Exploring the Plausibility of Pre-Purchase Decision Process in User Acceptance of Smart Wearable Technology Devices

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Abstract

The market for smart wearable technology products is growing rapidly. Although wearable technology is still in its early stages, a longer-term outlook is required. This study inspected the existence of consumers' pre-purchase stage for smart wearable technology devices. It further analyzed the factors that influenced customers' decisions in the pre-purchase phase. The methodology adopted was quantitative, using which 240 users of smart wearables were given a structured questionnaire to fill up. The Smart PLS 3.0 software was used for structural equation modeling and path analysis. The results indicated that customers go through a pre-purchase decision journey. Their decisions are influenced by individual characteristics, product description, information source utility, data usefulness, trust, visibility of the product, and demonstrability. Together, these factors resulted in the customers' successful transition from the pre-purchase stage to the purchase decision stage.

Keywords : **pre-purchase decision process, need recognition, information search, evaluation of alternatives, smart technology wearables (SWT), consumer behavior, purchase intention**

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Smart wearables predominately mean wristbands introduced by firms such as Fitbit, Jawbone, and Apple. These devices function as activity trackers and have gained significant momentum, thanks to people's growing awareness and interest in personal wellness. Advances in recent research backed by increased creativity have been influential in growing the wearable market demand, leading to new product categories such as smart footwear, ear wearables, etc., integrating high-end technology and design in everyday life. Customers are affected in three stages: the need to identify subconsciously, information search, and assessing alternatives, and the marketers should comprehend the driving force behind the pre-purchase decision process variables. Many studies have explored the post-purchase adoption and rejection factors that influence specific technology products like the smartwatch and smart glasses. However, there is still a lack of literature for industry analysis of smart wearable technology products.

An area identified where research is lacking is an exploration of the customer's pre-purchase decision process for smart wearable technology products, which is an important consideration to make as brands should understand the customer journey from the stage of thinking about the smart wearable products. Therefore, this study aims to fill the defined gaps that enable marketers to respond more effectively and accurately to the customers' needs by

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accurately identifying the relationship among the stages of the pre-buying process and how the factors influence customers' behavior.

Review of Literature

Technology Acceptance Models

The technology acceptance model (TAM) is one of the most widely accepted and influential models to study consumer acceptance of technological innovations in various situations. We reviewed 174 existing articles based on UTAUT to understand demographic details, methodological details, and limitations related to UTAUT. The review findings showed that UTAUT is widely used for general-purpose and specialized business systems.

A study by Zhang et al. (2008) on validation of an integrated model of innovation diffusion theory (IDT) and technology adoption model (TAM) in information technology adoption analyzed both the direct (e.g., perceived usefulness and perceived ease of use) and indirect factors (e.g., relative advantage, image, compatibility, result demonstrability, voluntariness, visibility, and trialability). These factors were analyzed using two methods in SPSS called the PLS method and SEM method. The results revealed that for the integrated model of IDT-TAM, perceived ease of use had more effect on actual use of technology than on perceived use. It also indicated that survey methods, cross-sectional approach, and structural equation modeling (SEM) were the most widely used methods to analyze technology products. Kim and Shin (2015) tried to find out the key factors (affective quality, relative advantage, mobility, availability, and subcultural appeal) in smartwatch adoption and formed an extended technology acceptance model (TAM) by integrating the findings into the original TAM. They did a confirmatory factor analysis and SEM using AMOS 22 statistical software. The results revealed that affective quality and relative advantage were directly related to perceived usefulness, while mobility and availability led to perceived ease of use. To form the user attitude, subcultural appeal and cost were the major determinants that finally led to the intention to use.

Search and Evaluation Process in the Pre-Purchase Process

Our study is based on a review of factors that affect customers' search behavior from the perspective of the information value they get from it. The variables analyzed were information search utility, information content, and formats such as video, print, radio, and offline mode. It also includes personal factors such as product knowledge, motivation, risk relating to purchase, skills in searching, and information processing capability. Other factors affecting the pre and post-purchase stage in impulse buying were studied by Ozer and Gultekin (2015). The variables taken into consideration for the study are pre-purchase mood and impulse buying tendency based on age, gender, education, and income. The authors analyzed the effect of the above variables on impulse buying, satisfaction, and post-purchase mood. The results revealed that consumers' impulse buying tendency and pre-purchase mood encouraged impulse buying positively. Moreover, satisfaction played the role of a partial mediator between pre-purchase mood and post-purchase mood. These studies demand further investigation of the existence of a structured pre-purchase behavior among consumers of technology products.

Device Adoption Factors of SWT (Smart Wearable Technology)

Dehghani et al. (2018) conducted a netnographic research to understand the motivational factors that led to the continuous adoption of smart technology devices, particularly smartwatches. Eight factors were found to have contributed the most, which are perceived usefulness, perceived ease of use, enabling technology, functionality, compatibility, fashionology, health technology, and complementary goods. Some of the factors like healthology, complementary goods, and enabling technology were analyzed for the first time and proved to influence the adoption and continuous use of smartwatches. Talukder et al. (2019) examined the factors responsible for facilitating and inhibiting the fitness wearable technology adoption and the motivation behind recommending these devices to others. The authors integrated two conceptual models: UTAUT and diffusion of innovation. The results post analysis based on SEM indicated that performance expectancy, effort expectancy, social influence, habit, compatibility, and innovativeness influenced technology adoption among customers directly or indirectly. Another research conducted by Kalantari (2017) on the smart wearable device that uses augmented reality, that is, augmented reality smart glasses, identified that benefits from using technological and privacy risk of using technology characteristics, descriptive social norms, and injunctive social norms are the factors that influence the adoption intention. The study highlighted smart wearable devices as a rapidly emerging technology that can influence a user's lifestyle and behavior. Through the study, factors such as perceived benefits, technology characteristics, individual characteristics, social factors, and perceived risks were found to have a major influence on the adoption of smart wearable technology devices. This strongly indicates that many common factors are responsible for the adoption of various technology products.

While studies proved that TAM and UTAUT are valid models for understanding the factors responsible for the adoption of technology products, Dehghani et al. (2018) further studied the factors affecting the intention to use popular smart wearable technology products continuously. The traditional technology acceptance model was thus extended by adding several value drivers, which affect the continuous intention and actual use of wearable technology products. The research was done on actual users of smart wearable technology devices, and the authors found out that the factors contributing to the continuous use of smart wearable technology devices are hedonic motivation, aesthetic appeal, complementary goods, and healthology.

SWT (Smart Wearable Technology) Products

Dehghani (2018) studied the factors that impacted the adoption of smartwatches and fitness bands based on the integrated model of UTAUT and some external factors. It also involved a study of the different adoption factors for early adopters. It was a qualitative study, and the factors that were found to have influenced the purchase intention and affected user behavior were performance expectancy, effort expectancy, social influence, hedonic motivation, price value, brand familiarity, and aesthetically appealing product design. Moreover, Pfeiffer et al. (2016) investigated the usage intention of wearable self-tracking technology devices. They developed an acceptance model for self-tracking devices based on the traditional TAM. The study identified adoption criteria such as perceived usefulness, perceived enjoyment, social influence, trust, personal innovativeness, and perceived support of well-being as the most critical drivers. A quantitative study was also done on the devices that integrate mobile computing and fashion characteristics.

Jung et al. (2016) analyzed consumer perception and their preference structure for smartwatches. The conjoint analysis was done on five major attributes: brand, price, standalone communication, display shape, and display size. The results suggested that standalone communication and display shape were the most important attributes for positive perception and preference. It was also evident that display shape did not affect the choice of smartwatches. Rauschnabel and Ro (2016) conducted a study on Microsoft Hololens and Google Glass, categorized as augmented reality smart glasses. The major findings revealed that drivers such as functional benefits, ease of use, individual difference variables, brand attitudes, and social norms affected the adoption of smart glasses. Less important drivers such as fashion accessories, self-presentation benefits, and privacy concerns did not affect the adoption of smart glasses. The few potential factors that were missing in the study are the identification of lead users and benefits other than functional ones, which can provide a much better insight into the adoption of smart glasses.

Customers' Expectations from SWT (Smart Wearable Technology)

Wu et al. (2016) conducted a study to determine the smartwatch acceptance factors and understand what customers expect and how companies can improve their products' user-centered design. The factors identified for the study were relative advantage, ease of use, compatibility, result demonstrability, enjoyment, and social behavior, taken from a consumer perspective, including innovation diffusion theory, technology acceptance model, and unified theory of acceptance and use of technology and perceived enjoyment. The factor identified to have a major influence on acceptance was attitude. The study tried to understand consumers' acceptance of smart wearables concerning various user interface aspects (Motti & Caine, 2016). The authors analyzed the responses by combing the qualitative analysis with the quantitative approach. The areas of concern in smartwatches identified were small screen size that limits the input and output options, hindered human interaction with the tactile GUIs, limited battery life, unintended user gestures that initiate an action, and integration of smartwatches with mobile applications.

Furthermore, a qualitative study by Rawassizadeh et al. (2014) looked into the market demand and direction in which smartwatches have been progressing. The standalone functionality is getting widely accepted, and thus brands are focusing more on developing smartwatches that can work independently, that is, without using any application on mobile phones. The authors found out that smartwatches are gaining more customer traction than other devices because of two reasons: their mount location and their continuing connection to the skin. Amyx (2014) identified a problem with real-time analytics done on consumer engagement with the brand based on their feelings and emotions and suggested how wearable technology products could be helpful to the brands in quantifying consumer perception of brands, and developed real-time brand-engagement feedback and optimization termed as wearable emotion-sensing marketing (WESM). The following eight dimensions are considered for the real-time analytics: biometric health data (which can measure heart rate, pulse oximetry, ECG waves, skin temperature, blood pressure, and goosebumps), geolocation, body movement, facial expression, eye movement, voice analysis, human tears, and neurochemicals.

SWT (Smart Wearable Technology) Rejection and Non-Usage Factors

Mani and Chouk (2017) tried to understand the factors responsible for consumers' resistance to smart and connected products. This research is important as the internet of things market is growing at a breakneck pace and offering new opportunities, although the underlying challenges need to be addressed to serve the customer better. A quantitative study was carried out, and SEM was used to test the conceptual model (technology acceptance model). The findings show that perceived usefulness, perceived price, intrusiveness, perceived novelty, and self-efficacy had a major impact on consumer resistance. Moreover, Lazar et al. (2015) conducted a detailed study on why there is a discontinuity in the use of smart devices, that is, why some people don't use smart devices and why some others use them. The factors responsible for adoption are usefulness, curiosity, novelty, and developing a routine. They also discussed the ways to reduce the impact of abandonment of smart devices, which are: lowering barriers of users by encouraging routine, appealing to identity, considering positive feedback, users' personal history, minimizing maintenance, employing user language, coaching the user, and providing concrete motivation.

In addition, from a demographic point of view, Lee and Coughlin (2015) conducted a study to understand the adoption factors and the barriers in the adoption of technology concerning the older generation. A quantitative research was done as it is explained that the adoption of technology for older adults is not simple but a complex matter as it is affected by multiple factors. The results suggested that the most significant factors responsible are value for money, usability, affordability, accessibility, technical support, social support, emotion, independence, experience, and confidence.

The gap identified was the lack of evidence for the existence of the pre-purchase decision process of consumers. The review also helped determine the factors responsible for the adoption and rejection of smart wearables. This proves that most studies focused on post-purchase behavior, and studies to identify the factors responsible for reaching the purchase stage were missing.

Rashel et al. (2017) measured the effects of product attributes on satisfaction through consumers' perceived value of using an analog wristwatch in the perspective of Bangladesh. A group of younger generation respondents was considered the population from which representatives were selected through cluster and simple random sampling techniques. The sample consisted of 294 educated young people from Dhaka city. The results showed that all the factors, excluding physical benefits, had a significant positive effect on satisfaction through customer perceived value. These relationships suggested a partial or a full mediating effect of customer perceived value on the relationship between product attributes and customer satisfaction. In addition, the gender of analog wrist users moderated the path between customer perceived value and customer satisfaction; however, the moderating effect of men users was greater than that of women users.

According to Kesharwani and Roy (2017), the convergence of mobile technology with an evolving healthcare delivery system has ushered in a wave of disruptive innovations that have bought a paradigm shift in healthcare delivery services, Health 3.0.

Objectives of the Study

- To access the relationship between the three stages of the pre-buying process.
- To identify the various factors customers consider during their pre-purchase decision concerning smart wearable technology devices.
- To analyze the impact of various factors on the pre-purchase decision.

Hypotheses

- **H1 :** There is a significant relationship between the need to subconsciously identify, information search, and assess alternatives in the pre-purchase decision process.
- **H2 :** The relationship between identifying the needs and assessing alternatives is positively mediated by searching for information.
- **H3a :** Individual characteristics positively affect the recognition of the needs stage regarding smart wearables.
- **H3b :** Social factors positively affect the recognition of the needs stage regarding smart wearables.
- **H4a :** Product characteristics positively affect the information search stage with respect to smart wearables.
- **H4b :** Retailer characteristics positively affect the information search stage with respect to smart wearables.
- **H4c :** The interface of wearables positively affects the information search stage with respect to smart wearables.
- **H4d :** The information search utility positively affects the information search stage with respect to smart wearables.
- **H4e :** Consumers' mood positively affects the information search stage with respect to smart wearables.
- **H5a :** Perceived benefits positively affect the evaluation of the alternatives stage with respect to smart wearables.

↳ **H5b :** Technology characteristics positively affect the evaluation of the alternatives stage with respect to smart wearables.

↳ **H5c :** Perceived risks positively affect the evaluation of the alternatives stage with respect to smart wearables.

↳ **H5d :** The inter-brand competition positively affects the evaluation of the alternatives stage with respect to smart wearables.

↳ **H5e :** The product design positively affects the evaluation of the alternatives stage with respect to smart wearables.

↳ **H5f :** In-store factors positively affect the evaluation of the alternatives stage with respect to smart wearables.

Research Methodology

Population

↳ Geographical : Bangalore.

↳ Demographic : Age group of less than 40 years and more than 20 years old.

↳ Considering the above two criteria, the population comprised 74% of the total population of Bangalore city, that is,

0.74*1, 300,000 = 9,620,000 (around 96 lakh).

Sample Size

↳ Option 1: 270 respondents using the formula with 6% error.

Sample size :
$$\frac{\dfrac{z^2 \times p\,(1-p)}{e^2}}{1 + \left(\dfrac{z^2 \times p\,(1-p)}{e^2 N}\right)}$$

where,

N = population size, e = Margin of error (percentage in decimal form), and z = z-score.

Inserting the following values in the above formula:

- $Z = 1.96$
- $p = 0.05$
- $e = 6\%$
- $N = 9{,}600{,}000$
- 240 – 267 respondents.

Sampling Method. Systematic sampling for equiprobability method.

Research Instrument. A questionnaire having closed-ended questions as part of the primary data collection and analysis.

Time Period of the Study. From the first week of January 2020 to the first week of March 2020.

Statistical Tools to be Used. Structural equation modeling using Smart PLS 3.0 software, factor analysis, correlation analysis, cross-tabulation analysis, and frequency analysis.

Measurements

The study aimed to understand why consumers choose to behave in a manner against their own professed beliefs and attitudes. Thus, the study adopted a quantitative assessment method for the responses collected from subjects. The research was measured using a validated multi-item scale adopted from past studies. A 5 - point Likert scale was used for independent and dependent factors ranging from *"strongly disagree"* (1) to *"strongly agree"* (5). The language of the questions was changed to fit the research context. Demographic information of the respondents (area in which they live, age, gender, education, and monthly income) and experience of usage information of the respondents were taken as control variables. It meant that the respondents had prior experience of using any smart wearable. The research model is described in Figure 1.

Figure 1. ***The Research Model***

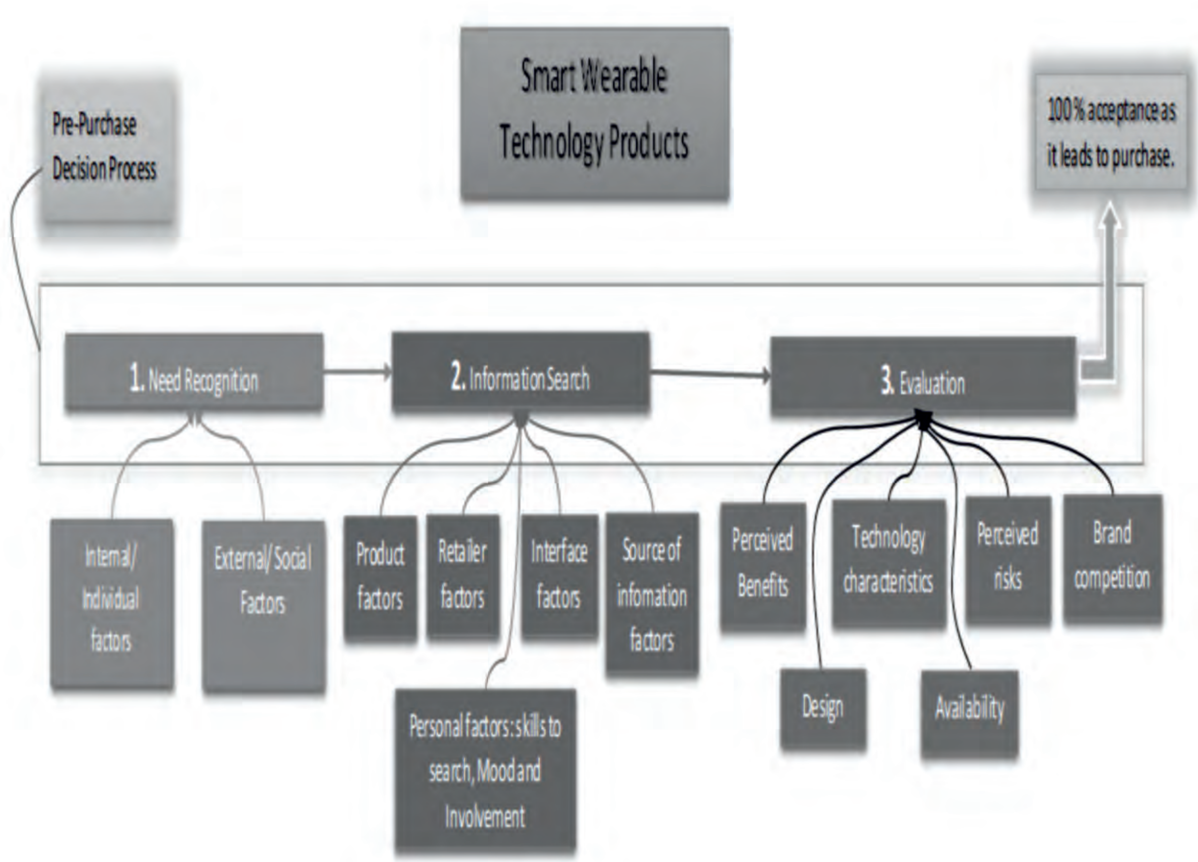


Figure 2. ***Pie-Chart for Gender and Bar Graph for Age-Wise Distribution***

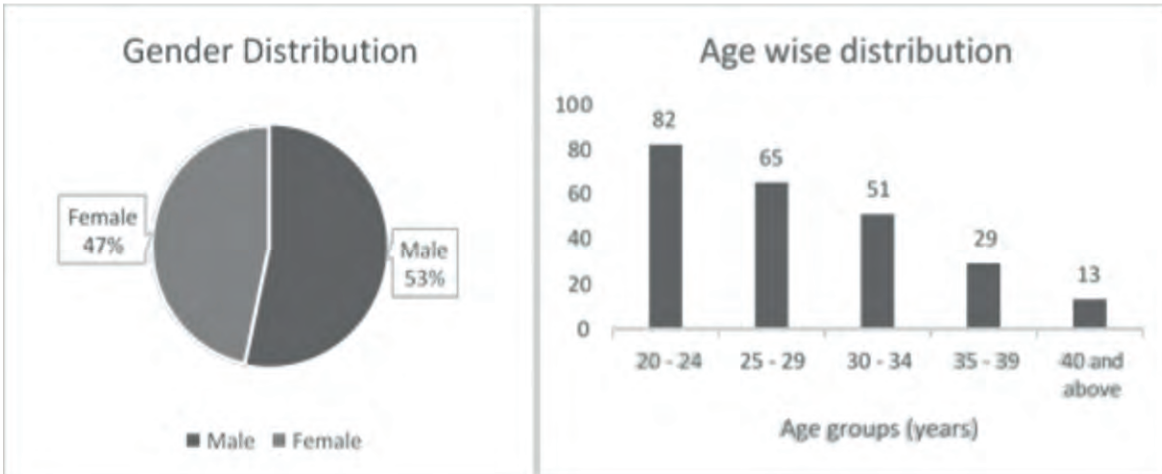


Table 1. ***Frequency Table for Educational Qualifications***

Educational Qualifications	Frequency	Percentage
Below Bachelor's Degree	24	10.0
Bachelor's Degree	114	47.5
Master's Degree	102	42.5
Total	240	100.0

As shown in Figure 2, out of the total responses considered for the study, the male population contributed to 53.3%. This indicates that males were more in number than females, which will also affect the results as the same would be skewed towards the male way of thinking.

Table 1 shows that users having an educational qualification below a bachelor's degree contributed to 10.0% of the total respondents using smart wearables, while bachelor's degree holders had a maximum contribution of 47.5%. This indicates that in the age group of 20 – 30 years, who contributed to almost 57.5% of the total respondents, the respondents were more exposed to the technology and had more inclination towards buying smart wearables. The monthly income of the respondents is shown in Figure 3.

Analysis and Results

Measurement Model Analysis

Path Analysis

The rectangular boxes in Figure 4 depict the indicators of independent variables. The values on the connecting line of two circles are the standardized regression weights. The values depicted between circles and rectangular boxes (indicators) are the factor loadings. The values inside the circles are R squares, and the percentage of variance is explained by the explanatory variables. In this case, the information search stage is explained by 15% of the variance, and the evaluation of alternatives is explained by 43.9% of the variance.

Figure 3. *Line Graph of the Monthly Income of the Respondents*

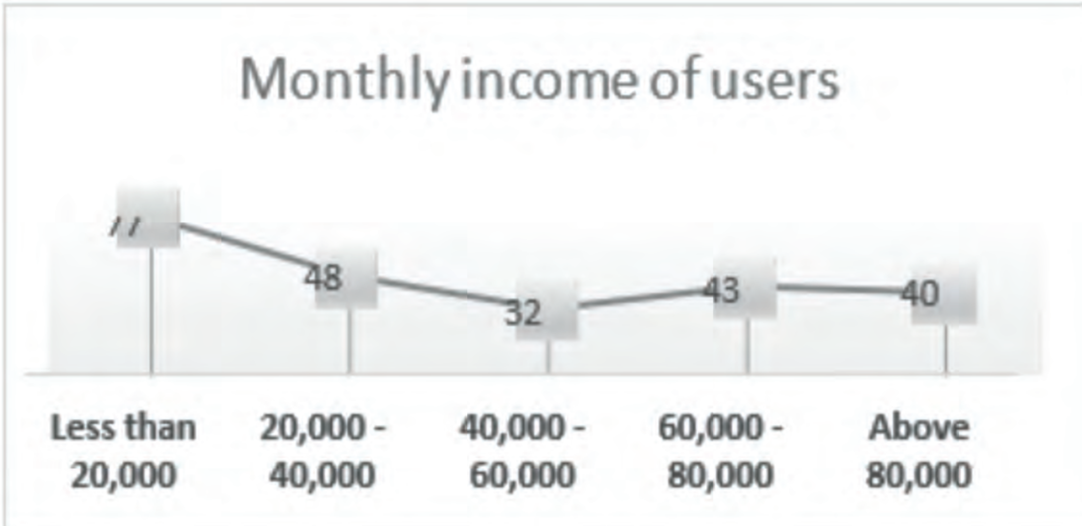


Figure 4. *SEM Path Analysis of the Conceptual Framework*

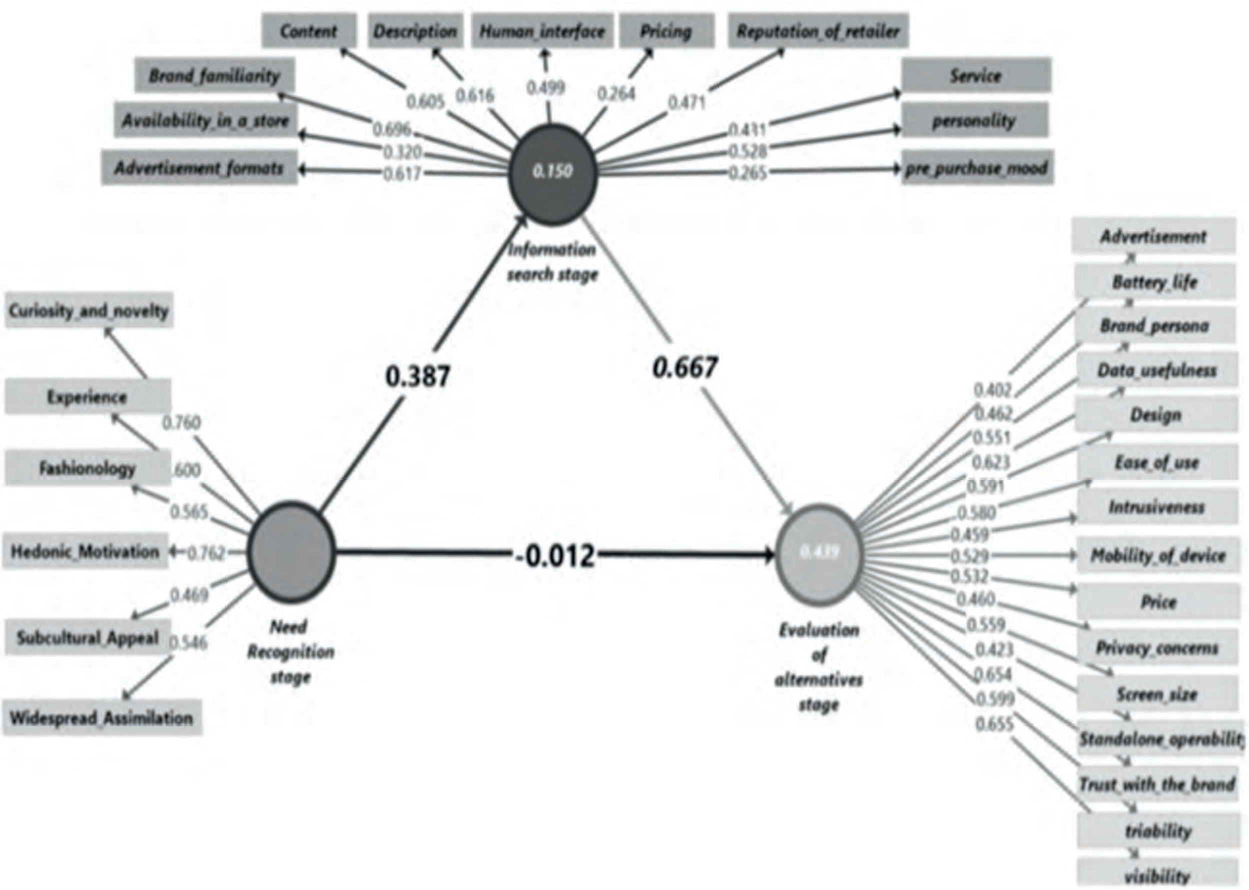


Table 2. ***Level of Significance at 0.05 or 95% Confidence Level***

	Original Sample (*O*)	*t*-Statistics (|O/STDEV|)	*p*-values
Information search stage → Evaluation of alternatives stage	0.667	9.625	**0.000**
Need recognition stage → Evaluation of alternatives stage	–0.012	0.236	**0.813**
Need recognition stage → Information search stage	0.387	6.951	**0.000**

Table 2 shows the *t*-statistic value at an alpha level of 0.05 for each connection. Any connection with a *t*-statistic value greater than 1.96 at alpha = 0.05 is significant.

Mediation Effect

There is a need to evaluate whether the information search stage mediates the direct relationship between the need recognition stage and assessing the alternatives stage. Table 2 shows that the direct effect between Need recognition stage → Evaluation of alternatives stage is $p1 = -0.012$.

The direct effect of Information search stage → Evaluation of alternatives stage is $p2 = 0.0667$ ...... (1)

The direct effect of Need recognition stage → Information search stage is $p3 = 0.387$ ...... (2)

Multiplying equation (1) with equation (2), we get the indirect effect between Need recognition stage → Evaluation of alternatives stage as 0.258. The same value is shown in Table 3 under specific indirect effects.

As shown in Figure 5, the *t*-statistic at 95% confidence level shows :

- The direct relation between the need recognition stage and evaluation of alternatives stage is 0.227, which is less than 1.96, and hence, is not significant;
- The direct relationship between the information search stage and the evaluation of alternatives stage is 9.453, which is greater than 1.96, and hence, is significant;
- The direct relationship between need recognition and the information search stage is 7.479, which is greater than 1.96, which is significant.

According to the procedure described, this case is of total mediation because the indirect effects of $p2$ and $p3$ are significant, but the direct effect of $p1$ is not significant.

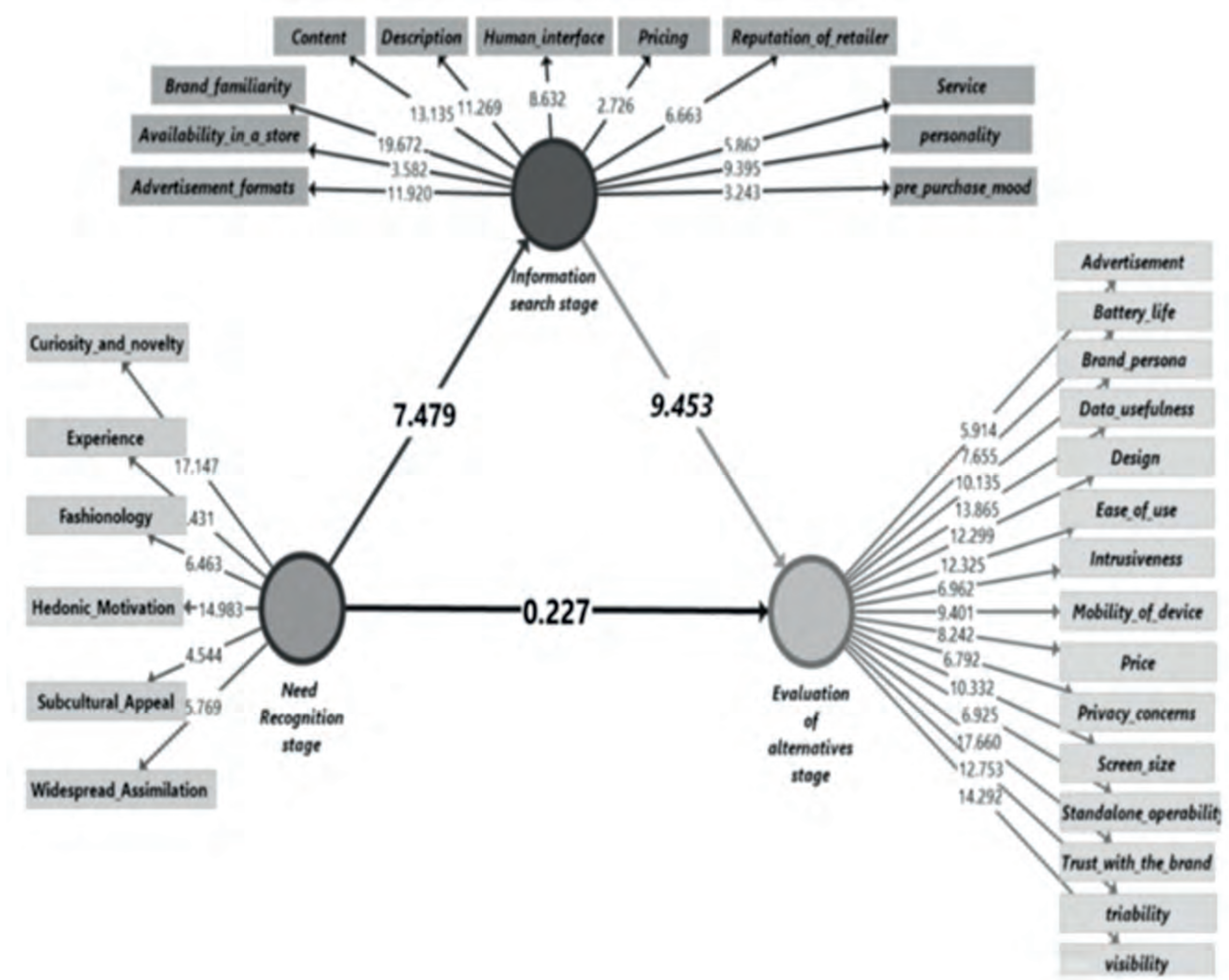
Structural Model

Structural equation modeling (SEM) was used to test and eliminate the causal relationship using statistical data and qualitative caused assumptions.

Table 3. ***Specific Indirect Effects***

	Specific Indirect Effects
Need recognition stage → Information search stage → Evaluation of alternatives stage	0.258

Figure 5. ***SEM Bootstrapping of the Conceptual Framework***



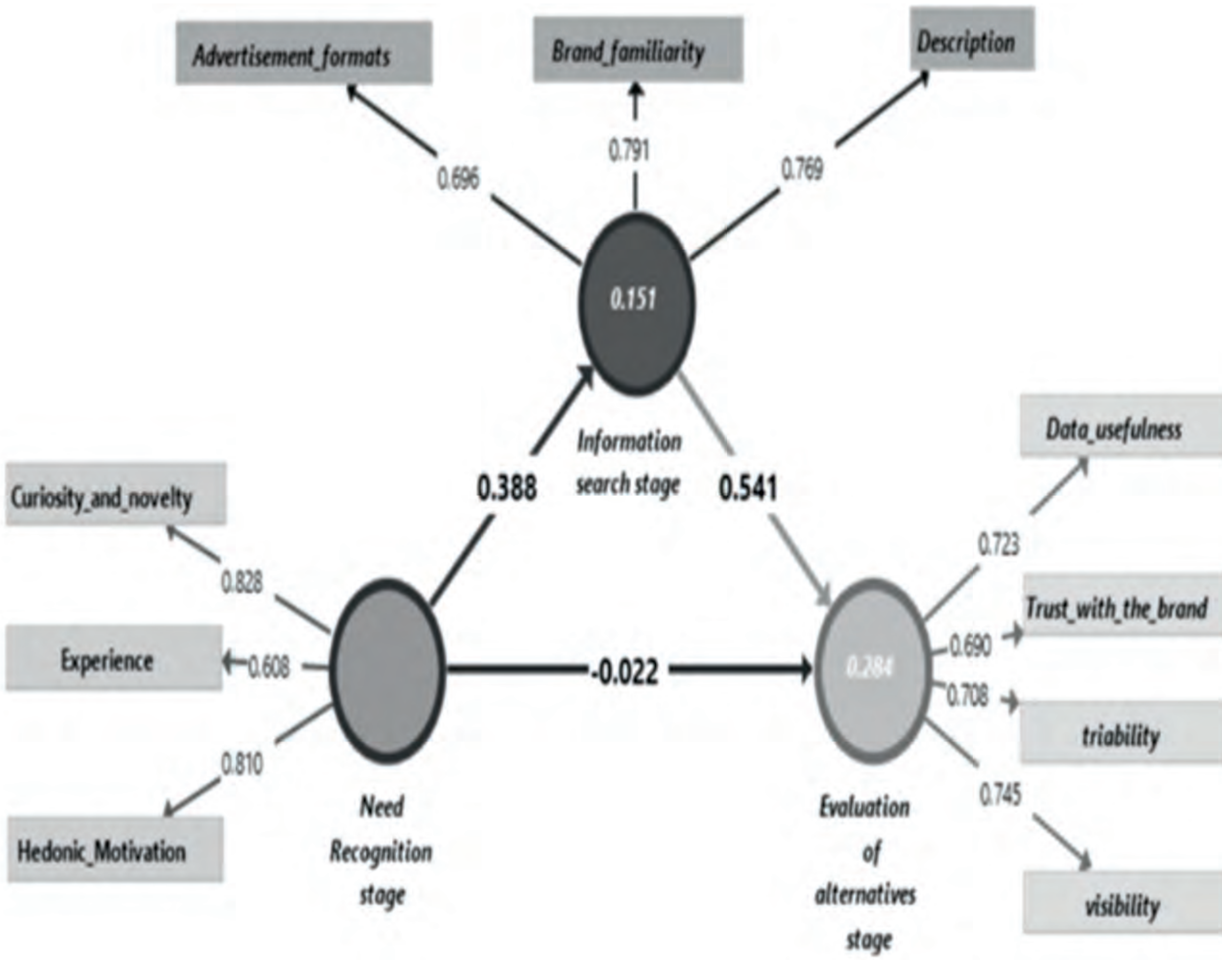
Modified Model

It is observed that when all the indicators are taken into consideration for analysis, some of the indicators' factor loadings are less than 0.6, which weaken the model. There is a need to eliminate these indicators and re-analyze them to strengthen the proposed model. After eliminating a few insignificant factor loadings, a new and modified model was developed, which is depicted in Figure 6. The level of significance at 95% confidence level for the modified model is shown in Table 4.

Table 4. ***Level of Significance at 0.05 or 95% Confidence Level for the Modified Model***

	Original Sample (*O*)	*t*-Statistics (|O/STDEV|)	*p*-values
Information search stage → Evaluation of alternatives stage	0.541	8.196	**0.000**
Need recognition stage → Evaluation of alternatives stage	–0.022	0.329	**0.742**
Need recognition stage → Information search stage	0.388	7.118	**0.000**

Figure 6. *SEM Modified Path Analysis of the Conceptual Framework for a Better Fit*



The Goodness of Fit of the Modified Model

The criteria for ideal fit indices are relative independence of sample size, accuracy and consistency to assess different models, and ease of interpretation aided by a well-defined pre-set range. The entire set of fit gives a good sense of how the model fits the sample data, as seen in Table 5.

The goodness of fit measure for PLS-SEM can be used to avoid model misspecification. In this case, the value is 0.098, which is less than 0.10, and hence, the model is a good fit. Consequently, the NFI results in values between 0 and 1. The closer the NFI to 1, the better the fit is. NFI values are 0.557, and it usually represents an acceptable fit for social science research.

Table 5. *Model Fit*

	Saturated Model	Estimated Model
SRMR	0.098	0.098
Chi-Square	215.764	215.764
NFI	0.557	0.557

Table 6. *Reliability and Validity of the Modified Model*

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Evaluation of alternatives stage	0.688	0.809	0.514
Information search stage	0.621	0.797	0.567
Need recognition stage	0.633	0.797	0.570

To construct the reliability and validity of the model, Table 6 depicts the Cronbach's alpha value of the independent variables. To test the convergent validity, which is achieved if the value of the average variance extracted (AVE) reaches 0.50 and each element has outer loads greater than 0.7, it is depicted that all the indicators' factor loadings greater than 0.7 are considered, and the AVE of all independent variables is greater than 0.5. Therefore, both the conditions of convergent validity satisfy.

Testing of Hypotheses

Table 7 shows the summarized test result, and Table 8 represents the results of the hypotheses testing.

Table 7. *Summarized Test Results*

	Hypotheses	Factor Loadings	*t* - Statistics (|O/STDEV|)	*p* - values	Results
H3	Hedonic motivation → Need recognition stage	0.762	13.947	0.0000	Supported – High impact
	Experience → Need recognition stage	0.600	7.094	0.0000	Supported – High impact
	Curiosity and novelty → Need recognition stage	0.760	16.555	0.0000	Supported – High impact
H4	Fashionology → Need recognition stage	0.565	6.386	0.0000	Supported – Medium to low impact
	Widespread assimilation → Need recognition stage	0.546	5.510	0.0000	Supported – Medium to low impact
	Subcultural appeal → Need recognition stage	0.469	4.570	0.0000	Supported – Medium to low impact
H5	Description → Information search stage	.616	10.335	0.0000	Supported – High impact
	Brand familiarity → Information search stage	.696	19.441	0.0000	Supported – High impact
	Pricing → Information search stage	.264	2.828	0.0049	Supported – Medium to low impact
H6	Availability in a store → Information search stage	.320	3.693	0.0002	Supported – Medium to low impact
	Reputation of retailer→ Information search stage	.471	6.752	0.0000	Supported – Medium to low impact
	Service → Information search stage	.431	5.662	0.0000	Supported – Medium to low impact
H7	Content → Information search stage	.605	12.371	0.0000	Supported – Medium to low impact
	Human interface → Information search stage	.499	7.660	0.0000	Supported – Medium to low impact
H8	Advertisement formats → Information search stage	0.617	11.894	0.0000	Supported – High impact
H9	Personality → Information search stage	.528	8.968	0.0000	Supported – Medium to low impact
	Pre-purchase mood → Information search stage	.265	3.159	0.0017	Supported - Medium to low impact
H10	Price → Evaluation of alternatives stage	.532	8.044	0.0000	Supported – Medium to low impact
	Ease of use → Evaluation of alternatives stage	.580	11.172	0.0000	Supported – Medium to low impact
	Data usefulness → Evaluation of alternatives stage	.623	13.901	0.0000	Supported – High impact
H11	Mobility of device → Evaluation of alternatives stage	.529	9.321	0.0000	Supported – Medium to low impact

	Battery life → Evaluation of alternatives stage	.462	7.534	0.0000	Supported – Medium to low impact
	Standalone operability → Evaluation of alternatives stage	.423	6.357	0.0000	Supported – Medium to low impact
H12	Privacy concerns → Evaluation of alternatives stage	.460	6.905	0.0000	Supported – Medium to low impact
	Trust with the brand → Evaluation of alternatives stage	.654	17.272	0.0000	Supported – High impact
	Intrusiveness → Evaluation of alternatives stage	.459	7.033	0.0000	Supported – Medium to low impact
H13	Brand persona → Evaluation of alternatives stage	.551	10.294	0.0000	Supported – Medium to low impact
	Advertisement → Evaluation of alternatives stage	.402	6.204	0.0000	Supported – Medium to low impact
H14	Design → Evaluation of alternatives stage	.591	11.775	0.0000	Supported – Medium to low impact
	Screen size → Evaluation of alternatives stage	.559	10.296	0.0000	Supported – Medium to low impact
H15	Triability → Evaluation of alternatives stage	.599	11.626	0.0000	Supported – High impact
	Visibility → Evaluation of alternatives stage	.655	13.288	0.0000	Supported – High impact

Table 8. ***Testing of Hypotheses***

Hypothesis	Statistically Correlated	Result
H1 : There is a significant relationship between the need to subconsciously identify, information search, and assess alternatives in the pre-purchase decision process.	Positively correlated	Accept the hypothesis
H2 : The relationship between identifying the needs and assessing alternatives is positively mediated by searching for information.	Positively correlated	Accept the hypothesis
H3a : Individual characteristics positively affect the recognition of the needs stage regarding smart wearables.	Significant	Accept the hypothesis
H3b : Social factors positively affect the recognition of the needs stage regarding smart wearables.	Not associated	Reject the hypothesis
H4a : Product characteristics positively affect the information search stage with respect to smart wearables.	Significant	Accept the hypothesis
H4b : Retailer characteristics positively affect the information search stage with respect to smart wearables.	Not associated	Reject the hypothesis
H4c : The interface of wearables positively affects the information search stage with respect to smart wearables.	Not associated	Reject the hypothesis
H4d : The information search utility positively affects the information search stage with respect to smart wearables.	Significant	Accept the hypothesis
H4e : Consumers' mood positively affects the information search stage with respect to smart wearables.	Not associated	Reject the hypothesis
H5a : Perceived benefits positively affect the evaluation of the alternatives stage with respect to smart wearables.	Associated	Accept the hypothesis
H5b : Technology characteristics positively affect the evaluation of the alternatives stage with respect to smart wearables.	Not associated	Reject the hypothesis
H5c : Perceived risks positively affect the evaluation of the alternatives stage with respect to smart wearables.	Associated	Accept the hypothesis
H5d : The inter-brand competition positively affects the evaluation of the alternatives stage with respect to smart wearables.	Not associated	Reject the hypothesis

H5e : The product design positively affects the evaluation of the alternatives stage with respect to smart wearables.	Not associated	Reject the hypothesis
H5f : In-store factors positively affect the evaluation of the alternatives stage with respect to smart wearables.	Significant	Accept the hypothesis

Discussion

Relationship Between the Three Stages of the Pre-Purchase Process

It is established that there exists a relationship between the three stages of the pre-buying process. The relationship between identifying the needs and assessing alternatives is positively mediated by information search. Customers go through the process of developing the need, searching for information, and assessing the alternatives to convince themselves to buy a product with some perceived value. In addition to that, other results show that all the factors that are taken into consideration have a positive influence on the respective stages of the pre-purchase decision process, that is, all hypotheses are supported (Table 7). However, a few factors in each stage of the pre-purchase decision process influence more than others.

Factors Related to the Need Recognition Stage

Three factors are identified to have ignited the recognition of the need to put smart wearables in the consideration set for buying. These are curiosity and novelty in the new smart wearables coming in the market, the experience of buying or using wearables, and the hedonic motivation.

Factors Related to the Information Search Stage

Three factors are identified to have played a significant role in information access and search. These are formats of advertisements, brand familiarity, and the technical and non-technical description of the smart wearables.

Factors Related to the Evaluation of Alternatives Stage

Four factors are identified to have influenced the assessment of alternatives. These are data usefulness, trust with the brand, options of trial and buy, and maximum visibility of smart wearables in the store. An interpretation of the results reveals that customers like to get relevant information about smart wearables, and hence, data usage is one of the major criteria at the evaluation stage. Again, due to the perceived privacy concerns, trust with the brand and the brand's reputation in the market play important roles. Lastly, as smart wearables are mostly mid-to high-range products, customers expect their visibility in the store so that they can touch, feel, and get hands-on experience with them before making a purchase.

Implications

Theoretical Implications

The study proposes a research model to better understand customers' behavior toward smart technology products before making purchasing decisions. The model is tested empirically in the Indian urban market. Smartwatches and fitness trackers are still in the early stage of market penetration, and, to the best of our knowledge, there is little research done so far on the topic. There are no related studies that focus on the validation of the pre-purchase decision process for smart technology wearable devices. The study emphasizes on the existence of the pre-purchase decision-making process and identifies factors responsible for transition through different phases of the pre-buying process. The results also confirm that there exists a psychological process that customers go through before making any purchase of smart technology products. Moreover, the customers consider a few important factors: product description, curiosity, novelty in the products, advertisement formats, trust with the brand, availability, and demonstrability to transit from the pre-purchase process to the purchase decision. This study is unique in terms of understanding consumer behavior even before the purchase and usage stages, and that is how it contributes to the body of knowledge.

Managerial Implications

This study provides a strategy for the marketers associated with technology products and brands. Although these products have huge potential in India, smart wearable technology is still at the nascent stage. The wearable category still hasn't proved itself as a long-term category. There is a growing opportunity for smart wearables on the business-to-business side. A user-focused approach will help many businesses. The construction industry is growingly adopting wearables to enhance safety measures. With the use of smart wearables and safety management software, employees can be alerted to a situation before it occurs. In the workplace, such devices might have a bigger impact because businesses have both the need and the ability to provide a supporting infrastructure. In some industries, smart wearables can prove to be lifesavers; for instance, a smart device can help detect a situation when a laborer is exposed to hazardous gases or in identifying healthy employees who can be assigned strenuous tasks. In other sectors, a smart device can gauge consumer satisfaction or train a worker using virtual reality. Rather than just implementing new safety features to an existing product line, more user-focused industrial designs are likely to penetrate new markets.

Limitations of the Study

This study has a few limitations and, therefore, opens doors for future research, which will contribute to the current study and find out new insights. One of the primary limitations of this study is that it was conducted for the population of Bangalore city only and thus has a geographical constraint. Moreover, only a few demographic factors were considered, and that too with the perspective of a metro city only. Another major limitation of the study is that users of smart wearables only were considered for the study. If non-users are also taken into account, then more refined results can be achieved.

Conclusion and Scope for Future Research

Smartwatches and fitness trackers are becoming a major interface that connects the customer with smartphones, and other IoT (Internet of things) enabled devices. Through a research model, this study finds evidence for the existence of the pre-purchase decision process in products like smart wearables. The results show that a customer develops the need to purchase a smart wearable through a process, starting from personal characteristics to reaching the stage of information search where product description, brand familiarity, and type of media used for advertisements play a significant role. After crossing the information search stage, the customer reaches the stage of assessing the alternatives where processed data usefulness, trust with the brand, visibility of devices in a store, and the provision of demonstrability help in the transition from the final stage of the pre-purchase process to the purchase decision.

There is scope for further refinement of the results if personality traits are taken into account when finding out the factors responsible for successful transition through the stages of the pre-purchase process. This will help the advertisers, and the manufacturers develop products that suit different personality types.

Authors' Contribution

Mr. Prateek Gupta conceived the idea and developed quantitative design to undertake the study. He extracted research papers with high repute, filtered these based on keywords, and generated concepts and codes relevant to the study design. Dr. Barkathunissa verified the analytical methods and supervised the study. Data collection was conducted by Prateek Gupta, and numerical computations were done by using Smart PLS 3.0. Both authors wrote the manuscript.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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