Is a Smarter Generation in the Offing? Empirical Evidence About the Use of Smart Wearable Devices Among Indian Youth

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ABSTRACT

The study explored the critical determinants of behavioral intention and willingness to use smart wearable devices among Indian youth. Data were collected using a survey instrument on India's youth aged between 20-30 years (N=262). The results showed that performance expectancy, hedonic motivation, and habits impacted the behavioural intention of the youth. Facilitating conditions impacted the youth's willingness to use. Behavioural intentions of the youth impacted their willingness to use smart wearable devices. Male youth moderated the effect of performance expectancy on behavioural intentions. Gender and purpose of use moderated the effect of hedonic motivation and habits on behavioural intention and behavioural intention on willingness to use. Only health and fitness moderated the effect of facilitating condition on willingness to use smart wearable devices among youth. Though the study is limited to the Indian context, its implications can benefit the wearable commerce providers in designing, positioning, and marketing the products in developing economies.

KEYWORDS

Behavioural Intentions, Effort Expectancy, Habits, Hedonic Motivation, Performance Expectancy, Price Value, Technology Acceptance Model, UTAUT2, Willingness to Use

INTRODUCTION

Technological developments have brought about a radical change in the attitudes of human beings about life and lifestyle, making specific dreams of the earlier few decades become authentic experiences. One such technological development is wearable technology, which has proliferated into many devices with magical powers that people only imagined in the past (Chang et al., 2016). The last two decades have been a tremendous acceleration in exploring and applying wearable technologies from several domains like industry, academia, research institutions, business, technology, and society (Lee et al., 2016). Gartner's prediction for the sale of smart wearable devices in 2020 stood at 52 billion and is expected to reach 63 billion in 2021, increasing 22% (Brown, 2019). The wearable devices market is growing rapidly, with the global smart-watch shipments alone growing by 42% at the end of the third quarter of 2019 (Strategy Analytics, 2019).

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Research Motivation and Objectives

There is a perennial interest from the industry and academia to conduct research studies on youth about the need to harness the potential of wearables. The term youth is a period that ranges from adolescence to middle age in a human life cycle. Various agencies have quantified this period; 15-24 years (United Nations, 2020), 15-29 years (National Youth Policy, 2014 India). This research study's motivation is multi-fold. The primary reason is that today's youth have better exposure and access to technology, and they are smart enough to exploit new technologies to their advantage. The changing lifestyles of the millennials, the knowledge industry, and service beyond boundaries led to the increased risk of unprecedented ailments at a much earlier age in their lives.

The objective of this research paper is two-fold.

First, to study the factors that significantly influence the acceptance of intelligent wearable devices among youth.

The second is to examine the moderating factors that affect youth's willingness and behavioral intention towards using smart wearable devices.

The research will seek answers to '*Why wearable devices are so much popular among youth, and what is their perception of the acceptance of wearables?*' '*What are the critical moderators that affect their behavioral intentions and willingness to use?*'

RELATED WORKS

This section converses the current literature from two significant perspectives. The first section deliberates the research on the application of smart wearable devices (SWD) to comprehend the authors' efforts in wearables technology research. The second section discusses the *Unified Theory of Acceptance and Use of Technology* (UTAUT2) model's relevance to ensure suitability, validity, and reliability while explaining technology adoption research in many scenarios. Finally, the section states the research gaps to reinforce the authors' attempt to extend the model's application to investigate the adoption of SWDs among youth.

Applications of Smart Wearable Devices (SWD)

That smart wearable devices will be the next generation of core information technology (IT) products (Chang et al., 2016) sprouts out of its advantages over other IT products. Designers and manufacturers require first-hand information about *what (type of wearable), who (users), when (time, duration, frequency), why (purpose of use), and how (functionality and process)* and to improve the features and capabilities so they can capture the market (Porter and Heppelmann, 2014; Lin et al., 2016).

Wearable devices might surpass or replace smartphones and laptops in performance (Kim and Park, 2019). Wen et al. (2017) argued that a significant gap existed between consumer expectations and the reliability of wearables data management. The market will complement the healthcare industry, given the interest among young people who aspire for a fit and healthy lifestyle (Ridgers et al., 2018; Goodyear et al., 2019).

Application of UTAUT2 in the SWD Research

Venkatesh et al. (2003), in their seminal work titled 'User Acceptance of Information Technology; Toward a Unified View', planned the *Unified Theory of Acceptance and Use of Technology*. The model is flexible and superior to other models and aims to explain user-intention and subsequent usage-behaviour to use an information system (Slade et al., 2015). Performance Expectancy, Effort Expectancy, Social Influence, Habit, Compatibility, and Innovativeness significantly impact the intention to adopt SWDs among students and employees, according to Talukder et al. (2019).

UTAUT (Venkatesh et al., 2003) is comparatively new among the technology acceptance theories. The model's popularity is its comprehensiveness in investigating the intention and actual usage of

information technology/systems. UTAUT2 (Venkatesh et al., 2012) extends its predecessor model UTAUT by including the user/consumer context, which is the “consumer acceptance and use of information technology” (UTAUT2). The new model comprises the first four factors and three new factors: “Hedonic Motivation,” “Price Value,” and “Habit.”

This research adopted the UTAUT2 model because of the parsimonious nature of smart wearable devices technology. Table 1 summarizes the results of seminal works that applied UTAUT2 in the recent past to reiterate the theory’s applicability and the parsimonious nature of the smart wearable devices technology.

Research Gap Identification

The overall understanding from previous paragraphs shows that the earlier studies have extensively applied the UTAUT2 (both in standard and customized versions) for understanding user intention to technology. There are widespread and abundant studies on healthcare wearable adoption. The target segments are general consumers, patients, employees, and students. Earlier studies have also recommended that future studies target new groups, explore new contexts, and include new moderators. In this direction, the current research believes that there is a *need to explore in-depth the impact of smart wearable devices on youth. Though there are comparative studies of countries worldwide (Ko et al., 2009; Dutot et al., 2019); in the Indian context, which has the largest youth population in the world, there is abundant opportunity for studies on the adoption of the technology targeting the youth segment (Gupta et al., 2018). It is a rare find from an Indian context, research about individual-level technology acceptance theories about next-generation gadgets/devices.*

Table 1. Summary of the Applications of UTAUT2 Theory

Studies by	Type of SWD	UTAUT2 Constructs (Independent Variables)						
		Performance expectancy (PE)	Effort expectancy (EE)	Social influence (SI)	Facilitating conditions (FC)	Hedonic motivation (HM)	Price value (PV)	Habit (HB)
Talukder et al., (2019)	Fitness Wearables	xxx	xxx	xxx				xxx
Sergueeva et al., (2019)	Personal Health Devices	xxx		xxx	xxx	xxx		xxx
Francis, (2019)	Patient self-monitoring devices	xxx				xxx	xxx	
Reyes-Mercado, (2018)	Fitness Wearables	xxx	xxx		xxx			
Zhou and Chen, (2018)	Mobile Intelligent Wearable Devices	xxx	xxx					xxx
Kalantari and Rauschnabel, (2018)	AR Smart Glass	xxx	xxx	xxx				
Choi et al., (2017)	Wearable Sensing Devices	xxx		xxx				
Rauschnabel et al., (2018)	AR Smart Glass	xxx	xxx			xxx		
Hein et al., (2017)	AR Smart Glass							
Yuan et al., (2015)	Health and Fitness wearables	xxx				xxx	xxx	xxx
Hwang, (2014)	Solar-powered clothing	xxx						
Turhan, (2013)	Smart clothing	xxx		xxx				
Wu et al., (2011)	Smart Healthcare Devices	xxx	xxx					

xxx Denotes ‘results significantly impacting Behavioural Intentions and/or Willingness to Use’

THEORETICAL BASIS AND DEVELOPMENT OF THE CONCEPTUAL MODEL

This section is about the underlying theoretical development and formulation of the study's hypotheses and then illustrates and justifies the proposed research model.

Research Model and Operationalization of Model Constructs

The authors examined if *Performance Expectancy (PE)*, *Effort Expectancy (EE)*, *Social Influence (SI)*, *Facilitating Conditions (FC)*, *Hedonic Motivation (HM)*, *Price Value (PV)*, *Habit (HB)* have a significant relationship with *Behavioral Intention (BI)* of youth towards intelligent wearable devices. Does *Age*, *Gender*, and *Purpose of Use* have any moderating effect on the factors mentioned above to *Behavioral Intention or Willingness to Use* or not for smart wearable devices among youth? *Last, is there is any relation between behavioral intention and willingness to use.* Table 2 presents the operationalization of model constructs.

The subsequent paragraphs explain the components of the causal model and enumerate the underlying hypotheses.

Table 2. Operationalization of Model Constructs (Venkatesh et al., 2012)

Constructs	Items	Code
<i>Performance expectancy (PE)</i>	<ul style="list-style-type: none"> • I find wearable smart devices useful in my daily life • Using wearable smart devices increases my productivity • Using wearable smart devices helps me accomplish things more quickly • Using wearable smart devices increases my chances of achieving things that are important to me 	PE1 PE2 PE3 PE4
<i>Effort expectancy (EE)</i>	<ul style="list-style-type: none"> • Learning how to use wearable smart devices is easy for me • My interaction with wearable smart devices is clear and understandable • I find wearable smart devices easy to use • It is easy for me to become skillful at using wearable smart devices 	EE1 EE2 EE3 EE4
<i>Social influence (SI)</i>	<ul style="list-style-type: none"> • People who are important to me think that I should use wearable smart devices • People who influence my behaviour think that I should use wearable smart devices • Wearable smart devices use is a status symbol in my environment 	SI1 SI2 SI3
<i>Facilitating conditions (FC)</i>	<ul style="list-style-type: none"> • I have the resources necessary to use wearable smart devices • I have the knowledge necessary to use wearable smart devices • Wearable smart device is compatible with other technologies I use • I can get help from others when I have difficulties using wearable smart devices 	FC1 FC2 FC3 FC4
<i>Hedonic motivation (HM)</i>	<ul style="list-style-type: none"> • Using wearable smart devices is fun • Using wearable smart devices is enjoyable • Using wearable smart devices is entertaining 	HM1 HM2 HM3
<i>Price value (PV)</i>	<ul style="list-style-type: none"> • Wearable smart devices are reasonably priced • Wearable smart devices are reasonably priced comparing with other smart devices • Wearable smart devices are a good value for the money • At the current price, wearable smart devices provide a good value 	PV1 PV2 PV3 PV4
<i>Habit (HB)</i>	<ul style="list-style-type: none"> • The use of wearable smart devices has become a habit for me • I am addicted to using wearable smart devices • I must use wearable smart devices • Using wearable smart devices has become natural to me 	HB1 HB2 HB3 HB4
<i>Behavioural intention (BI)</i>	<ul style="list-style-type: none"> • I intend to continue using wearable smart devices in the future • I plan to continue to use wearable smart in my daily life/routine • I wish use of smart wearable devices frequently 	BI1 BI2 BI3

Development of the Research Hypothesis

Venkatesh et al. (2012) defined performance expectancy (PE) as the level to which technology adoption will enable the user to conduct certain activities effectively. PE is a primary construct recurring in several consumer perception studies involving wearable technologies. If youngsters believe the outcomes are valid, they will adopt the technology. Performance expectancy is one of the essential factors that directly impact behavioral intention. Therefore, the hypothesis is:

H1: “The effect of performance expectancy (PE) on behavioral intention (BI) will be significant.”

Effort Expectancy (EE) is the level of ease related to the utilization of smart wearable devices (Venkatesh et al., 2012). In this research context, ease of use may not be a barrier for technology acceptance because youngsters are pretty aware, savvy enough to explore (*set-up, sync with other devices, operation*), and be comfortable with smart wearables. The user-friendliness of intelligent wearable devices infers a higher willingness to use. Hence, the hypothesis is:

H2: “The effect of effort expectancy (EE) on behavioral intention (BI) will be significant.”

According to Venkatesh et al. (2003; 2012), social influence (SI) captures the normative beliefs of a social group, which means how important it is for the youngsters to value the opinion of others who are significant or significantly contribute to one’s own decision about using smart wearable devices. Those who are significant comprise friends, well-known colleagues/ /classmates, and family members majorly. The hypothesis is:

H3: “The effect of social influence (SI) on behavioral intention (BI) will be significant.”

Price value (PV) is the “consumers’ cognitive trade-off between the perceived benefits of using the smart wearable device and the monetary cost of using it” (Venkatesh et al., 2012). It includes device cost, maintenance cost, replacement cost, switching cost, exchange value. The price value measures the users’ quality dimension, including the ergonomic design, weight, look and feel of the product, the brand, and variants that appeal to youngsters/youth. Therefore, the hypothesis is:

H4: “The effect of price value (PV) on behavioral intention (BI) will be significant.”

Hedonic motivation refers to “the level of fun or pleasure derived from using the smart wearable device” (Venkatesh et al., 2012). What are the fun elements of using smart wearable devices? Also known as perceived enjoyment, hedonic motivation is critical because inherent motivation has a more substantial effect than explicit motivation on a person’s behavioral intentions for smart devices (Yang et al., 2016; Kim and Park, 2019). The youngster expects the devices he is wearing to be entertaining, fun-filled, yet informative. So, the hypothesis stated here is:

H5: “The effect of hedonic motivation (HM) on behavioral intention (BI) will be significant.”

Facilitating conditions refer to “how people believe that technical infrastructures exist to help them use the system whenever necessary” (Venkatesh et al., 2003). Li et al., 2019 argue that facilitating conditions are crucial for accepting novelty. According to the UTAUT2 model, the hypothesis is:

H6: “The effect of facilitating conditions (FC) on behavioral intention (BI) will be significant.”

H6a: “The effect of facilitating conditions (FC) on a willingness to use (WtU) will be significant.”

Habits reflect “the multiple results of previous experiences” (Venkatesh et al., 2012), and “the frequency of past behavior is considered being one of the principal determinants of present behavior” (Ajzen, 2002). A smart wearable device, to be well-accepted post initial exploration and tests, its usage becomes a routine activity (Tamilmani et al., 2018). Alternatively, the user gets habituated with the smart wearable device, which agrees with the UTAUT2 model. The hypothesis is given as:

H7: “The effect of habit (HB) on behavioral intention (BI) will be significant.”

H7a: “The effect of habit (HB) on the willingness to use (WtU) will be significant.”

UTAUT2 supports the belief that “behavioral intention has a substantial influence on technology use” (Venkatesh et al., 2003). Behavioural intentions best predict willingness to use. A youth inclines to engage in certain behaviours. An inclination to engage oneself in smart wearable devices is exciting for marketers to convert intentions into realizations. So, the hypothesis is:

H8: “The effect of behavioral intention (BI) on the willingness to use (WU) will be significant.”

This study identified two moderation variables affecting the relationship between the above variables and behavioral intention, namely gender and purpose of use.

According to Venkatesh et al. (2012), the male gender is more vital in moderating PE on BI, while the female gender is more noticeable in moderating EE and SI’s effect on BI. Performance is an essential concern among boys, while the girls show concerns about the ease of use and their closest others’ sentiments. Hence, the moderating hypotheses are:

H9a: “Gender will moderate the effect of performance expectancy on behavioral intention.”

H9b: “Gender will moderate the effect of effort expectancy on behavioral intention.”

H9c: “Gender will moderate the effect of social influence on behavioral intention.”

H9d: “Gender will moderate the effect of price value on behavioral intention.”

H9e: “Gender will moderate the effect of hedonic motivation on behavioral intention.”

H9f: “Gender will moderate the effect of facilitating conditions on behavioral intention.”

H9g: “Gender will moderate the effect of facilitating conditions on “willingness to use.”

H9h: “Gender will moderate the effect of habit on behavioral intention.”

H9i: “Gender will moderate the effect of habit on Willingness to Use.”

H9j: “Gender will moderate the effect of behavioral intention on Willingness to Use.”

There can be varied purposes for which youngsters engage with smart wearable devices such as general, health and fitness, lifestyle, and entertainment (Zallio et al., 2019). It is important to study if a purpose or reason can be a worthy moderator. Therefore, the moderating hypotheses are:

H10a: “Purpose of use will moderate the effect of performance expectancy on behavioural intention.”

H10b: “Purpose of use will moderate the effect of effort expectancy on behavioral intention.”

H10c: “Purpose of use will moderate the effect of social influence on behavioral intention.”

H10d: “Purpose of use will moderate the effect of price value on behavioral intention.”

H10e: “Purpose of use will moderate the effect of hedonic motivation on behavioral intention.”

H10f: “Purpose of use will moderate the effect of facilitating conditions on behavioral intention.”

H10g: “Purpose of use will moderate the effect of facilitating conditions on willingness to use.”

H10h: “Purpose of use will moderate the effect of habit on behavioral intention.”

H10i: “Purpose of use will moderate the effect of Habit on Willingness to Use.”

H10j: “Purpose of use will moderate the effect of behavioral intention on Willingness to Use.”

Based on the hypotheses stated above, figure 1 presents the hypothesized research model.

DATA ANALYSIS AND RESULTS

Sample Selection and Survey

The data collection targeted youngsters/youth aged 20-30 years in India, majorly living in metropolitan/ big cities such as Mumbai, Bengaluru, Chennai, Hyderabad, and Pune. The primary reason for the choice of the cities is to solicit responses from the youth who are trying to manage a fast-paced educational and professional lifestyle, particularly in service industries such as IT and Telecom. The lifestyle has increased awareness about the use of digital and smart devices to monitor health and wellness. The authors sent out a structured questionnaire online through their peer and alumni networks. The reasons for fixing the sample size to 300 are; a sample size of 200 to 300 allows an acceptable margin of error and drops before the diminishing returns point (Ahmed and Halim, 2017). Only 262 responses were complete and eligible. The survey period was August 2018 to December 2018. The questionnaire contained three distinct segments: (i) UTAUT2 model, data constructs, (ii) awareness, the purpose of use parameters, and (iii) general information. The survey instrument used a seven-point Likert scale for measuring each item from “strongly disagree” (1) to “strongly agree” (7). Table 3 presents the primary descriptive statistics.

Table 3 shows a healthy representation of female respondents (45.4%) to the study. Health and Fitness constitute nearly three-fourths (72.9%) of the sample concerning the use of smart wearable devices (SWDs). Only 9.5% of the sample stated that they were unaware of SWDs.

Table 4 presents the mean and standard deviation of the 30 variables that form part of the questionnaire administered to the 262 samples.

Figure 1. Hypothesized Research Model

Table 3. Demographic characteristics of respondents

Characteristics	Items	N*	%	Cumulative %
Gender	Female	119	45.4	100
	Male	143	56.6	
Purpose of Use	Health and Fitness	191	72.9	100
	Lifestyle and Fashion	71	27.1	
Awareness about SWD	Extremely Aware	24	9.2	100
	Moderately Aware	53	20.2	
	Somewhat Aware	92	35.1	
	Slightly Aware	68	26.0	
	Not at all Aware	25	9.5	

Analysis of the Hypothesized Research Model

The Partial Least Squares (PLS) Structural Equation Modeling (SEM) method (Wong, 2013) was applied to test and validate the hypothesized research model (Figure 2). PLS-SEM is a prevalent method/tool because of its know-how for the research model calculation with sample sizes not large (Ringle et al., 2012). PLS-SEM modeling software (Version 3.2.8) was used to develop the research model, as shown in Figure 1. The moderation analysis was experimented with by exporting the relevant data from the PLS tools to a spreadsheet file known as the ‘Statistical Tools Package’ (Gaskin, 2016).

Measurement Model

The measurement model (Figure 2) comprises *an explanation of target endogenous variable variance, inner model path coefficient sizes and significance, external model loadings and significance, indicator reliability, internal consistency reliability, convergent validity, and discriminant validity*. The following paragraphs explain the results.

Explanation of Target Endogenous Variable Variance

The R^2 value for the endogenous latent variable *behavioural intention (BI)* is 0.615. It means that the seven explanatory variables viz., *performance expectancy (PE)*, *effort expectancy (EE)*, *social influence (SI)*, *price value (PV)*, *hedonic motivation (HM)*, *facilitating conditions (FC)*, and *habits (HB)* explain 61.5% of the variance in *BI*. The other endogenous latent variable, *willingness to use (WtU)*, has an R^2 value of 0.362, which implies that the explanatory variable *BI* can describe 36.2% of the variance.

Inner Model Path Coefficient Sizes and Significance

The sizes and significance of the inner model path coefficients (Table 5), *BI* has a sizable effect on *WtU* (0.410), followed by *FC* (0.308) and *HB* (0.007).

The inner model path coefficient of *HB* has the most substantial effect on *BI* (0.588), followed by *HM* (0.243), *PE* (0.164), *FC* (0.018), *EE* (0.035). *PV* and *SI* have a negative effect on *BI* with the values 0.066 and 0.006, respectively.

Outer Model Loadings and Significance

The loadings denote the strength of variables in describing the constructs (Figure 2). Higher the value, more robust, is the strength of the explaining capability (representation). After the first iteration, the

Table 4. Descriptive Statistics of the ‘Questionnaire-Variables’

Variables	N	Mean	Std. Deviation
PE1	262	4.60	1.461
PE2	262	4.55	1.418
PE3	262	4.62	1.441
PE4	262	4.57	1.433
EE1	262	5.10	1.495
EE2	262	4.91	1.440
EE-3	262	5.05	1.355
EE4	262	4.93	1.377
SI1	262	4.15	1.531
SI2	262	4.10	1.558
SI3	262	4.22	1.662
FC1	262	4.51	1.505
FC2	262	4.89	1.481
FC3	262	4.89	1.352
FC4	262	4.60	1.440
HM1	262	4.91	1.430
HM2	262	4.97	1.423
HM3	262	4.76	1.463
PV1	262	3.73	1.602
PV2	262	3.92	1.519
PV3	262	4.13	1.443
PV4	262	4.08	1.449
HB1	262	3.40	1.620
HB2	262	3.05	1.652
HB3	262	3.67	1.612
HB4	262	3.52	1.679
BI1	262	4.35	1.614
BI2	262	4.26	1.596
BI3	262	3.71	1.965
WtU	262	4.82	1.428

outer loading showed comparatively weak values (0.530) and (0.577) for two variables, namely SI3 (Wearable smart devices use is a status symbol in my environment) and BI3 (I wish to use smart wearable devices frequently) respectively. Such low values can weaken subsequent analysis results, hence the two variables were removed.

Table 6 shows the outer model loadings of the 28 variables (BI1, BI2,....., WtU1) that make up the nine constructs (BI, EE,....., WtU) of the theoretical model.

Table 5. Inner Model Path Coefficient Sizes and Significance

Variables	BI	WtU
BI		0.410
EE	0.035	
FC	0.018	0.308
HB	0.588	0.007
HM	0.243	
PE	0.164	
PV	-0.006	
SI	-0.066	

Figure 2. Measurement Model of UTAUT2

Indicator Reliability

Indicator reliability is a test of squaring the value of each factor loading (Table 7). Hulland (1999) suggested a value higher than 0.7 (0.4 or higher for exploratory research). All, except two variables, had values greater than or nearer to 0.70 and statistically significant (0.05 level) which confirms the instrument's reliability and qualified for further analysis requirements.

Table 6. Outer Model Loading and Significance

	BI	EE	FC	HB	HM	PE	PV	SI	WtU
BI1	0.935								
BI2	0.933								
EE1		0.862							
EE2		0.917							
EE3		0.891							
EE4		0.828							
FC1			0.789						
FC2			0.854						
FC3			0.844						
FC4			0.776						
HB1				0.866					
HB2				0.875					
HB3				0.812					
HB4				0.893					
HM1					0.895				
HM2					0.887				
HM3					0.888				
PE1						0.821			
PE2						0.900			
PE3						0.907			
PE4						0.872			
PV1							0.762		
PV2							0.785		
PV3							0.891		
PV4							0.855		
SI1								0.940	
SI2								0.925	
WtU									1.000

For indicator reliability, all the loading values should be greater than 0.7, and below 0.4 should be eliminated (Churchill, 1979).

Internal Consistency Reliability

In PLS-SEM, the measure equivalent to the famous ‘Cronbach Alpha’ is the ‘Composite Reliability Value.’ In the past, research works have recommended using this reliability value (Hair et al., 2013; Henseler et al., 2016).

The composite reliability values on all the nine reflective latent variables are well above the required value of 0.6, which denotes adequate and an acceptable degree of reliability (Straub, 1989). Table 8 gives the scores.

Table 7. Indicator Reliability

	BI	EE	FC	HB	HM	PE	PV	SI	WtU
BI1	0.874								
BI2	0.870								
EE1		0.743							
EE2		0.841							
EE3		0.794							
EE4		0.686							
FC1			0.623						
FC2			0.729						
FC3			0.712						
FC4			0.602						
HB1				0.750					
HB2				0.766					
HB3				0.659					
HB4				0.797					
HM1					0.801				
HM2					0.787				
HM3					0.789				
PE1						0.674			
PE2						0.810			
PE3						0.823			
PE4						0.760			
PV1							0.581		
PV2							0.616		
PV3							0.794		
PV4							0.731		
SI1								0.884	
SI2								0.856	
WtU									1.000

Convergent Validity

Convergence validity comprises of analysis of the average variance extracted (AVE) values. All the construct values are more significant than the minimum acceptable value of 0.50 (Fornell & Larcker, 1981; Henseler et al., 2016).

Table 9 presents the AVEs of the latent variables above 0.50 for all nine reflective latent variables, confirming the prevalence of convergent validity.

Discriminant Validity

The measurement of discriminant validity comprised of two tests; the Fornell Larcker criteria and the new HTMT ratio (Henseler et al., 2016). As seen in table 10, the square root values of the AVE

Table 8. Internal Consistency Reliability

Variable	Composite Reliability
BI	0.854
EE	0.899
FC	0.833
HB	0.885
HM	0.869
PE	0.898
PV	0.846
SI	0.850

Table 9. Convergent Variability

Variable	Average Variance Extracted (AVE)
BI	0.872
EE	0.766
FC	0.666
HB	0.743
HM	0.792
PE	0.767
PV	0.680
SI	0.643

Table 10. Discriminant Variability (Fornell and Larcker Criterion)

	BI	EE	FC	HB	HM	PE	PV	SI	WtU
BI	0.934								
EE	0.372	0.875							
FC	0.371	0.669	0.816						
HB	0.707	0.212	0.261	0.862					
HM	0.504	0.538	0.52	0.293	0.89				
PE	0.561	0.574	0.452	0.455	0.578	0.876			
PV	0.511	0.279	0.36	0.615	0.382	0.48	0.825		
SI	0.483	0.349	0.341	0.548	0.485	0.565	0.497	0.932	
WtU	0.529	0.497	0.462	0.377	0.535	0.603	0.324	0.407	1

(given in bold fonts) are stored along the diagonal, which verifies the condition “greater than the correlation between constructs” (Fornell and Larcker, 1981).

HTMT criterion is a measure of the average correlations of the indicators across the constructs of the UTUAT2 model.

According to Henseler et al. (2016), the acceptable levels of discriminant validity (< 0.90), which in this case is valid (Table 11).

Checking Structural Path Significance in Bootstrapping

The test of statistical significance of the *path coefficients, reliability, validity, R2 values, and bootstrapping* followed a nonparametric procedure. It is to be noted that PLS-SEM does not assume the data to be distributed normally, which means the coefficients such as *outer weights, outer loadings, and path coefficients are irrelevant to parametric significance testing*. Instead, the bootstrapping procedure in PLS-SEM examines the statistical significance of the estimated path coefficients (Hair et al., 2011; Ringle et al., 2012). Figure 3 gives the bootstrapping results. Table 9 presents the structural path significance, which denotes t-statistic (higher than 1.96) and p Values (less than 0.05) to validate the statistical significance.

Structural Model and Hypotheses Testing

Based on the standardized paths, the analysis of the research hypothesis was performed. A bootstrap resampling method estimated the path significance levels (Henseler et al., 2016), with a resampling of 1000 iterations (Chin et al., 2008). The model explained 61.3% variability in behavioral intention (BI) and 36.7% willingness to use.

Behavioral intention (BI) is explained by performance expectancy (PE), hedonic motivation (HM), and habit (HB) in the model, and all were statistically significant (H1, Hyp5, H6a). Facilitating conditions (FC) and behavioural intentions significantly impact willingness to use; both had $p < 0.05$ (H7, and H8).

Effort Expectancy (EE) (H2), Social Influence (SI) (H3), Price Value (PV) (H4), and Facilitating Conditions (FC) (H6) are not statistically significant ($p > 0.05$) on Behavioural Intentions (BI). Habits (HB) are not statistically significant on the willingness to use (WtU) smart wearable devices among the youth (H7a) (Table 12).

Moderator Analysis

The moderator analysis of gender (Gen) and purpose-of-use (PoU) was conducted by splitting the dataset based on *male and female* for Gen, *health & fitness and lifestyle, and fashion* for PoU. Table 13 presents the results of the gender and purpose of use split analysis state that all the seven explanatory variables considerably explain the variance for BI with males (61.2%), females (66.2%), health and fitness (53.4%), and lifestyle and fashion (79.4%) respectively.

Table 11. Heterotrait-Monotrait Ratio

	BI	EE	FC	HB	HM	PE	PV	SI	WtU
BI	1								
EE	0.41	1							
FC	0.438	0.77	1						
HB	0.805	0.219	0.303	1					
HM	0.583	0.603	0.613	0.326	1				
PE	0.64	0.635	0.523	0.504	0.657	1			
PV	0.579	0.302	0.429	0.697	0.431	0.531	1		
SI	0.565	0.393	0.408	0.628	0.56	0.645	0.575	1	
WtU	0.573	0.521	0.504	0.396	0.572	0.638	0.346	0.44	1

Figure 3. Structural Path Significance in Bootstrapping

Table 12. Overall Path Coefficients

Path	Hypothesis ID	T-Statistic	P Values	Hypothesis Result
PE → BI	H1	2.2480	0.0250	<i>Supported</i>
EE → BI	H2	0.5310	0.5950	Not supported
SI → BI	H3	1.1560	0.2480	Not supported
PV → BI	H4	0.1010	0.9200	Not supported
HM → BI	H5	4.1490	0.0000	<i>Supported</i>
FC → BI	H6	0.3130	0.7540	Not supported
FC → WtU	H6a	5.5940	0.0000	<i>Supported</i>
HB → BI	H7	10.8050	0.0000	<i>Supported</i>
HB → WtU	H7a	0.1090	0.9140	Not supported
BI → WtU	H8	5.1210	0.0000	<i>Supported</i>

On the contrary, the seven variables *moderately explain the variance* for WtU with males (46.9%), females (29.6%), health and fitness (33.8%), and lifestyle and fashion (43.1%), respectively.

Table 14 shows the path coefficients show that the impact of hedonic motivation (HM) and habits (HB) on the behavioural intentions (BI) of youth towards SWDs is statistically significant irrespective

Table 13. R² values explained by gender and purpose of use

	R Square Values			
	Gender		Purpose of Use	
	Male	Female	Health and Fitness	Lifestyle and Fashion
BI	0.612	0.662	0.534	0.794
WtU	0.469	0.296	0.338	0.431

Table 14. Moderator Path Coefficients for Gender and Purpose-of-Use

Path	Moderator - Gender			Hypothesis Result
	Hypothesis ID	Male	Female	
PE -> BI	H9a	2.602	0.242	Supported only for male sample
EE -> BI	H9b	0.17	0.773	Not supported
SI -> BI	H9c	1.329	0.241	Not supported
PV -> BI	H9d	0.797	0.897	Not supported
HM -> BI	H9e	2.735	2.651	Supported
FC -> BI	H9f	0.557	1.319	Not supported
FC -> WtU	H9g	5.046	4.026	Supported
HB -> BI	H9h	7.133	7.858	Supported
HB -> WtU	H9i	1.187	1.243	Not supported
BI -> WtU	H9j	4.956	2.199	Supported
Path	Moderator – Purpose of Use			Hypothesis Result
	Hypothesis ID	Health & Fitness	Lifestyle & Fashion	
PE -> BI	H10a	1.608	1.312	Not supported
EE -> BI	H10b	0.507	0.326	Not supported
SI -> BI	H10c	0.117	1.903	Not supported
PV -> BI	H10d	1.781	0.873	Not supported
HM -> BI	H10e	3.802	2.304	Supported
FC -> BI	H10f	0.33	0.277	Not supported
FC -> WtU	H10g	5.449	1.791	Supported only for Health & Fitness
HB -> BI	H10h	8.38	5.904	Supported
HB -> WtU	H10i	0.217	0.497	Not supported
BI -> WtU	H10j	3.763	4.249	Supported

of gender and purpose of use (Hypothesis H9e, H9h, and H10e, H10h). Similarly, the impact of behavioural intentions (BI) of the youth on their willingness to use (WtU) SWDs is statistically significant across the two moderating variables (H9j and H10j).

Performance expectancy significantly impacts the behavioural intentions of only *males* but not females (H9a). The youth perceive that facilitating conditions will significantly impact

willingness to use if the devices are used only for *health and fitness purposes* and not for Lifestyle and Fashion (H10g).

The results open up a healthy discussion in the next section, considering the relevance of the current research to its earlier counterparts.

DISCUSSION

The subsequent paragraphs discuss the significant outcomes, reason out the factors that were not significant, and last, discuss the results of moderating factors.

The study finds Indian youth perceive the performance of the smart wearables should meet their expectation which corroborates with several earlier studies (Talukder et al., (2019); Sergueeva et al., (2019) Francis, (2019); Zhou and Chen (2018); Choi et al., (2017); Krey et al., (2016).

The fun-loving and exciting nature of the Indian youth has matched with this study's results, which finds hedonic motivation as a significant factor for the adoption of smart wearables. The results reinforced the earlier works by Rauschnabel et al. (2018) and Yuan et al. (2015).

The habit of youth impacted their behavioural intentions significantly to use smart wearable devices, which is yet another significant result from this study. There is a trend towards fitness and wellness as a habit, given the stressful work environment and lifestyle disorders, particularly in the knowledge industry. Hence, the results finds that habit significantly impacts the behavioural intentions of the youth about the use of smart wearable devices, which supports earlier studies by Sergueeva et al. (2019); Zhou and Chen (2018); Yuan et al. (2015).

Facilitating conditions impact willingness to use, which it did not when bypassed (mediated) through behavioural intentions, which corroborates the previous works by Sergueeva et al. (2019). The primary reason can be that the explosive growth of cloud computing has enabled seamless interoperability of infrastructure, software, and applications to enhance user experience.

According to this study, behavioural intentions of the youth strongly impact their willingness to use smart wearable devices, a finding that supports the core belief of UTAUT2 theory. *Effort efficiency, Social influence, Price value, and Facilitating conditions* were the factors that did not result in a statistically significant impact on the behavioural intentions and willingness to use smart wearable devices among youth.

The tech-savvy nature of the Indian youth has gained extensive experience operating the technology gadgets and orchestrating with different devices as early as their childhood; hence, effort expectancy needs were not an impact factor here. On the contrary, several studies earlier had identified effort expectancy as a vital factor (Talukder et al., (2019); Reyes-Mercado, (2018); Zhou and Chen, (2018).

In this study, social influence did not impact the youth's behavioural intentions about smart wearable devices. Though the outcome is surprising, earlier research has also given mixed empirical evidence to the effect of social influence on youth (Kim and Shin, 2015; Weiz et al., 2016).

However, in this study, the price value of smart wearable's impact is not on the behavioural intention of the youth. The reason is not that the Indian youth is insensitive to price. Still, given the growth, competition, and a flurry of new products entering the market, the customers can reap the benefits of the price-product-features combination. The results of this study support two (hedonic motivation and habit) out of the three new factors added to UTAUT2. Thus, the study validated the need for extending the application and validity of UTAUT2 to a more unique domain of technology, customers, and geographies.

The two moderators, namely *gender* and *purpose of use*, did not emerge as significant contributors to the youth's behavioral intentions and willingness to use smart wearable devices. Males moderated the impact of performance expectancy of wearables on behavioural intention, while females did not moderate. For the purpose-of-use as a moderator, the study found that facilitating conditions only for *health and fitness* and not for lifestyle and fashion purposes moderated the youngsters' willingness

to use smart wearable devices. It indicates the motive and expectation of today's youth about smart wearable devices.

CONCLUSION AND FUTURE DIRECTIONS

This research paper focused on the main factors influencing youths' smart wearable device adoption and suggested a comprehensive user adoption framework. Based on the UTAUT2 model, this research developed a robust model that examined smart wearable devices' adoption intention of youth in India from technology, health, and privacy perspectives. This paper extensively explored smart wearable technology issues from a behavioral perspective, a solid foundation for future work.

This paper contributes to the theoretical and practical research field in a big way, though with certain limitations. The scope of the research was limited to the Indian context, so it cannot generalize the results to other geographies. Different geographies will differ in their cultural and technological maturity. This research paper concentrates on smart wearable devices; it will interest the comparative analysis of the adoption process of different wearable devices among youth in India. So, knowledge brought out of this study can guide wearable commerce providers in designing the products, which will enhance the popularity and acceptance of smart wearables among youth.

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