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BEHAVIORAL INTENTION OF SMARTWATCH USAGE - AN EMPIRICAL ANALYSIS USING UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT) MODEL

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ABSTRACT

Purpose: Technology-driven insurance companies use disruptive technologies to innovate, improve, and automate their products and services. With the help of connected devices, especially wearable, health insurance companies can access the customers' risk profile, customize suitable products, and charge premiums based on the physical activities of the customer tracked with the help of smartwatches. Customers consider several factors before using a Smartwatch. The current research is undertaken to determine the factors that determine the usage of the Smartwatch.

Theoretical framework: This study has employed the Unified Theory of Acceptance and Use of Technology (UTAUT) with Trust as an extended variable to determine the influence of variables on behavioral intention while also discussing the explanatory power (R square) and effect size (f square) of the model. UTAUT also tests the moderating effect of Gender on behavioral intention.

Design/methodology/approach: A Survey was conducted among the general population over eighteen years of age and using the smartwatch. The sample size was 131 and the responses were collected through a structured questionnaire. All the items of the constructs were measured on a five-point Likert scale and responses were quantified. Variance-based Structural Equation Modelling (SEM) using Smart PLS (version 4.0) is used to test and validate the model.

Findings: From the results, it is inferred that performance expectancy and Trust significantly affect behavioral intention, while effort expectancy, facilitating conditions, and social influence don't.

Research, Practical & Social implications: The study will create awareness in society about the importance of staying healthy to prevent or minimize the impact of non-communicable diseases by tracking physical activities using a Smartwatch. Insurance companies can customize fitness-based products, provide a discount on premiums, and pass on other benefits to customers. Insurance companies can leverage this technology to create health awareness among the general public improve profit and reduce claims.

Originality/value: The data was analyzed using Smart PLS (version 4.0) software by measuring the measurement and structural models. From the path coefficients, it is inferred that performance expectancy and Trust significantly affect behavioral intention. R square value indicates the proposed model has a medium explanatory power in explaining the behavioral intention. f square value indicates that performance expectancy and trust have a moderate effect on the behavioral intention of using the smartwatch.

Keywords: Unified Theory of Acceptance and Use of Technology (UTAUT); Smartwatch; Behavioral Intention; Trust; Non Communicable diseases (NCDs);

Introduction

The Internet has taken the digital transformation towards an unbelievable phase, bringing out innovative processes and payment methods in banking, insurance, and other industries. Like Fintech in the Banking and Financial Services Industry (BFSI), the Insurance industry witnessed a massive digital transformation and innovation in its products and processes. The disruption embraced by the Insurance Industry is termed as InsurTech. The technology-driven companies use the latest technologies such as Artificial Intelligence (AI), Drones, Big Data, BlockChain, Robots, and the Internet of Things (IoT), all of which help to innovate, improve, and automate their products and services. According to the World Health Organization (WHO), seventy-seven percent of deaths occur in low and middle-income countries due to Non-Communicable Diseases (NCDs), namely, cardiovascular diseases, cancers, chronic respiratory diseases and diabetes. Further, the report stated that detection, screening, treatment, and palliative care are critical in handling NCDs. Wearable devices can track, store, and communicate basic physical and physiological properties, which can help in the detection and screening of NCDs in their early stages.

Any physical and tangible device a user can interact with is called an interactive device. The subcategory of these devices is the wearables. A Wearable is an electronic device embedded with an inbuilt sensor and microprocessor, which can track activities like physical activity, biometric identification, and location. Some examples of wearable devices are Smartwatches, Smart rings, Smart earphones, Smart glasses, Smart clothing, etc. (HP Tech Takes). Depending on the usage, wearable technology can be classified as smartwatches, fitness trackers, VR headsets, smart jewelry, web-enabled glasses, and Bluetooth headsets. With the advancement of IoT and AI, wearable technology can be used in the areas of health monitoring, entertainment, gaming, smart clothing and fashion, military, sports, and fitness. Smartwatches and fitness trackers are prominent examples of wearable technology in consumer electronics categories. (TechTarget). Wearable technology can be classified into health-related wearable technology, textile-based wearable technology, and wearable consumer electronics. (Çiçek, Mesut, 2015).

Globally, the market size of wearable technology is projected to reach USD 265.4 billion by 2026 growing at a Compound Annual Growth Rate (CAGR) of 18% from 2022, the reason being the increase in demand for IoT devices and smart devices in healthcare applications. (Markets and Markets). In India, the growth rate is expected to grow with a five-year CAGR of 5.1%, with units of shipments reaching 628.3 million by 2026. (IDC).

With steady market growth and advanced design, wearable devices have the capacity as an information system that can change the lifestyle and healthcare behavior of the user. (Madhav Sharma, 2019). People know that wearable devices are widely used in sports, followed by the medical field. Lesser awareness was observed in the field of security and no awareness was observed concerning implantable wearable devices. The younger age group between 15-25 is more aware of wearable devices. The level of awareness is based on education and income level, among health-conscious people and people in the medical field. (Shweta Nanda and Bhupender K Som, (2018). In addition to fitness and wellness applications, wearable devices are capable of the prevention of disease rather than the treatment of disease. Under the acceptable level of economic standard, data privacy, and technical conditions, two out of three Americans are willing to adopt health insurance wellness programs using wearable devices if the benefits are health promotion and disease prevention with financial incentives (Diego Soliño-Fernandez Et al, 2019). The latest technologies like Big Data Analytics, Robo Advisors, blockchain, and InsurTechs are challenging the existing insurance companies functioning. Hence traditional insurance companies are forced to experiment with innovative technologies or collaborate with InsurTechs (Michael Greineder et al, 2018). Smart wearables with AI techniques track and report the user's physical activity status, step count, heart rate, blood pressure, and calories. These data are used to predict and prevent early diseases for better health in the future. Health insurance companies can use these data to improve profits, maintain customers' lifestyles, offer discounts or vouchers, and reduce customer premiums (Apeksha Shah, 2021).

Wearable devices can be improved, especially in determining Heart Failure (HF) by improving their precision. The development of wearable technology and information interfaces with consumers, patients, and healthcare professionals, will support better lifestyle choices and disease prevention. Future developments in wearable technology should inform medical decision-making, support better self and remote monitoring, and offer more personalized surveillance and therapy adjustments (Arvind Singhal, 2020). Wearable sensors combined with tailor-made algorithms are used for the detection of abnormal heart conditions, hypertension, and diabetes. These tools can reduce hospital admission costs, improve post-surgical and rehabilitation outcomes, assist with aging in-home patients, and prevent serious, preventable, and costly medical events. Wearables can inform medication side effects or interactions, and provide automated just-in-time interventions and emergency medical care (accidents, military settings, athletics, and resource-constrained environments). Wearable and environmental sensors collect and transfer the data rapidly to off-site experts and enable automated real-time medical support and can also be employed in resource-constrained environments with the help of suitable algorithms. (Jessilyn Dunn, 2018). Wearable technology helps in patient diagnosis, treatment, and care. The habitual data are collected separately over time under all circumstances and are integrated into the cloud environment. (A. Godfrey et al., 2018). For the insurance industry, technology is a two-sided coin. Improving long-standing client engagement and trust problems, creating new products to meet current needs, or fulfilling existing needs better are some of its merits. On the flip side, the threat is due to the disruptive InsurTechs who use the latest technology, which transfers risk from the customer to risk-takers (A. Spender, 2019). Zhongwei Gu & June Wei (2020) developed a trust model based on the product characteristics of wearable devices. The research points out the direction of product development for wearable device manufacturers.

Theoretical background

The user of wearable devices form their perceptions about the device's trustworthiness and information acceptance based on the initial trust between the users and wearable systems. The three dimensions of a wearable system are Devices, Organizations (manufacturers and App makers), and the Internet. The design, functionality, and usability of the wearable device must be accessible and the user should trust the information provided by the wearable device. The theory of reasoned actions takes into account the characteristics of the user, the perception of the user about the device and the associated organization, and the overall perception of the wearable device. The theory further states that trusting beliefs should lead to trusting intention, leading to trust-related behavior. For predicting new technology acceptance, the Unified Theory of Acceptance and Use of Technology (UTAUT) model was employed by the researchers proposed by Venkatesh et al., 2003. The theory was further extended and UTAUT 2 was proposed by Venkatesh et al. (2012). As per the comprehensive review by Venkatesh et al. (2013), between 2003 and 2014 there were four UTAUT extensions were used by the researchers, viz., new exogenous mechanisms, new endogenous mechanisms, new moderation mechanisms and new outcome mechanisms with a total of 37 UTAUT extensions fall under these four categories. Hence this research used the UTAUT theory with Trust as a new endogenous variable and Gender as a moderating variable. The constructs used in this research are as follows:

Performance Expectancy (PE)

Performance expectancy is defined as "the degree to which the usage of technology will provide benefits to consumers in performing certain activities" [Venkatesh et al. (2012)]. Consumers will adopt any technology if it benefits them to perform different tasks quickly and easily.

H1: There is a significant influence of PE on behavioral intention (BI) on smartwatch usage.

Effort Expectancy (EE)

Effort expectancy is defined as “the degree of ease associated with the use of the system” [Venkatesh et al. (2012)].

H2: There is a significant influence of EE on behavioral intention on smartwatch usage.

Social Influence (SI)

Social influence is defined as “the degree to which an individual perceives the notion of others in his usage of the new system” [Venkatesh et al. (2012)].

H3: There is a significant influence of SI on behavioral intention on Smartwatch

Facilitation Conditions (FC)

Facilitating conditions are defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" [Venkatesh et al. (2012)].

H4: There is a significant influence of FC on behavioral intention on Smartwatch.

Trust (TR)

Trust is related to the need for people to control or at least feel that they can understand the social environment where they interact. Hence trust can be faith or confidence that the other party will meet obligations outlined in an exchange. (Ahmad Alaiad, Lina Zhou, 2014).

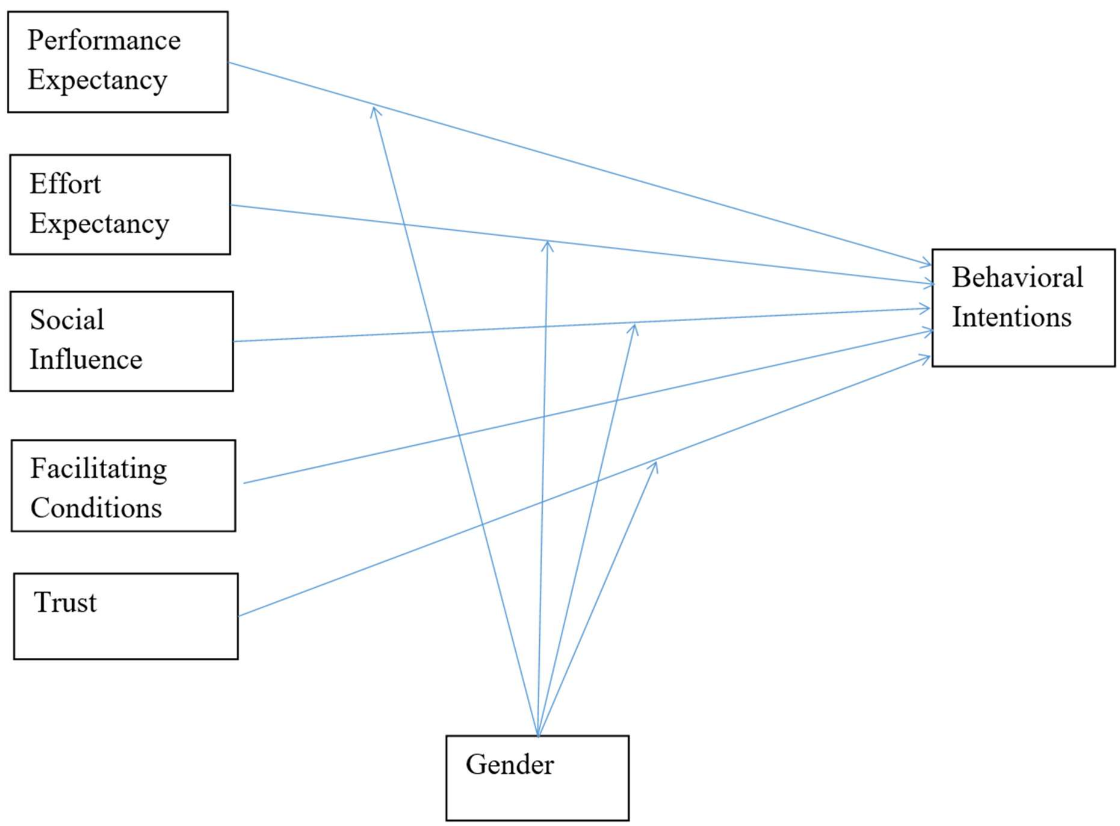
H5: There is a significant influence of TR on behavioral intention on Smartwatches.

Gender

The research tests the moderating effect of Gender on the constructs PE, EE, SI, and TR. The following hypothesis was formulated.

H6: The influence of PE, EE, SI, and TR is moderated by Gender.

Fig 1: Proposed Research Model



Literature review

Madhav Sharma and David Biros, 2019, proposed an initial trust model according to the theory of reasoned action. According to the model, the disposition to trust should have a positive relationship with the user's institution-based trust. The user's trusting beliefs and intentions should lead to trust-related behavior. Though the users' lifestyles and healthcare behavior can change with the help of wearable devices and their advanced technologies, some factors influence the change. The formation of initial trust will overcome the barriers to wearing wearables. (Madhav Sharma, 2019). The awareness of wearable devices is largest in the medical field next to the sports and fitness fields. Wearables in the security field are the lowest and no one was aware of implantable wearables with the male respondents having more familiarity than female respondents. The younger generation has more awareness of wearable devices. Education does not play a vital role in the awareness of wearable devices. The awareness differs based on the various income groups. (Shweta Nanda and Bhupender K Som, 2018). AI-enabled smart wearables are used in the healthcare system to track health status, fitness tracking, and early detection of diseases. Health insurance companies can use these data to increase revenue and profits and create value for the customer by creating a health awareness system. Awareness about wearable devices is affected by the education and personal income of the general public. These devices help health insurance companies collect and measure various types of health data and price the policy based on the data collected. The awareness level is not significant between the health insurance policyholder and the public who does not have a health insurance policy. (Aswin C Prakash et al, 2021). The predictors for wearable adoption are perceived usefulness, perceived ease of use, perceived enjoyment, perceived self-expressiveness, and perceived privacy risk. (Chenming Peng et al, 2022). As wearables are helpful in fields like healthcare, sports, fitness management, and many more, researchers have a growing interest in studying the acceptance of this technology. The factors to find out the acceptance of wearable technology are "performance expectancy," "effort expectancy," "social influence," and "facilitating conditions." The factors for use intentions are "use intention" and "user behavior." Limited sample size and wearable still being an emerging technology are the main limitations and the researcher suggested that future research should extend the model. (Chiau-Ching Chen and Hsu-Shih Shih, 2014). For the adoption of wearable devices, Initial Trust is the most determinant and influencing factor. The other factors determining adoption are health interest, consumer innovativeness, and perceived ease of use. (Shahla Asadi, 2019). Perceived Compatibility, Perceived usefulness, and Perceived Technology accuracy have a significant positive effect on Perceived product value. Health consciousness, Perceived critical mass, and Perceived product value have a significant positive effect on the intention to use wearable medical devices. Perceived product value has mediated the relationship between the intention to use wearable medical devices and Perceived compatibility, Perceived usefulness, Perceived product value, and Perceived technology accuracy. The researcher also suggested reducing the cost of wearable medical devices to improve their value of the wearable medical device. (Yang Q et Al. 2022). Ramkumar, B. and Liang, Y. (2020), in their study using the consumption-value approach of perceived value theory, showed that there are no significant differences in consumer perceptions of a smartwatch across all price point levels. The study also showed that the risk, quality, value for money, Trust, and purchase intention were different between known and unknown brands and known and unknown brands have unique advantages in marketing smartwatches. Performance expectancy has the strongest significant impact on the use of COVID-19 Digital Tackling Technology (CDTT). Performance expectancy, facilitating conditions, and social influence had a significant impact on an individual's intention to accept and use CDTT. Facilitating conditions have a positive and significant relationship with behavioral intentions and Social influence has a significant relationship with behavioral intentions, which shows that people use new technology due to social influence. The research also found out that the effort expectancy, perceived cost, public awareness, data security, and privacy, organization influence and benefit, and government expectancy and benefit have no significance on behavioral intention to use CDTT. The moderating variables age, Gender, and voluntariness had no significance at that time for using CDTT. (Boluwaji A. Akinnuwesi et. Al. (2021). The researchers Armando Papa et al. (2018) have hypothesized the impact of perceived usefulness (PU), perceived ease of use (EOU), intrusiveness (INTR), and comfort (C) on attitude and intention to use towards adoption of smart wearable healthcare (SWH) devices. The research concluded that the INTR had a significant impact on the PU of SWH devices and comfort has a strong significant impact on the PU and EOU of smart wearables. The research further concluded that INTR, C, does not have a significant direct impact on the intention to use behavior intention (BI) of SWH devices. Eun-Jung Lee (2020), in her academic paper, concluded that the perceived visual typicality of the smartwatch design significantly decreased the perceived performance and playfulness of the Smartwatch. Perceived visual typicality negatively impacts purchase intention. Perceived playfulness was most significant in the relationship between visual typicality and purchase intention. The paper also found that the moderating effect of Gender was partially supported as visual typicality significantly decreased purchase intention for females and had no impact on males. Gopinath Krishnan et al. (2022), in their meta-analysis titled "Determination of the adoption of wearable devices for health fitness," reviewed fifty-six empirical studies from fifty-two articles which were examined wearable device acceptance with 16648 total samples. The researchers performed a series of meta-analyses using the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and an integrated conceptual model that provided a comprehensive understanding of the adoption of wearable technologies. The TAM framework analysis confirmed that perceived usefulness is the strongest determinant of attitude and intention toward wearable health devices. Perceived ease of use was a significant predictor of perceived usefulness and attitude. The analysis also reported the inconsistencies between perceived ease of use and attitude. The analysis also supported the attitude and behavioral intention. The analysis of the UTAUT framework established the significance of all the original UTAUT relationships. The behavior intention was significantly influenced by the combined effect sizes of performance expectancy, effort expectancy, facilitating condition, and social influence. The analysis further stated that the relationship between effort expectancy and behavioral intention suffered publication bias and hence the researchers removed this relationship in the revised conceptual model. The simultaneous meta-analysis based on TAM and UTAUT frameworks proved that both theories were extremely valuable for understanding the behavior of the individual's adoption of wearable technologies. The analysis further stated that the TAM was a powerful framework to investigate the emerging technology aspects since the number of studies that used TAM relationships was higher than that of the UTAUT. The result of the meta-analysis in the integrated conceptual model indicated that a. the perceived usefulness and attitude are the strong predictors of behavioral intention, b. perceived ease of use is the predictor of perceived usefulness, attitude, and behavioral intention, c. the relation between social influence and the behavioral intention was supported, d. innovativeness and compatibility positively affected behavioral intention, e. the relationship between self-efficacy and the behavioral intention was supported, f. the relationship between perceived privacy risk and behavioral intention not supported, g. the moderating effect of culture and user type was partially supported by the behavioral intention.

Research Methodology

Sampling, Data Collection, and Measurement Items

The nature of the research is descriptive. The target population was the general public over eighteen years old and using Smartwatches. The primary data was collected through a questionnaire using a non-probability convenient sampling method. The sample size was 131, of which 89 were males and 42 were females. The secondary data was collected from books, websites, insurance company websites, and relevant publications. All the items of the constructs were measured on a five-point Likert scale and responses were quantified. There were six demographic questions and two health insurance-related questions.

Table 1: Constructs and Items :

Construct	Number of Items	Adopted and Modified from
Performance Expectancy (PE)	4	Venkatesh et al, (2012)
Effort Expectancy (EE)	3	Venkatesh et al, (2012)
Social Influence (SI)	3	Bhattacherjee, (2000)
Facilitating Conditions (FCON)	4	Venkatesh et al., (2012)
Trust (TR)	3	Pushpatil (2020)
behavioral intention	3	Venkatesh et al., (2012)

The data was analyzed using Smart PLS software by measuring the measurement and structural models.

Data analysis and interpretation

Measurement Model

The measurement model is the sub-model in Structural Equation Modeling (SEM), which helps assess the constructs' reliability and validity. Reliability is concerned with the scale's consistency, accuracy, and predictability. The scale's validity refers to the measurement process being free from systematic and random errors.

Construct Reliability and Validity:

Outer loading of all the items, Cronbagh's alpha, Rho_a, and Composite reliability (rho_c) were checked.

The outer loading of all the items is more than 0.700 and ranges from 0.749 to 0.928, except the item Facilitating Conditions 4 (FCON 4), which is 0.635. Hence, the FCON4 has less explanatory power. Though the FCON4 has lesser explanatory power, the item was retained since the Cronbach alpha, Composite reliability (rho_a & rho_c) (more than 0.700) and Average Variance Extracted (AVE) is more than 50%, the item FCON4 has been retained.

From Table 2,

Cronbagh's alpha: The reliability is measured by Cronbagh's alpha. Cronbagh's alpha values range from 0.770 to 0.905 and hence the reliability of the scale is established.

Rho_a: These values lie between Cronbach's alpha and Composite reliability, which is a good indication of reliability.

Composite reliability (rho_c): As the composite reliability value is more than 0.700, it ranges from 0.839 to 0.935, and the scale's reliability is established.

Table 2: Construct Reliability and Validity - Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	The average variance extracted (AVE)
BI	0.895	0.900	0.935	0.827
EE	0.770	0.783	0.866	0.683
FCON	0.752	0.779	0.839	0.568
PE	0.905	0.921	0.933	0.776
SI	0.829	0.846	0.897	0.743
TR	0.890	0.890	0.932	0.820

Validity:

Convergent validity:

Convergent validity and Discriminant validity are subcategories of construct validity. Convergent validity was measured by Average variance extracted (AVE), defined as a measure of the amount of variance captured by a construct in relation to the amount of variance due to measurement error. A measure of more than 0.50 is considered to be adequate convergent.

The average variance extracted (AVE): As the values are more than 0.5, the items have no convergent validity issue. (Table 2)

Discriminant validity: In discriminant validity measures, no construct should be theoretically and statistically related to each other. In the research, Discriminant validity was measured in three ways.

Fornell-Larcker criterion: The value of each construct in the Fornell-Larcker criterion is exactly the square root AVEs of each construct. Also, this value is higher than the correlation underneath between the constructs, and hence discriminant validity is established.

Table 3: Fornell-Larcker criterion:

	BI	EE	FCON	PE	SI	TR
BI	0.909					
EE	0.384	0.826				
FCON	0.366	0.667	0.753			
PE	0.628	0.466	0.440	0.881		
SI	0.441	0.305	0.409	0.518	0.862	
TR	0.605	0.330	0.289	0.420	0.525	0.905

Hetrotrait-Monotrait Ratio: This ratio measures the average correlations of the indicators across constructs. Henseler et al. (2015) suggested that the acceptable value levels are less than 0.90 and hence the discriminant validity is established.

Table 4: Heterotrait-Monotrait Ratio (HTMT)

	Heterotrait-monotrait ratio (HTMT)
EE <-> BI	0.453
FCON <-> BI	0.425
FCON <-> EE	0.886
PE <-> BI	0.684
PE <-> EE	0.547
PE <-> FCON	0.468
SI <-> BI	0.501
SI <-> EE	0.372
SI <-> FCON	0.493
SI <-> PE	0.58
TR <-> BI	0.672
TR <-> EE	0.396
TR <-> FCON	0.366
TR <-> PE	0.461
TR <-> SI	0.612

Cross-Loading: Discriminant validity is established when an indicator's loading on a construct is higher than all of its cross-loading with other constructs. Cross-loading measures how well the items of a particular construct load onto that construct. For example, PE1, PE2, PE3, and PE4 should load well onto PE and not on other constructs.

Table 5: Cross Loading

	BI	**EE**	**FCON**	**PE**	**SI**	**TR**
BI1	0.896	0.312	0.390	0.574	0.378	0.433
BI2	0.910	0.367	0.326	0.563	0.425	0.598
BI3	0.921	0.365	0.290	0.577	0.399	0.607
EE1	0.351	0.822	0.565	0.300	0.210	0.244
EE2	0.254	0.799	0.576	0.348	0.195	0.259
EE3	0.333	0.857	0.522	0.505	0.342	0.315
FCON1	0.360	0.425	0.749	0.509	0.429	0.175
FCON2	0.254	0.586	0.801	0.280	0.179	0.250
FCON3	0.249	0.592	0.816	0.247	0.268	0.207

FCON4	0.184	0.434	0.635	0.180	0.314	0.280
PE1	0.658	0.445	0.539	0.874	0.497	0.388
PE2	0.511	0.398	0.323	0.900	0.456	0.339
PE3	0.447	0.305	0.278	0.853	0.353	0.324
PE4	0.554	0.465	0.356	0.896	0.491	0.414
SI1	0.298	0.230	0.322	0.369	0.847	0.474
SI2	0.411	0.315	0.459	0.552	0.873	0.386
SI3	0.412	0.237	0.271	0.399	0.866	0.504
TR1	0.564	0.335	0.353	0.437	0.521	0.872
TR2	0.527	0.260	0.221	0.341	0.431	0.915
TR3	0.550	0.297	0.207	0.357	0.468	0.928

STRUCTURAL MODEL

After assessing the reliability and validity of the measurement model, the study assessed the structural equation model by testing the hypothesis. The systematic approach, as given by Hair et. Al (2013) to the structural model assessment is

1. Assessment of the structural model for collinearity issues
2. Assessing the significance and relevance of structural model relationships
3. Assessing the coefficient of determination R2
4. Assessing effect sizes f2
5. Assessing the predictive relevance of Q2 and the q2 effect sizes.

Collinearity between Constructs: To assess any significant level of collinearity between the predictor variables PE, EE, SI, FCON and TR, this study analyzed the variance inflation factor (VIF). As per the guidelines of Hari et al. (2013), VIF greater than 5 indicates the presence of collinearity between the constructs. The result of VIF is well below five and it concluded that no collinearity exists in this study.

Assessing the significance and relevance of structural model relationships

The Smart PLS 4 software was used in the research to assess the structural model relationships. As per the guideline of Hair et al. (2013), the bootstrapping technique with 5000 samples was used to assess the significant relationships between the constructs. A total of 9 hypotheses were tested. Hypothesis H1 & H5 were found to have a positive significant relationship with BI since 't' statistics is >1.96 and this was complemented by p values which were > = 0.00. As the 'p' values are > 0.05, there is no significant relationship between FCON, SI, and EE, and hence H2, H3, and H4 have no significance on BI. This has been established as the path coefficient between FCON-BI, SI-BI, and EE-BI values ranges from negative to positive, indicating the presence of Zero.

Table 6: Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
PE -> BI	0.437	0.423	0.105	4.158	0	supported
TR -> BI	0.417	0.406	0.087	4.767	0	supported
FCON -> BI	0.055	0.059	0.092	0.597	0.551	not supported
SI -> BI	-0.031	-0.023	0.088	0.353	0.724	not supported
EE -> BI	0.016	0.033	0.099	0.16	0.873	not supported

Table 7: Path Coefficients - Confidence intervals

	Original sample (O)	Sample mean (M)	2.50%	97.50%
EE -> BI	0.016	0.033	-0.149	0.235
FCON -> BI	0.055	0.059	-0.124	0.236
PE -> BI	0.437	0.423	0.211	0.618
SI -> BI	-0.031	-0.023	-0.19	0.159
TR -> BI	0.417	0.406	0.23	0.569

Moderating effect of Gender on BI

As per the "Welch-Satterthwait test', the 'p' values are more than 0.05 for all the constructs and hence it is concluded that there is no significant difference in the effect of Gender on behavioral intention. Hence H6 has no significant impact on BI.

Table 8: Total effect - Bootstrap Multi-Group Analysis (MGA)

	Difference (Male-Female)	t value (|Male vs Female|)	p-value (Male vs. Female)
EE -> BI	-0.143	0.599	0.552
FCON -> BI	-0.165	0.605	0.548
PE -> BI	0.315	1.67	0.101
SI -> BI	-0.207	1.059	0.295
TR -> BI	0.104	0.536	0.594

Assessing the coefficient of determination R2

The coefficient of determination, R square, will help determine how much change in the dependent variable can be accounted for by one or more independent variables. Hair et al. (2013) define R square as "a measure of the model's predictive accuracy and is calculated as the squared correlation between a specific endogenous construct's actual and predicted values". The R square values of 0.25–0.49 - small, 0.50–0.74- medium, and greater than 0.75 – substantial - (Henseler et al., 2009). R square value (0.539) indicates that a 53.9 percentage change in BI can be explained by the dependent variables. The proposed model has medium explanatory power in explaining behavioral intention.

Table 9: R-square and R-square adjusted

	R-square	R-square adjusted
BI	0.539	0.521

Assessing effect sizes f2

The f square is the change in the R square when an exogenous variable is removed from the model. Removing the exogenous variable can affect the endogenous variable and as per Cohen, 1988, f square values > = 0.02 is small; > = 0.15 is medium; > =0.35 is large. PE and TR were found to have a medium effect on BI.

Table 10: f square

	BI
BI	
EE	0.000
FCON	0.003
PE	0.254
SI	0.001
TR	0.256

Assessing the predictive relevance Q2 using the bind folding technique

The Q square of the blindfolding procedure represents a measure of how well the path model can predict the originally observed values. As developed by Stone-Geisser (1974), Q square values greater than zero for a certain reflective endogenous latent variable indicate the path model's predictive relevance for the construct BI. The threshold specified for Q square predictive relevance is: 2% < Q2 < 15% - weak, 15% < Q2 < 35% - moderate, Q2 > 35% - strong.

In the research, as the Q2 predict is 48%, the model has strong predictive relevance.

Table 10: Q^2predict

	Q^2predict	RMSE	MAE
BI	0.48	0.738	0.552

Results and discussion

The present research used the UTAUT model by incorporating exogenous variables namely the Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FCON), and extending the UTAUT model by adding Trust as an additional exogenous variable and Gender as a moderating variable. The research found that the total variance accounted for in BI is 53.90% in the UTAUT model, with TR as an additional exogenous variable and Gender as a moderating variable in the usage of Smart watch. Among all the exogenous variables, PE and TR significantly affect the smart watch's behavioral intention. The effect size of TR is 0.256 and PE is 0.254, which has a medium effect on BI. The predictive relevance of the model is 48%. The moderating effect of Gender does not affect the usage of Smartwatches, as the 'p-value for values is more than 0.05.

Conclusions, limitations, practical and social implications, and future research

The model was tested for reliability and validity. From the path coefficients, it is inferred that performance expectancy and Trust significantly affect behavioral intention, whereas effort expectancy, facilitating conditions, and social influence have no significant influence on behavioral intention. R square value (0.539) indicates that the proposed model has medium explanatory power in explaining behavioral intention. Assessing effect size (f square) indicates that effort expectancy and social influence have no effect and performance expectancy and Trust have a moderate effect. As per the "Welch-Satterthwait test', the 'p' Values are more than 0.05 for all the constructs and hence concluded that there is no significant difference in the effect of Gender on behavioral intention.

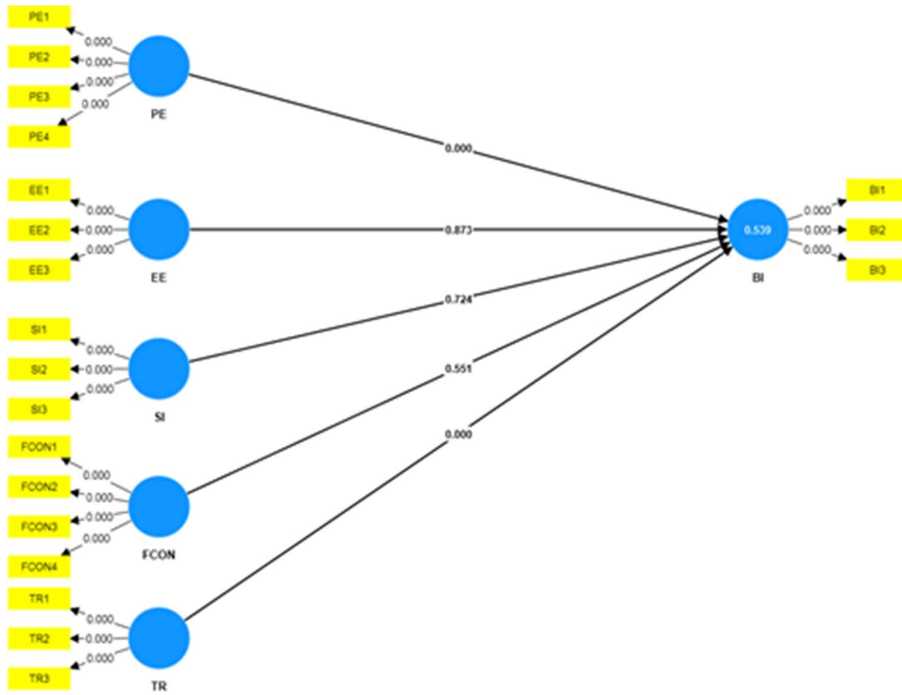
This study has the limitation of considering only one exogenous variable TR. It can also be done using UTAUT2 and Extended UTAUT models, by including more exogenous variables and other moderating variables, like age, income, qualifications, etc. The study did not consider the brand of the smartwatches and the number of respondents is limited to 131. A future study can be done by including more exogenous variables and moderating variables. The study will create awareness in society about the importance of staying healthy to prevent or minimize the impact of non-communicable diseases by tracking physical activities using a Smartwatch. Insurance companies can customize fitness-based products, provide a discount on premiums, and pass on other benefits to customers. Insurance companies can leverage this technology to create health awareness among the general public improve profit and reduce claims.

Appendix 1 - Final survey measurements

Construct	***Code***	**Items**
Performance expectancy	PE1	I find Smart watch useful in my daily life for tracking fitness activity
	PE2	Using Smartwatch increases my chances of achieving my physical fitness goals
	PE3	With the help of a Smartwatch, I can achieve my fitness-tracking activity more quickly
	PE4	With the help of my Smartwatch, my fitness activity level increases

Effort Expectancy	EE1	Learning how to use a Smartwatch is easy for me
	EE2	My interaction with the Smartwatch is clear and understandable
	EE3	It is easy for me to become an expert at using Smartwatch
Social influence	SI1	People who are important to me think that I should use a smartwatch.
	SI2	People who influence my behavior think that I should use a smartwatch.
	SI3	People whose opinions I value prefer that I use Smartwatch
Facilitating Conditions	FCON1	I have the resources (like mobile data/Bluetooth) necessary to use Smartwatch
	FCON2	I have the knowledge necessary to operate the smartwatch.
	FCON3	Smartwatch has compatible features with other technologies I use like the Internet, mobile data, and smartphone.
	FCON4	I can get help from others when I have difficulties using Smartwatch
Trust	TR1	I trust Smartwatch to be reliable
	TR2	I trust data storage and transmission by Smartwatch to be secure
	TR3	I believe Smartwatch to be trustworthy
Behavioral Intention	BI1	I plan to continue using Smartwatch in the future
	BI2	I will always try to use the Smartwatch in my daily life
	BI3	I plan to continue to use the smart watch frequently

Appendix 2 - Path Analysis Output using Smart PLS 4.0



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