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

Vijayakumar Bharathi S., Symbiosis Centre for Information Technology, Symbiosis International University (Deemed), India
Saikat Ghosh, CitiusTech Healthcare Technology Private Limited, India

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).
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           |
| Reyes-Mercado, (2018) | Fitness Wearables     | xxx                         | xxx                     |                         |                         |                         | xxx           |
| Zhou and Chen, (2018) | Mobile Intelligent Wearable Devices | 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           |
| Hein et al., (2017)  | AR Smart Glass        | xxx                         |                         |                         |                         |                         | xxx           |
| Yuan et al., (2015)  | Health and Fitness wearables | xxx                         |                         |                         |                         |                         | xxx           |
| Hwang, (2014)        | Solar-powered clothing | xxx                         |                         |                         |                         |                         | 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 Willingess 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 |
|------------------------------|----------------------------------------------------------------------|------|
| Performance expectancy (PE)  | • I find wearable smart devices useful in my daily life               | PE1  |
|                              | • Using wearable smart devices increases my productivity              | PE2  |
|                              | • Using wearable smart devices helps me accomplish things more quickly| PE3  |
|                              | • Using wearable smart devices increases my chances of achieving things that are important to me | PE4  |
| Effort expectancy (EE)       | • Learning how to use wearable smart devices is easy for me           | EE1  |
|                              | • My interaction with wearable smart devices is clear and understandable| EE2  |
|                              | • I find wearable smart devices easy to use                          | EE3  |
|                              | • It is easy for me to become skillful at using wearable smart devices| EE4  |
| Social influence (SI)        | • People who are important to me think that I should use wearable smart devices | SI1  |
|                              | • People who influence my behaviour think that I should use wearable smart devices | SI2  |
|                              | • Wearable smart devices use is a status symbol in my environment    | SI3  |
| Facilitating conditions (FC) | • I have the resources necessary to use wearable smart devices        | FC1  |
|                              | • I have the knowledge necessary to use wearable smart devices        | FC2  |
|                              | • Wearable smart device is compatible with other technologies I use   | FC3  |
|                              | • I can get help from others when I have difficulties using wearable smart devices | FC4  |
| Hedonic motivation (HM)      | • Using wearable smart devices is fun                                | HM1  |
| Price value (PV)             | • Using wearable smart devices is enjoyable                          | HM2  |
|                              | • Using wearable smart devices is entertaining                        | HM3  |
|                              | • Wearable smart devices are reasonably priced                        | PV1  |
|                              | • Wearable smart devices are reasonably priced comparing with other smart devices | PV2  |
|                              | • Wearable smart devices are a good value for the money               | PV3  |
|                              | • At the current price, wearable smart devices provide a good value   | PV4  |
| Habit (HB)                   | • The use of wearable smart devices has become a habit for me         | HB1  |
|                              | • I am addicted to using wearable smart devices                       | HB2  |
|                              | • I must use wearable smart devices                                  | HB3  |
|                              | • Using wearable smart devices has become natural to me               | HB4  |
| Behavioural intention (BI)   | • I intend to continue using wearable smart devices in the future     | BI1  |
|                              | • I plan to continue to use wearable smart in my daily life/routine  | BI2  |
|                              | • I wish use of smart wearable devices frequently                    | 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.
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

| Characteristics | Items                  | N | %  | Cumulative % |
|-----------------|------------------------|---|----|--------------|
| Gender          | Female                 | 119| 45.4| 100          |
|                 | Male                   | 143| 56.6|              |
| Purpose of Use  | Health and Fitness     | 191| 72.9|              |
|                 | 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 |              |

Table 3. Demographic characteristics of respondents
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.
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 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.
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.
Convergent Validity

Convergent 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
(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.

### 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    |
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.

|       | BI  | EE  | FC  | HB  | HM  | PE  | PV  | SI  | WtU |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| BI    | 1   |     |     |     |     |     |     |     |     |
| EE    |     | 0.41|     |     |     |     |     |     |     |
| FC    | 0.438| 0.77|     |     |     |     |     |     |     |
| 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   |
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
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

### 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 ID | Male | Female | Hypothesis Result                  |
|------------|---------------------|---------------|------|--------|------------------------------------|
| 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 ID | Health & Fitness | Lifestyle & Fashion | Hypothesis Result                  |
|------------|----------------------------|---------------|-------------------|---------------------|------------------------------------|
| 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                           |
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.
REFERENCES

Ahmad, H., & Halim, H. (2017). Determining Sample Size for Research Activities. Selangor Business Review, 2(1), 20-34. Retrieved from http://sbr.journals.unisel.edu.my/ojs/index.php/sbr/article/download/12/20

Ajzen, I. (2002). Residual effects of past on later behavior: Habituation and reasoned action perspectives. Personality and Social Psychology Review, 6(2), 107–122. doi:10.1207/S15327957PSPR0602_02

Brown, B. (2019). Gartner Predicts $52 Billion 2020 Wearable Market. Retrieved from https://healthtechinsider.com/2019/11/22/gartner-predicts-52-billion-2020-wearable-device-spending/

Chang, H. S., Lee, S. C., & Ji, Y. G. (2016). Wearable device adoption model with TAM and TTF. International Journal of Mobile Communications, 14(5), 518–537. doi:10.1504/IJMC.2016.078726

Chin, W. W., Peterson, R. A., & Brown, S. P. (2008). Structural equation modeling in marketing: Some practical reminders. Journal of Marketing Theory and Practice, 16(4), 287–298. doi:10.2753/MTP1069-6679160402

Choi, B., Hwang, S., & Lee, S. (2017). What drives construction workers’ acceptance of wearable technologies in the workplace?: Indoor localization and wearable health devices for occupational safety and health. Automation in Construction, 84, 31–41. doi:10.1016/j.autcon.2017.08.005

Dutot, V., Bhatiasovei, V., & Bellallahom, N. (2019). Applying the technology acceptance model in a three-countries study of smartwatch adoption. The Journal of High Technology Management Research, 30(1), 1–14. doi:10.1016/j.jhitech.2019.02.001

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. JMR, Journal of Marketing Research, 18(1), 39–50. doi:10.1177/002224378101800104

Francis, R. P. (2019). Examining Healthcare Providers’ Acceptance of Data From Patient Self-Monitoring Devices Using Structural Equation Modeling With the UTAUT2 Model. International Journal of Healthcare Information Systems and Informatics, 14(1), 44–60. doi:10.4018/IJHISI.2019010104

Gaskin, J. (2016). Name of tab. Stats Tools Package. Retrieved from http://statwiki.kolobkreations.com

Gupta, V., Rodrigues, L. L., & Mathew, A. O. (2018). Identifying opportunities for wearable technology for product development and market positioning. International Journal of Product Development, 22(4), 247–275. doi:10.1504/IJPD.2018.091133

Hair, J. F. Jr, Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. Long Range Planning, 46(1-2), 1–12. doi:10.1016/j.lrp.2013.01.001

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. Industrial Management & Data Systems, 116(1), 2–20. doi:10.1108/IMDS-09-2015-0382

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. Strategic Management Journal, 20(2), 195–204. doi:10.1002/(SICI)1097-0266(199902)20:2<195::AID-SMJ13>3.0.CO;2-7

Hwang, C. (2014). Consumers’ acceptance of wearable technology: Examining solar-powered clothing. Graduate Theses and Dissertations. 13950. Retrieved from https://lib.dr.iastate.edu/cgi/viewcontent.cgi?article=4937&context=etd

Kalantari, M., & Rauschnabel, P. (2018). Exploring the early adopters of augmented reality smart glasses: The case of Microsoft HoloLens. In Augmented Reality and Virtual Reality (pp. 229–245). Springer. doi:10.1007/978-3-319-64027-3_16
Kim, J., & Park, E. (2019). Beyond coolness: Predicting the technology adoption of interactive wearable devices. *Journal of Retailing and Consumer Services, 49*, 114–119. doi:10.1016/j.jretconser.2019.03.013

Ko, E., Sung, H., & Yun, H. (2009). Comparative analysis of purchase intentions toward smart clothing between Korean and US consumers. *Clothing & Textiles Research Journal, 27*(4), 259–273. doi:10.1177/0887302X08327086

Lee, J., Kim, D., Ryoo, H. Y., & Shin, B. S. (2016). Sustainable wearables: Wearable technology for enhancing the quality of human life. *Sustainability*, 8(5), 1-16. 10.3390/su8050466

Li, J., Ma, Q., Chan, A. H., & Man, S. S. (2019). Health monitoring through wearable technologies for older adults: Smart wearables acceptance model. *Applied Ergonomics, 75*, 162–169. doi:10.1016/j.apergo.2018.10.006 PMID:30509522

Lin, K. Y., Chien, C. F., & Kerh, R. (2016). UNISON framework of data-driven innovation for extracting user experience of product design of wearable devices. *Computers & Industrial Engineering, 99*, 487–502. doi:10.1016/j.cie.2016.05.023

National Youth Policy. (2014). Retrieved from https://www.yas.nic.in/sites/default/files/National-Youth-Policy-Document.pdf

Porter, M. E., & Heppelmann, J. E. (2014). How smart, connected products are transforming competition. *Harvard Business Review, 92*(11), 64–88. Retrieved June 2019, from https://hbr.org/2014/11/how-smart-connected-products-are-transforming-competition

Rauschnabel, P. A. (2018). Virtually enhancing the real world with holograms: An exploration of expected gratifications of using augmented reality smart glasses. *Psychology and Marketing, 35*(8), 557–572. doi:10.1002/mar.21106

Reyes-Mercado, P. (2018). Adoption of fitness wearables: Insights from partial least squares and qualitative comparative analysis. *Journal of Systems and Information Technology, 20*(1), 103–127. doi:10.1108/JSIT-04-2017-0025

Ridgers, N. D., Timperio, A., Brown, H., Ball, K., Macfarlane, S., Lai, S. K., Richards, K., Mackintosh, K.A., McNarry, M.A., Foster, M., & Salmon, J. (2018). Wearable activity tracker use among Australian adolescents: usability and acceptability study. *JMIR mHealth and uHealth, 6*(4), 1-10. 10.2196/mhealth.9199

Ringle, C. M., Wende, S., & Will, A. (2010). *Finite mixture partial least squares analysis: Methodology and numerical examples*. In *Handbook of Partial Least Squares*. Springer. doi:10.1007/978-3-540-32827-8_9

Sergueeva, K., Shaw, N., & Lee, S. H. (2019). Understanding the barriers and factors associated with consumer adoption of wearable technology devices in managing personal health. Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration. doi:10.1002/cjas.1547

Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers’ adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust. *Psychology and Marketing, 32*(8), 860–873. doi:10.1002/mar.20823

Strategy Analytics. (2019). *Strategy Analytics: Global Smartwatch Shipments Leap to 14 Million Units in Q3 2019*. Retrieved from https://news.strategyanalytics.com/press-release/devices/strategy-analytics-global-smartwatch-shipments-leap-14-million-units-q3-2019

Straub, D. W. (1989). Validating instruments in MIS research. *Management Information Systems Quarterly, 13*(2), 147–169. doi:10.2307/248922

Talukder, M. S., Chiong, R., Bao, Y., & Hayat Malik, B. (2019). Acceptance and use predictors of fitness wearable technology and intention to recommend: An empirical study. *Industrial Management & Data Systems, 119*(1), 170–188. doi:10.1108/IMDS-01-2018-0009

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2018). Use of ‘Habit’ is not a habit in understanding individual technology adoption: a review of UTAUT2 based empirical studies. In *International Working Conference on Transfer and Diffusion of IT* (pp. 277-294). Springer. doi:10.1007/978-3-030-04315-5_19

Turhan, G. (2013). An assessment towards the acceptance of wearable technology to consumers in Turkey: The application to smart bra and t-shirt products. *Journal of the Textile Institute, 104*(4), 375–395. doi:10.1080/00405000.2012.736191
United Nations. (2020). *Youth*. Available at https://www.un.org/en/sections/issues-depth/youth-0/index.html

Venkatesh, V., Morris, M. G., Hall, M., Davis, G. B., Davis, F. D., & Walton, S. M. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly, 27*(3), 425–478. doi:10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *Management Information Systems Quarterly, 36*(1), 157–178. doi:10.2307/41410412

Wen, D., Zhang, X., Liu, X., & Lei, J. (2017). Evaluating the consistency of current mainstream wearable devices in health monitoring: a comparison under free-living conditions. *Journal of Medical Internet Research, 19*(3), 1-20. 10.2196/jmir.6874

Wong, K. K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin, 24*(1), 1–32. Retrieved July 2018, from https://www.researchgate.net/profile/Arumugam_Raman/post/What_is_the_interpretation_of_SmartPLS/attachment/59d646c2c49f478072eae9ca/AS:273837248188417@1442299297149/download/Smartpls.pdf

Wu, L., Li, J. Y., & Fu, C. Y. (2011). The adoption of mobile healthcare by hospital’s professionals: An integrative perspective. *Decision Support Systems, 51*(3), 587–596. doi:10.1016/j.dss.2011.03.003

Yuan, S., Ma, W., Kanthawala, S., & Peng, W. (2015). Keep using my health apps: Discover users’ perception of health and fitness apps with the UTAUT2 model. *Telemedicine Journal and e-Health, 21*(9), 735–741. doi:10.1089/tmj.2014.0148 PMID:25919238

Zallio, M., Berry, D., & Leifer, L. J. (2019). Meaningful Age-Friendly Design. Case Studies on Enabling Assistive Technology. In *International Conference on Applied Human Factors and Ergonomics* (pp. 779-790). Springer. doi:10.1007/978-3-030-19135-1_76

Vijayakumar Bharathi S. is a Post Graduate in Commerce and in Management. He earned his Ph.D in Computer Studies from the Symbiosis International (Deemed University) (SIU), Pune in the area of ERP Risk Assessment for SMEs. He is an ICWA (Inter) Qualified. He has over 27 years of experience including 5 plus years in the Industry at an Indo-Swiss JV manufacturing textile machinery. He is a PhD guide for the Faculty of Management and Faculty of Computer Studies at SIU and PhD thesis reviewer and examiner at MDI, Gurgoan. He has over 90 publications in the form of research papers, conference proceedings and case studies. The case studies are published in the Case Centre (formerly ECCH) and PMI. He is a reviewer of journals in Springer, Emerald, IGI Global, Sage & Inderscience. He has also worked/working on six funded projects, one from European Union (Erasmus+), one from PMI, two from SIU, two from industry. He is the recipient of the Outstanding Academic Award, 2013 for SAARC Region from SAP University Alliances, APJ at Shanghai China, during March 2014. He also received performance awards for teaching, research and consultancy at the Institute level.

Saikat Ghosh is a senior executive, Data Analytics at CitusTech Healthcare Technology P Ltd, in Navi Mumbai, India. He is an MBA in Information Technology Business Management, specializing in Data Sciences from the Symbiosis Centre for Information Technology, Symbiosis International (Deemed University), Pune India. Apart from data sciences, Mr. Ghosh is keenly interested in researching the implications of smart and digital technologies on human welfare.