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Amalgamation of Technology Adoption Model (TAM) and Conjoint Analysis to Understand Consumers' Perception of Wearable Health-Tech Devices

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Abstract

Wearable health-tech devices (WHTD) are increasingly used by individuals for early identification of symptoms and treatment. This study investigates the factors influencing consumers' attitudes and intentions towards adopting WHTD in the southern states of India. The research study uses the Technology Acceptance Model (TAM) and conjoint analysis. Data was collected from 259 respondents through a structured questionnaire. Structural equation modelling was employed to analyze the data. The findings reveal that perceived benefits, technology characteristics, individual characteristics, health interests, and perceived risk significantly influence consumers' attitudes towards WHTD and their intention to adopt these devices. The conjoint analysis revealed that tracking heart rate, steps, and breathing were considered the most important attributes for a WHTD. The study provides valuable insights for marketers and developers to understand the drivers and preferences of consumers regarding WHTD, which can contribute to the design and promotion of innovative wearable healthcare technologies. This study used an amalgamation of the Technology Acceptance Model and Conjoint Analysis to understand the factors influencing the adoption of WHTD. The study further explores the combination of features that consumers prefer in these devices, which provides valuable insights into the design and manufacture of the WHTD.

Keywords: Consumer attitudes, Conjoint analysis, Intention to adopt, Perceived benefits, Technology acceptance model, Wearable health-tech devices.

Introduction

One of the most promising applications of the Internet of Things (IoT) is wearable technology. In recent times, the technology market has been flooded with commercial wearable devices, which have received favorable responses from consumers. This has paved the way for an increase in the production of such devices, thereby offering customers a wide range of choices, especially in the domain of health-tech devices. Wearable health tech devices (WHTD), also called smart healthcare devices, are described as wearable sensors or technologies in the form of accessories or clothing fitted to the body of the user (1). These WHTDs have been modelled to give their users access to uninterrupted real-time data. It is a combination of hardware, software, and sensors through which data can be captured in real time and stored in the cloud for analytical purposes. The main focus of WHTD is to help its users achieve a state of self-connected mode with the help of sensors or technology (2). This can pave the way for the exchange and transmission of data on a real-time basis, for example, between the user and the healthcare facility (3). In comparison with smartphones, laptops, or computers, WHTD provides more convenience to its customers. Accessibility and the possibility to use the devices in motion, coupled with voice and hand gesture recognition, provide the user with access to more data relating to their vital parameters. Wearable devices have the potential to surpass phones and computers in performance and act as a potential replacement for them in the near future. These devices have been positioned in the market as a fashion statement rather than with a technology focus (4). Wearable devices in healthcare range from simple fitness trackers and accessories to sophisticated devices available from all leading brands. These devices have the capability to transform people's lifestyles and behaviors, impacting their well-being positively. Such devices are increasingly being used for preventive medicine in order to identify the symptoms well in

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advance rather than cure the disease after it has progressed to an advanced stage. The use of WHTD can lead to a healthier lifestyle for an individual and reduce the health care costs involved. This is all the more important for the older generation, which needs continuous and accurate monitoring of their vital parameters.

Applications of WHTD are manifold. In sports, WHTD is used in an emerging practice known as 'physiolytics,' which applies advanced machine learning techniques to the data obtained from such devices, resulting in not only performance tracking but also planning preventive interventions leading to sustained positive performance in sports (5). Smart clothing, which is another wearable technology, can have varied applications in the industrial sector, especially where they need to handle harmful chemicals and dangerous materials. Even though there are many advantages to WHTD, the sudden increase in usage leads to debates and discussions about the safety aspects relating to the collection, sharing, and usage of data. There are questions being raised about the protection, privacy, and reliability of the same. As most of the data is stored in the cloud, the exact location of the data becomes a point of huge concern. With this interesting context of the increase in usage and acceptance of such devices on the one hand and the debate on the safety and security aspects on the other, this study aims to understand what drives consumers to buy WHTD. This study was conducted in two parts. The first part ascertains the factors influencing attitudes and intentions towards the usage of wearable health-tech devices. The second part identifies features relating to consumers' preferences for a wearable health-tech device.

Smart objects are defined as "entities that have a physical existence with communicative capabilities and have unique identifiers like name and address" (6). The Internet of Things (IoT) comprises various devices that help with sensing, routing, and communicating, along with cloud compatibility. A smartphone, which was originally intended to make and receive phone calls, is projected to evolve into a portal that channels a rich source of personal information in and out of a cloud system such as a server (7). A smart-wearable device is stated as a compact communication gadget that can be easily fitted simply by using a velcro strap (8). At the initial stage, smart wearable healthcare devices were made only in the form of wrist watches, but now they have progressed into other advanced devices such as smart glasses, smart wearable shirts, wearable defibrillators, thumb-nailed sensors, etc. (9,10). In the recent past, most of the research has aimed at the development and improvement of smart wearable healthcare devices and systems used for health monitoring. Innovations in nano and micro sensor technologies and a simultaneous increase in healthcare costs have paved the way for the increasing usage of wearable healthcare devices. WHTD devices are increasingly transforming the scene of healthcare by supporting customers with technologies and tools for managing and monitoring their health continuously on a real-time basis (10). Several users of smartphones and wearable sensors use their devices to automatically measure and track their health parameters, such as sleep and exercise (11). In the near future, most routine lab tests will also be accessible to consumers with smart kits, thereby enabling the process of shifting personal data from patients to healthcare providers. Some of the most popular wearable devices are listed below in Table 1 (12).

Adoption of wearable healthcare technology by customers is influenced by various factors, including health concerns, how technologically advanced the product is, the safety of the data collected, etc. (13). The WHTD can not only be used for monitoring fitness but also as a precautionary gadget in the field of medicine (14). The information gained through such constant monitoring helps customers plan their fitness training and get instant feedback on its effectiveness (15). Such data would complement the medical health record of the customer, and if merged together electronically, it could serve as a comprehensive source of the medical health record of the person, which could be accessed by multiple stakeholders depending on the need. Considering how sensitive and confidential such data is, it is very important to focus on the security aspects of the data (16). Concerns regarding the collection, storage, and privacy of data are factors that pose a hindrance to the adoption of WHTD.

Table 1: Popular wearable devices

Wearable Device Name	Uses	Leading manufacturers
Wearable fitness tracker	A wristband device with sensor used to monitor heart rate and physical activity	Fitbit, Amazfit, Garmin
Smart health watches	A kind of watch with facilities to act as a viable clinical tool in healthcare sector	Fitbit, Samsung, Apple
Wearable ECG monitors	Used to measure electrocardiogram through which users can track their heart rate and blood pressure	AliveCor, Wellue VivaLNK
Wearable biosensors	Used to create two-way communication between user and their doctor for disease diagnosis and monitoring health.	Philips, Biofourmis
Wearable blood pressure monitor	Used to measure blood pressure, calories burned and steps taken throughout the day	Omron, Withings, Lifesource

The vulnerable issues regarding health data collection from smart wearable devices are customers themselves collecting data using wearable devices, data transition between devices and software programs, and the storage of aggregated data in a database. The ownership of the data that is being collected from the user rests with the manufacturer of the device rather than the owner of the device (17). While the user only has access to aggregated data, the raw data collected can be sold to third parties. Basically, data collected through smart wearables is stored in a single database of the company, and in the unfortunate situation of a security breach, there would be a high potential and threat to expose the data (18). This kind of issue in WHTD increases privacy concerns for the users (19).

A study by the PwC Health Research Institute stated that more than 86 percent of customers have concerns about security breaches regarding smart wearable devices. The Pentagon stated that the fitness tracking application Strava breached the details of the locations of soldiers in the war zones of Iraq and Syria. It was also stated that Strava allows unidentified users to share medical data (20). In most developed countries, like the USA and Italy, wearable devices are used for various health monitoring and fitness monitoring systems, whereas in developing countries, the awareness level with regard to the application and data security is very low, leading to data theft. The Baetylus Theorem (based on a Greek myth) states that consumers mistakenly assume that purchasing wearable technology will enhance their health or well-being (21). The irony is that purchasing a sensor has no effect on one's health or well-being. Seram and Dharmakeerthi (22) stated in their paper that there seems to be a gap between the expectations of the people and the product perceptions. This is primarily due to issues such as poor trust levels, a lack of product experience, low customer motivation, and inadequate market research.

The innovation adoption model covers the marketing tools and strategies developed by marketers that are used to push customers from awareness to evaluation (3). In 1989, Davis (23) proposed a highly influential and validated model called the technology acceptance model, which dealt with customer acceptance based on new technological innovations in different areas (24). In this model, Davis proposed two factors: perceived usefulness and perceived ease of use, which can affect the behavioral intentions of customers to accept emerging technologies. Perceived usefulness is defined as “the point to which the customer trusts that his or her job performance would be enhanced using the particular new technology innovations, and perceived ease of use is defined as the point to which the customer believes he or she will be free of putting more effort into using this new innovation” (23). In accordance with the Technology Acceptance Model, when the user believes that the new technology will be easy to handle, the product is successful, and the positive attitude towards the new innovation surges. This may also work on the contrary if the consumers perceive the device as complex (5). For the first part of the study, the well-established technology adoption model (TAM) is used and for the second part of the study Conjoint analysis has been applied. The advantages gained by augmenting the results of the TAM model with Conjoint analysis have been exploited successfully by some authors. Leveraging conjoint analysis to gain a better understanding of the adoption of technology helps garner deeper insights into aspects pertaining to not only why technology has been accepted and adopted by individuals but also what aspects or attributes of the technology drive its acceptance. The models have been combined to study the adoption of mobile banking (25), cloud archiving (26), mobile health (27), robo-advisors (28), e-commerce adoption (29), and learning management systems (30).

A literature review identified variables such as perceived benefits, technology characteristics, individual characteristics, health interests, and perceived risk as independent variables, and attitude and intention to adopt health-tech devices as dependent variables (Fig. 1).

Based on the literature review, the following hypotheses was formulated

H_1: There is a significant positive relationship between perceived benefits and attitude towards using health-tech devices.

H_2: There is a significant positive relationship between technology characteristics and attitude towards using health-tech devices.

H_3: There is a significant positive relationship between individual characteristics and attitude towards using health-tech devices.

H_4: There is a significant positive relationship between health interest and attitude towards using health-tech devices.

H_5: There is a significant positive relationship between perceived risk and attitude towards using health-tech devices.

H_6: There is a significant positive relationship between attitude towards using health-tech devices and intention to adopt health tech devices

Methodology

The population for the study is those who use health-tech devices and reside in the southern states of India. In the first stage the TAM model was implemented to ascertains the factors influencing attitudes and intentions towards the usage of wearable health-tech devices using a structured questionnaire and analyzed using Warp PLS software. The questionnaire had two sections. The first section covered the demographic characteristics of the respondents. The second part of the questionnaire consisted of seven sections pertaining to perceived benefits, technology characteristics, individual characteristics, health

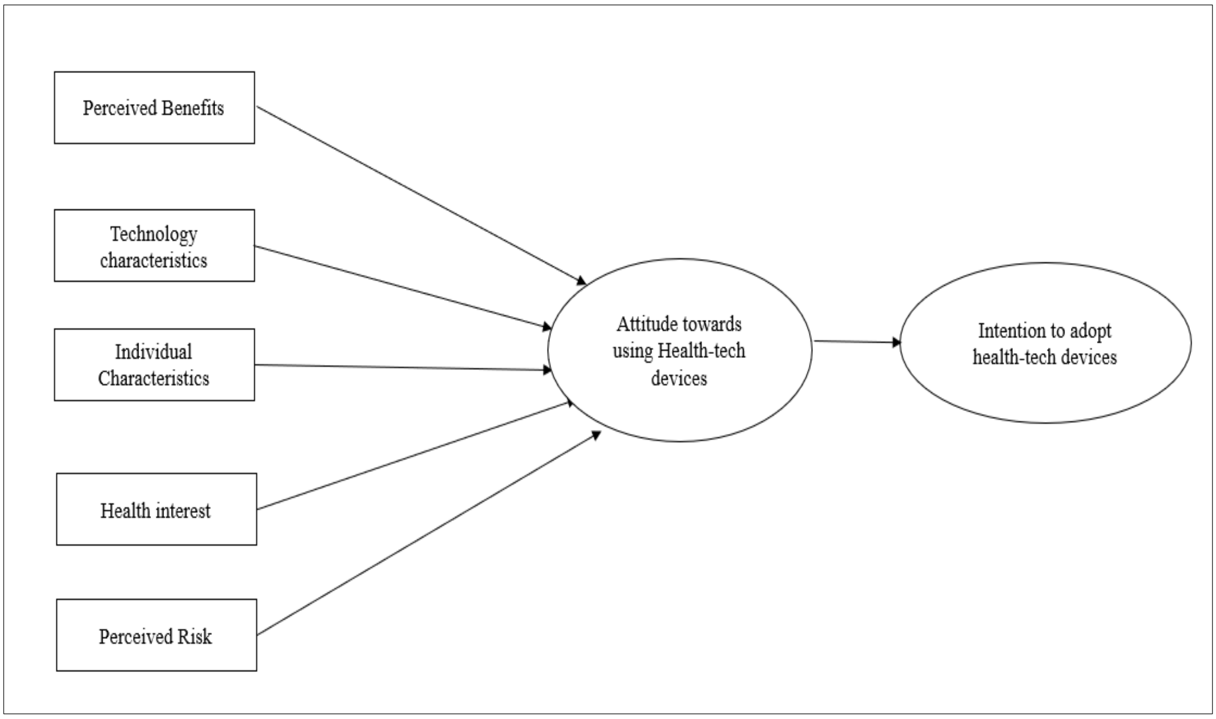

Figure 1: Proposed Research model

interests, perceived risk, attitude and intention to adopt health-tech devices. A total of 32 questions formed this part of the instrument. They were framed using a 5-point Likert scale ranging from strongly disagreeing to strongly agreeing. A pilot test was conducted with a sample size of 30 to test the reliability of the questionnaire. The modified questionnaire was used for the final data collection. Data was collected from 345 respondents, of which around 86 were incomplete. Therefore, with a response rate of 75%, data from 259 respondents belonging to all age groups was considered for this study.

The software 'WarpPLS' was used to create the structural equation modelling for this investigation. WarpPLS is a partial least squares method-based graphical user interface software (31). First, the impact of the constructs of perceived benefits, technology characteristics, individual characteristics, health interests, and perceived risk on attitudes towards health tech devices was investigated. Then the impact of attitude on the intention to adopt health technology devices was found. The positive and negative relationships between the constructs employed in the study are investigated using a correlation analysis. Convergent and discriminant validity are used to assess the model's reliability and validity. Cronbach's alpha, average variance, and composite reliability were used to assess convergent validity.

In the next stage, the market research tool, conjoint analysis, was used as a statistical tool for evaluating attributes (32) relating to consumers' preferences for a wearable health-tech device. Traditional methodologies are usually able to measure consumer preferences for individual attributes; on the other hand, conjoint analysis helps consolidate individual utility for every attribute. It gives a much clearer and more precise understanding of the customer's needs and their decision-making process (33) through trade-offs between attributes. Rightfully, conjoint analysis is also referred to as "trade-off analysis" (32). The analysis works on a set of assumptions that the product or service can be defined by multiple levels of attributes and that the preference of the consumer is based on these levels. The utility value is defined as the importance of the feature of the product or service. Consumers are able to choose among the combinations of multiple features based on the utility value of the individual attributes. (34). The dependent variable 'y' represents the consumer's preference, and x_1 to x_n represent the independent variables, which could be both metric and non-metric. Conjoint analysis could be represented using the following equation (34).

$y = x_1 + x_2 + x3 + \ldots\ldots\ldots + xn$

In conjoint analysis, the attributes of the product are first identified, the different levels of the attributes are listed, and finally a combination of these levels is created. This is then presented to the sample population to determine the preferences of the consumers (35).

Results and Discussion

The descriptive statistics of the demographic data is presented in Table 2.

Reliability and Validity

The quality of the constructs in the study is assessed by establishing their reliability and validity. Reliability is assessed using Cronbach's alpha and composite reliability. The Cronbach alpha value ranged from 0.630 to 0.864, whereas composite reliability values ranged from 0.781 to 0.896. Both indicators of reliability should ideally have values above 0.70 (36). As the current values satisfy the condition, construct reliability is established. Convergent validity is confirmed when the AVE value is greater than or equal to the recommended value of 0.50. According to the results, all the constructs have an AVE value greater than 0.50. Hence, convergent validity is also established. The results are presented in Table 3.

Discriminant validity is the degree to which measures of different constructs are distinct. The notion is that if two or more constructs are unique, then valid measures of each should not correlate too highly. According to Fornell and Larcker (37), discriminant validity is established when the square root of AVE for a construct is greater than its correlation with all other constructs. The analysis provided in Table 4 ensures discriminant validity.

The questionnaire items pertaining to each construct loaded high on the respective construct. The combined loadings and cross loadings of the questions on the various constructs are shown in Table 5.

Table 2: Demographic characteristics

Variable	Category	Percentage (in %)
Age	18 -30 years	88.7
	31-49 years	8.8
	50 years and above	2.5
	Total	100
Gender	Female	48.4
	Male	51.6
	Total	100
State	Andhra Pradesh	3.8
	Karnataka	18.2
	Kerala	23.3
	Tamil Nadu	50.9
	Telangana	3.8
	Total	100
Educational Qualification	Diploma	3.8
	Doctorate	4.4
	Others	7.5
	Post Graduate	37.7
	Under Graduate	46.5
	Total	100
Occupation	Government	6.9
	Others`	9.4
	Own Business	11.3
	Private	37.1
	Student	35.2
	Total	100

Table 3: Model evaluation parameters

Variable	Variable name	Cronbach's alpha	Composite reliability	Average Variance
Perceived Benefits	Perben	0.864	0.894	0.513
Technology characteristics	Techcha	0.776	0.837	0.502
Individual characteristics	Indv	0.738	0.836	0.563
Health Interest	Health	0.744	0.886	0.796
Perceived Risk	Risk	0.630	0.781	0.526
Attitude towards health-tech devices	Attitude	0.826	0.896	0.742
Intention to adopt SWH	Intent	0.752	0.859	0.671

Table 4: Correlation among the constructs

Variable	Perceived Benefits	Technology characteristics	Individual characteristics	Health Interest	Risk	Attitude	Intention
Perceived Benefits	0.716						

Technology characteristics	0.416	0.708					
Individual characteristics	0.593	0.316	0.750				
Health Interest	-0.119	-0.165	-0.087	0.892			
Perceived Risk	-0.515	-0.386	-0.381	0.435	0.725		
Attitude	0.618	0.432	0.544	-0.060	-0.390	0.862	
Intention	0.674	0.403	0.519	-0.166	-0.421	0.692	0.819

Table 5: Loadings and cross loadings

	Perceived Benefits	Technology characteristics	Individual characteristics	Health Interest	Risk	Attitude	Intention
PB1	**0.732**	0.098	0.148	0.239	0.048	0.084	-0.164
PB2	**0.709**	-0.157	-0.064	0.053	-0.255	0.042	-0.313
PB3	**0.782**	0.076	0.104	0.005	0.308	0.242	-0.319
PB4	**0.713**	0.052	0.134	-0.028	0.310	0.138	-0.050
PB5	**0.780**	0.034	-0.071	0.020	-0.090	-0.118	0.230
PB6	**0.758**	0.100	-0.064	0.038	-0.082	0.012	0.335
PB7	**0.714**	-0.041	-0.074	-0.120	-0.183	-0.176	0.082
PB8	**0.734**	-0.192	-0.115	-0.244	-0.035	-0.231	0.162
TC1	0.170	**0.763**	-0.079	0.135	-0.025	-0.102	0.376
TC2	0.013	**0.773**	0.014	0.307	-0.214	-0.283	0.502
TC3	0.114	**0.782**	-0.213	0.114	0.045	0.034	-0.076
TC4	-0.153	**0.824**	-0.098	0.216	-0.069	0.100	0.009
TC5	-0.278	**0.797**	-0.160	-0.379	-0.050	0.202	-0.189
TC6	-0.242	**0.731**	-0.233	-0.377	-0.097	0.214	-0.286
TC7	0.178	**0.839**	0.630	-0.211	0.262	-0.095	-0.335
TC8	0.293	**0.851**	0.516	-0.100	0.330	-0.096	-0.274
IC1	0.078	0.049	**0.885**	-0.160	-0.068	-0.047	-0.055
IC2	-0.179	-0.134	**0.871**	-0.369	0.199	0.170	0.063
IC3	0.053	-0.059	**0.831**	0.151	0.020	-0.014	-0.038
IC4	0.028	0.131	**0.801**	0.290	-0.129	-0.088	0.034
HI1	0.065	0.022	0.079	**0.892**	0.063	-0.111	0.078
HI2	-0.065	-0.022	-0.079	**0.892**	-0.063	0.111	-0.078
PR1	-0.252	0.013	-0.079	-0.377	**0.792**	0.007	0.051
PR2	-0.028	-0.020	-0.203	-0.480	**0.753**	0.024	0.015
PR3	0.315	-0.034	0.073	0.500	**0.793**	-0.013	0.038
PR4	0.056	0.042	0.287	0.605	**0.799**	-0.026	-0.124
A1	-0.106	0.029	0.121	-0.052	0.076	**0.836**	0.131
A2	0.049	-0.009	0.006	0.062	-0.040	**0.869**	-0.167
A3	0.052	-0.019	-0.120	-0.012	-0.033	**0.879**	0.041
I1	-0.080	-0.072	-0.153	-0.101	0.036	0.089	**0.861**
I2	0.071	0.010	0.274	0.016	-0.084	0.120	**0.728**
I3	0.019	0.064	-0.079	0.088	0.035	-0.191	**0.862**

Structural Equation Model

Once the validity and reliability of the questionnaire were tested, the model was built. A structural equation model is used for the first part of the study. The model showed that all the hypotheses except hypothesis 5 had a p value less than 0.05, indicating the statistical significance of the structural paths. The validated research model is shown in Fig. 2. The results of hypothesis testing are given in Table 6.

Consumers' preferences towards WHTD

In the second part of the study, the advanced market research technique of conjoint analysis is performed to identify consumer preferences for the product attributes. One of the most prominent WHTDs, the smart watch, is considered for this purpose. Conjoint analysis was performed using the following steps:

Step 1: Identification of attributes of the product

Different health attributes such as tracking distance, sleep, steps, calories burned, heart rate, oxygen saturation, and breathing were considered. In addition to this, product features included display type, battery life, charging time, water resistance, compatible device, operating range, charging type, number of buttons, and sports mode.

Step 2: Identification of categories of attributes

The various attributes and the categories pertaining to the same are presented in Table 7.

Step 3: Fractional factorial design

The attributes and categories are utilized to build options in this step. The number of options will vary depending on the number of categories. Factorial design could be used to create these options. A factorial design is a technique that involves factors (attributes) and their many subdivisions (categories). There are two methods for doing this: complete factorial design and fractional factorial design. In a full factorial design, all the combinations based on the attributes and categories are considered (38). In this case, as there are 9,95,328 options through a fractional factorial design, a fraction of such options is created. For this study, we have considered ten options relating to the health activity tracker, including tracking of distance, sleep, steps, calories burned, heart rate, oxygen saturation, and breathing. The options used for the survey are presented in Table 8.

Step 4: Creation of choice card

In this stage, the options were created in the form of a choice card (Fig. 3). The respondents were asked to rank the options on a scale of 1 to 10, with 1 being the best ranking and 10 being the worst.

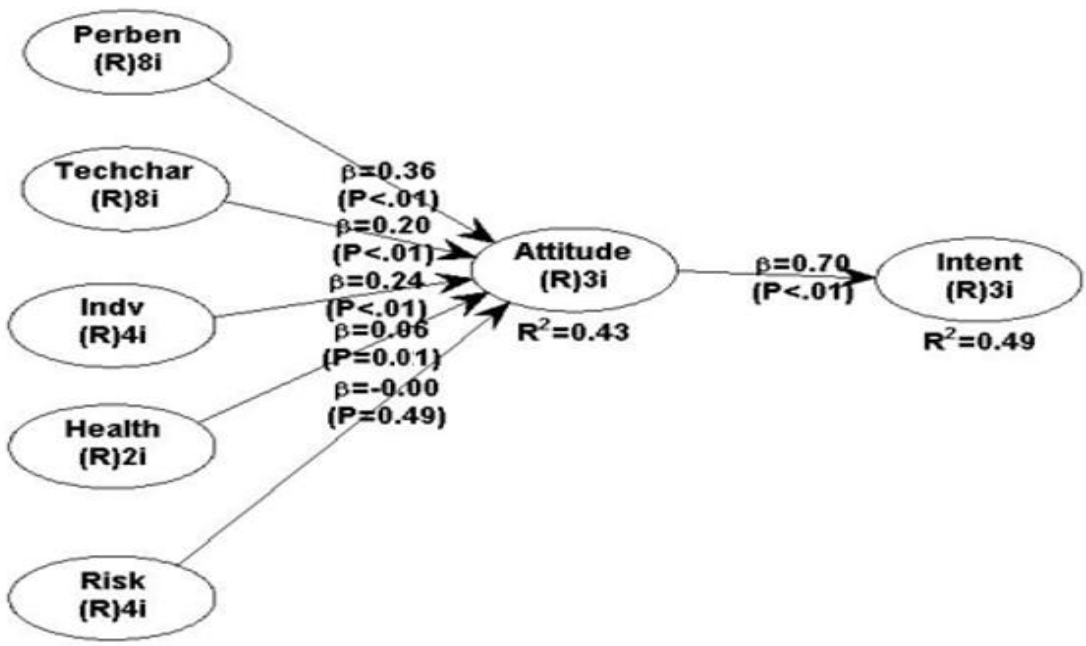

Figure 2: Structural Equation Model for Adoption of WHTD

Table 6: Results of Hypothesis testing

Hypothesis	P value	Result
H_1: There is a significant positive relationship between perceived benefits and attitude towards using health-tech devices	<0.01	Supported
H_2: There is a significant positive relationship between technology characteristics and attitude towards using health-tech devices	<0.01	Supported
H_3: There is a significant positive relationship between individual characteristics and attitude towards using health-tech devices	<0.01	Supported
H_4: There is a significant positive relationship between health interest and attitude towards using health-tech devices	0.01	Supported
H_5: There is a significant positive relationship between perceived risk and attitude towards using health-tech devices	0.49	Not-supported
H_6: There is a significant positive relationship between attitude towards using health-tech devices and intention to adopt health tech devices	<0.01	Supported

Table 7: Categories of attributes

Sl No	Attribute	Category 1	Category 2	Category 3	Category 4
1	Display	LCD	AmoLED	OLED	
2	Distance tracking	Yes	No		
3	Sleep tracking	Yes	No		
4	Steps tracking	Yes	No		
5	Calories burnt tracking	Yes	No		
6	Heart rate tracking	Yes	No		
7	Oxygen tracking	Yes	No		
8	Breathing tracking	Yes	No		
9	Battery life	Upto 5 days	Upto 10 days	Upto 15 days	
10	Charging time	Within 1 hour	Within 2 hours	Within 3 hours	
11	Water resistance	Yes	No		
12	Compatible devices	Android	IOS		
13	Operating range	Upto 5 mtrs	Upto 10 mtrs	Upto 15 mtrs	
14	Charging type	Type B	Type C	Wireless	Core detachable
15	Number of buttons	zero	One	two	
16	Sports mode	Yes	No		

Table 8: Options based on fractional factorial design

Option	Distance	Sleep	Steps	Calories Burnt	Heart Rate	Oxygen	Breathing
1	Yes	No	No	No	No	Yes	No
2	No	Yes	Yes	No	Yes	Yes	No
3	Yes	No	Yes	Yes	Yes	Yes	No
4	Yes	No	Yes	No	No	Yes	Yes
5	No	No	Yes	Yes	Yes	No	Yes
6	No	No	Yes	No	No	Yes	Yes
7	No	Yes	No	Yes	No	No	Yes
8	No	Yes	No	Yes	No	Yes	No
9	Yes	Yes	No	No	No	Yes	Yes
10	Yes	No	Yes	No	Yes	Yes	No

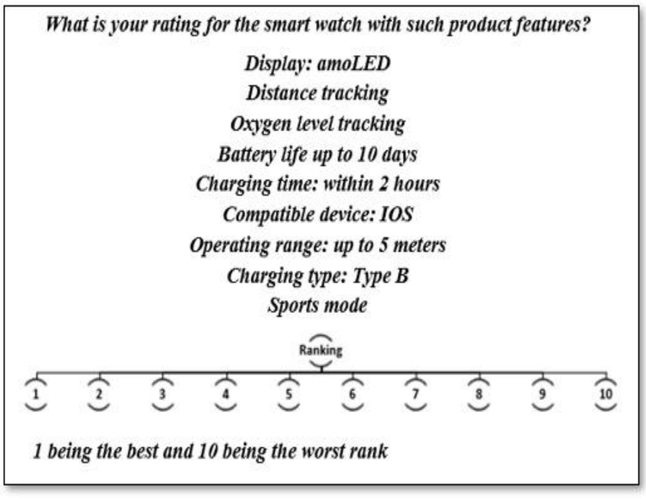

Figure 3: Choice card

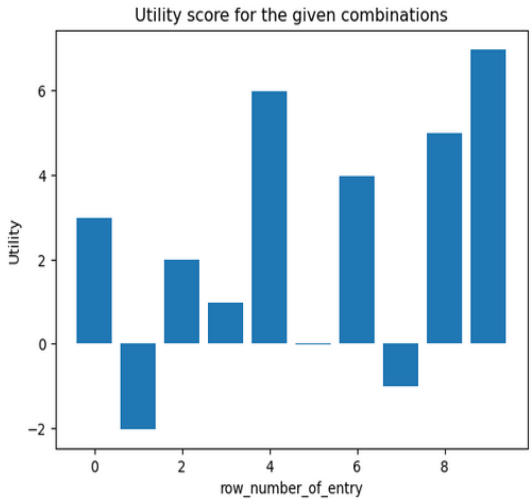

Figure 4: Attribute importance chart

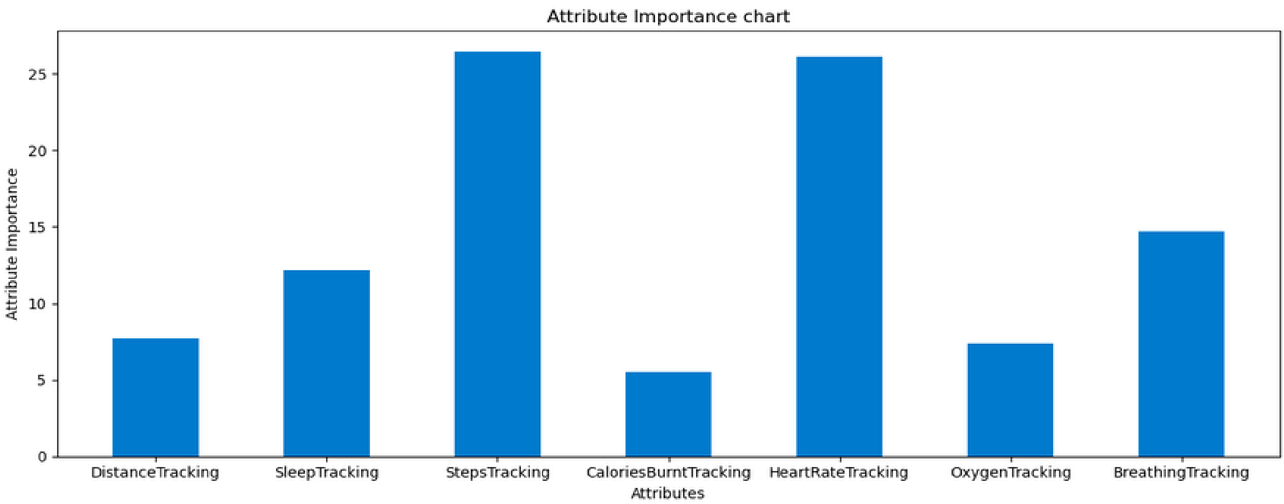

Figure 5: Utility score chart

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The preferred Display is AmoLED
The preferred DistanceTracking is Distance tracking
The preferred SleepTracking is No Sleep tracking
The preferred StepsTracking is Steps tracking
The preferred CaloriesBurntTracking is No Calories Burnt tracking
The preferred HeartRateTracking is Heart rate tracking
The preferred OxygenTracking is Oxygen level tracking
The preferred BreathingTracking is Breathing tracking
The preferred BatteryLife is Upto 10 days
The preferred ChargingTime is Within 3 hr
The preferred WaterResistance is Not Water resistance
The preferred CompatibleDevice is IOS
The preferred OperatingRange is Upto 15 mtrs
The preferred ChargingType is Type C
The preferred NumberofButtons is Two
The preferred SportsMode is Sports mode
-------------------------------------------
Utility_Score_of_the_optimal_combination is  11.893
The current highest utility score in the given combination 6.9816
The new combination brings in additional 4.911 units of utility.
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Figure 6: Optimal combination of features

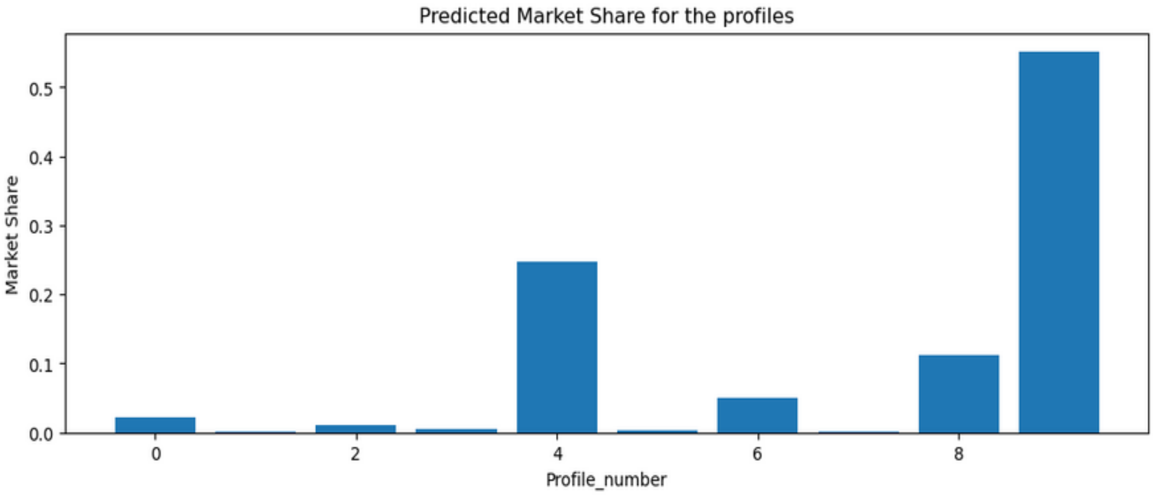

Figure 7: Predicted market share of the product profile

What is your ranking for the smart watch with such product features?

Display: amoLED

Distance tracking

Steps tracking

Heart rate tracking

Oxygen level tracking

Battery life: Up to 10 days

Charging time: Within 3 hours

Water resistant

Compatible device: Android

Operating Range: Up to 15 meters

Charging type: Core detachable

Number of buttons 2

Figure 8: Product profile with the highest market share

Table 9: Conjoint analysis

TAM results	Conjoint results
Technology characteristics	amoLED display, battery life of 10 days, a charging time of 3 hours, a compatible device with iOS, an operating range of 15 meters, type C charging with two buttons, and sports mode
Health interest	tracking distance, steps, heart rate, oxygen, breathing

Step 5: Insights from conjoint analysis

The output of conjoint analysis showed that tracking heart rate, steps, and breathing were considered the most important attributes. The study showed that the optimal combination with a utility score of 11.893 was a device having an amoLED display, tracking distance, steps, heart rate, oxygen, breathing, a battery life of 10 days, a charging time of 3 hours, a compatible device with iOS, an operating range of 15 meters, type C charging with two buttons, and sports mode.

The state of wellness in societies is of paramount importance to all countries, and in particular to those with high population growth rates. As the general public becomes aware of the need to prioritize health, they are also willing to invest in devices and fitness programs to track their health status. One such growing trend in the context of fitness monitoring is WHTD. The goal of this research is to identify factors influencing WHTD adoption among customers. Variables such as perceived benefits, technology characteristics, individual characters, health interest, perceived risk, attitude towards WHTD, and intention to adopt WHTD have been examined. This study used structural equation modelling to validate the research model. The results indicated that perceived benefits, technology characteristics, individual characteristics, and health interest emerged as important factors positively influencing attitude, which in turn positively influenced intention to adopt smart health-tech devices. Many users keenly look for the benefits while adopting such devices. The intention to buy the devices would increase if the developers could provide clear information about the devices and educate the customers about the benefits that could be derived from their usage. It is also essential that this communication reaches the customers through the right channels.

The perceived benefits deal with perceived usefulness, ease of use, value, and enjoyment. It is important that customers believe that WHTD will help them track their health performance through their daily routine activities. The customers need to feel comfortable using the device, and the user interface needs to be made as simple, clear, and understandable as possible. They should also trust that the device offers value for their money and will be a worthy investment in the long run. At the same time, they should feel the excitement of owning such a device. It should be capable of generating some joy and pride in the minds of the consumers. The technological aspects of the device play a major role in influencing the attitude of the customer towards the device. The technology component includes perceived quality, visibility, comfort, and compatibility aspects. The model shows that health interest significantly influences attitudes towards WHTD. Post-pandemic, increasing awareness of the various devices available to monitor self-health so as to take precautionary care in the initial phases of diseases or infections has led to health tracking becoming the primary focus.

The model shows that perceived risk does not significantly influence attitudes towards WHTD. The variable 'perceived risk' pertains to the risk and privacy concerns involved with the devices. Lack of awareness among the general public relating to data privacy issues or the risks involved in sharing their personal data could be the reason for the insignificant impact. Also, the majority of the respondents of the study belong to the 18–30 age category and are not particularly concerned about sharing their personal data. The results of the conjoint analysis provide valuable information that helps in informed decision-making not only with respect to the design and development of the product but also with product positioning, branding, and promotion. This information is crucial for manufacturers to strengthen their position in the minds of consumers in an extremely competitive market.

The findings of the study show that nearly 50 percent of an individual's intention to adopt WHTD is based on their attitude towards using it. The findings shed light on the importance of perceived benefits, technology characteristics, and individual preferences in shaping consumers' attitudes and intentions towards WHTD. The results of conjoint analysis show that tracking distance, steps, heart rate, oxygen, and breathing are important attributes that a customer expects from a smart watch. These attributes are extremely crucial for the physical and mental well-being of the individual. The heart rate is an important metric to help analyze the stress levels of an individual (39). It is continuously monitored, and any slight deviation is captured and escalated, which would help in early intervention. The count of steps indicates the mobility routine of the individual and is pertinent for overall health. The apps associated with smart watches capture a lot of data regarding the daily routine of an individual. The data collected helps in deciding our exercise routines, setting goals, and tracking our progress. They serve as motivation by setting goals, celebrating small achievements, and encouraging people to push slightly harder (40). There is also better awareness about sleep patterns and eating habits due to the 24/7 tracking and monitoring mechanism (41)

In this study, the two models of TAM and conjoint serve two objectives: to ascertain the factors influencing attitudes and intentions towards the usage of wearable health-tech devices (TAM) and to identify features relating to consumers' preferences for a wearable health-tech device(conjoint). The results obtained from the TAM model about the factors influencing adoption of WHTD and the output of the conjoint analysis indicate a high correlation in terms of the factors and the attributes identified. The output of the conjoint analysis gives us very specific details regarding the attributes that could prove immensely beneficial in designing the product. The product design needs to be simple while at the same time adding value to the customers. It is important to provide more information about the devices and communicate the same through the right channels to consumers. The TAM model results indicated that perceived benefits, technology characteristics, individual characteristics, and health interest emerged as important factors positively influencing attitude, which in turn positively influenced intention to adopt smart health-tech devices. This is reiterated with the results of the Conjoint analysis which is represented in Table 9.

India is one of the fastest growing markets for WHTD worldwide. Changing lifestyles and increasing disposable income have paved the way for increased usage of WHTD in India. In conclusion, the study utilizing the amalgamation of the TAM and Conjoint Analysis provides valuable insights into consumers' perceptions of WHTD. By combining these two methodologies, researchers gain a comprehensive understanding of the factors influencing consumer adoption and preferences for such devices.The findings as a whole paint a complete picture of not just the factors influencing technology acceptance and adoption, but also demonstrate with an example how conjoint analysis gives more specific clarity in terms of features and attributes preferred. This complete understanding provides clarity and feedback for developers and helps create the appropriate marketing strategy to help reach the correct audience through proper channels. This knowledge can be used by manufacturers and marketers to develop and promote innovative products that align with consumer expectations, ultimately driving greater adoption and acceptance in the market.

Abbreviation

Wearable health-tech devices (WHTD); Technology Adoption model (TAM); Internet of things (IoT).

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Conflict of Interest

The authors declare no conflict of Interest.

Ethics Approval

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