioral Intention, indicating that the independent variables collectively provide substantial predictive capability.

Table 8. Model tests

Label	X^2	df	p
User Model	825	288	<.001
Baseline Model	6889	351	<.001

Table 9. Model Fit Indices

SRMR	RMSEA	CFI	TLI
0.060	0.058	0.918	0.900

3.6. Hypotheses Testing and Path Analysis

The results of the path analysis are illustrated in Table 10 and path diagram is shown in Fig.2. The findings indicate that several factors significantly influence behavioral intention towards wearable payment systems. Precisely, Effort Expectancy (β = 0.248, p = 0.004), Social Influence (β = 0.125, p = 0.033), Hedonic Motivation (β = 0.204, p = 0.034), Habit (β = 0.243, p = 0.031), and Trust (β = 0.199, p < 0.001) exhibit a positive and statistically significant impact on behavioral intention, thereby supporting the corresponding hypotheses. Among these, Effort Expectancy and Habit demonstrate relatively stronger effects, while Trust remains a key determinant, highlighting the importance of perceived reliability and security in the adoption of passive payment technologies.

Table 10. Hypothesis Test Results

Hypothesis	Path	β	t-value	p-value	Result
H1	PE → BI	0.008	0.124	0.901	Not Supported
H2	EE → BI	0.248	2.854	0.004	Supported
H3	SI → BI	0.125	2.137	0.033	Supported
H4	FC → BI	-0.083	-1.223	0.221	Not Supported
H5	HM → BI	0.204	2.125	0.034	Supported
H6	PV → BI	0.118	1.104	0.270	Not Supported
H7	HB → BI	0.243	2.156	0.031	Supported
H8	TR → BI	0.199	3.592	<0.001	Supported

In contrast, Performance Expectancy (β = 0.008, p = 0.901), Facilitating Conditions (β =

-0.083, p = 0.221), and Price Value (β = 0.118, p = 0.270) have no significant effect on behavioral intention, leading to the rejection of the respective hypotheses. These findings suggest that users place greater importance on ease of use, social influence, enjoyment, habitual behavior, and trust rather than performance benefits or cost considerations when adopting wearable payment systems.

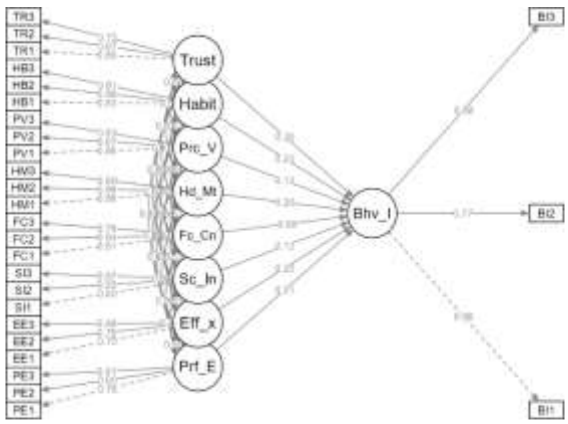

Figure 2. Path Diagram

3.7. Moderation Analysis

Moderation Analysis was performed to determine whether demographic variables, such as age and gender, moderate the relationship between the independent variables and behavioral intention toward wearable payment devices. The model showed strong explanatory power, indicating 86.3% (R^2=0.863, group 1) and 84.6% (R^2=0.846, group 2) of the variance in Behavioral intention, indicating that the independent variables collectively provide substantial predictive capability.

The model fit indices for the moderation analysis indicate a marginal but acceptable fit, with values approaching recommended thresholds of CFI = 0.895 and TLI = 0.872. Although slightly below the conventional cutoff of 0.90, such values are considered acceptable in multi-group SEM analyses, particularly in complex models and reduced subgroup sample sizes. Therefore, the model is deemed adequate for examining moderating effects.

3.7.1. Moderating effect of Age

The results in the Table 11 demonstrate that age significantly moderates key relationships. Younger users, particularly aged between 18 – 34 years, exhibit stronger effects from effort expectancy, habit and trust, suggesting that ease of use, routine behaviour and trust plays an important role in their adoption intentions. In contrast, older adults display heightened influence of trust, reflecting the greater importance of security, privacy, and system reliability concerns.

Table 11. Moderating Results – Age Moderation

Hypothesis	Path	β	p-value	Result Interpretation
H9 (Young)	PE → BI	0.001	0.987	Not Supported
	EE → BI	0.257	0.008	Significant, Ease of Use
	SI → BI	0.140	0.051	Close to Significant
	FC → BI	-0.105	0.178	Not Supported
	HM → BI	0.074	0.479	Not Supported
	PV → BI	0.037	0.762	Not Supported
	HB → BI	0.517	<0.001	Strongest Predictor
	TR → BI	0.141	0.018	Significant, Trust is a Concern
H9 (Old)	PE → BI	-0.126	0.497	Not Supported
	EE → BI	0.404	0.074	Not Supported
	SI → BI	0.090	0.401	Not Supported
	FC → BI	-0.184	0.222	Not Supported
	HM → BI	0.591	0.010	Significant, Enjoyment or Comfort of use
	PV → BI	0.261	0.305	Not Supported
	HB → BI	-0.048	0.085	Not Supported
	TR → BI	0.502	<0.001	Significant, Trust is a Concern

3.7.2. Moderating Effect of Gender

Gender also emerged as a significant moderator as indicated in Table 12. Female users are more strongly influenced by trust, highlighting the importance of security and reliability in their adoption decision. Male users, conversely, showed more balanced impacts across multiple factors, including hedonic motivation, effort expectancy, and trust, suggesting a comprehensive assessment of both utilitarian and experiential technology factors.

Table 12. Moderating Results – Gender Moderation

Hypothesis	Path	β	p-value	Result Interpretation
H10 (Female)	PE → BI	-0.002	0.986	Not Supported
	EE → BI	0.222	0.083	Not Supported
	SI → BI	0.160	0.264	Not Supported
	FC → BI	-0.033	0.717	Not Supported
	HM → BI	0.042	0.839	Not Supported
	PV → BI	0.331	0.072	Not Supported
	HB → BI	0.161	0.257	Not Supported
	TR → BI	0.198	0.035	Significant, Trust is a Strongest driver
H10 (Male)	PE → BI	0.095	0.198	Not Supported
	EE → BI	0.267	0.027	Significant, Ease of use
	SI → BI	0.045	0.496	Not Supported
	FC → BI	-0.165	0.103	Not Supported
	HM → BI	0.247	0.039	Significant, Enjoyment
	PV → BI	0.089	0.504	Not Supported
	HB → BI	0.262	0.085	Not Supported
	TR → BI	0.228	0.002	Significant, Trust is a Strongest driver

3.8. Mediation Analysis

The mediation analysis examined the indirect effects of the predictors on behavioral intention (BI) through trust (TR). Trust significantly mediated the relationship between social influence (SI) and BI ($\beta = 0.204$, $p < 0.001$, 95% CI [0.074, 0.281]), representing the strongest indirect effect in the model and indicating that higher social endorsement enhances trust, which in turn strengthens intentions to use wearable payment systems. Trust also significantly mediated the effect of hedonic motivation (HM) on BI ($\beta = 0.248$, $p = 0.010$, 95% CI [0.053, 0.383]), suggesting that users' enjoyment of the technology increases their trust, thereby indirectly promoting adoption intentions. In contrast, the indirect effects of performance expectancy, effort expectancy, facilitating conditions, and price value on BI via TR were non-significant, with all corresponding confidence intervals including zero, implying that these factors influence BI through mechanisms other than trust. Overall model fit was acceptable for a complex mediation structure (SRMR = 0.093, RMSEA = 0.093, 90% CI [0.087, 0.100], CFI = 0.884, TLI = 0.861), and the model demonstrated substantial explanatory power, accounting for 52% of the variance in TR ($R^2 = 0.520$) and 62% of the variance in BI ($R^2 = 0.618$).

4. Findings and Discussion

One of the key findings of the study is that trust shapes user's behavioral intention to use wearable solutions. Trust emerged as the strongest predictor of behavioral intention, outperforming all other UTAUT2 constructs in explanatory power. This underscores the central role of perceived security, reliability, and confidence in shaping users' intentions to adopt wearable payment systems. The finding highlight that trust plays a crucial role in shaping behavioral intention and enabling its transformation into actual use. These finding advances theoretical understanding by demonstrating that in high-risk, trust-sensitive domains such as digital finance psychological factors may outweigh traditional utilitarian drivers. Beyond trust, the results confirm that effort expectancy, social influence, hedonic motivation, and habit all exert positive direct impacts on behavioral intention, indicating that users simultaneously value ease of use, social endorsement, enjoyment, and routine familiarity when evaluating these technologies. In addition to these direct effects, social influence and hedonic motivation show significant indirect effects on intention through their relationship with trust, suggesting that social approval and enjoyment strengthen adoption partly by enhancing users' trust in the system. The results show Performance Expectancy, Price Value and Habit do not influence Behavioral Intention.

Age-based differences further refine these insights. Younger respondents placed greater emphasis on ease of use and habit formation, implying that intuitive interfaces and support for routine usage are particularly important for this segment. Older respondents, in contrast, cited trust as the primary determinant of their adoption decisions, highlighting heightened sensitivity to perceived risk, security, and reliability concerns. Gender differences also emerged: female respondents emphasized trust more strongly, whereas male respondents tended to balance trust with enjoyment and ease-of-use considerations. Collectively, these findings suggest that effective promotion of wearable payments should focus on trust-building across all users, while tailoring messages about usability, enjoyment, and habit support to specific age and gender segments.

Interestingly, the findings suggest that usage was not significantly affected by social influence. This shows that personal view and trustworthiness may have a greater impact on adoption than peer pressure or outside forces. Overall, the results indicate that a complex interaction of environmental, functional, demographic, and psychological factors shapes the adoption of wearable payment systems in emerging economies such as India. The study highlights trust as a fundamental factor that affects intention and usage behavior and emphasizes the moderating role of generational and contextual differences.

5. Conclusion

The study extends the knowledge of digital payment solutions and offers insights about the adoption of wearable payment systems in India. Notably, it was found that Trust influences Use Behavior directly and indirectly, through Behavioral Intention. Trust is the strongest predictor and not performance expectancy unlike what other previous studies have suggested. The results highlight the heightened salience of psychological enablers in the context of wearable payments, which differ from mobile payments in their passive, less consciously controlled nature. User's reliance on wearable devices for financial transactions appears to focus more on their confidence in the system's security, privacy and reliability than on perceived functional efficiency. Though Trust is a decisive determinant, habitual factors also have a significant influence on adoption intentions. As users become accustomed to wearable payments, the behavior can evolve into a habit, thereby increasing usage.

The study also identified demographic differences. Clear generational divides emerged. Younger respondents prioritised convenience and ease of use, while older respondents emphasised security and trust as key factors influencing adoption. This indicates that device manufacturers and financial service providers should develop targeted marketing strategies. For younger consumers, emphasis should be on user-friendly interfaces, seamless transactions, and features that focus on convenience. Conversely, for older consumers, safety, security, and reliability should be the focus.

The implication for fintech firms and device manufacturers is that they should provide a secure, transparent and user-friendly ecosystem for financial payment systems. Also in passive payments focus should be on security, control and transparency of transactions. Thus, transaction notification and authentication methods are some of the strategies that can be implemented. There is a need for regulatory policy guidelines to guarantee security and data privacy. Transition to a cashless economy will depend on resolving the concerns of user safety.

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