A STUDY TO UNDERSTAND THE FACTORS INFLUENCING THE ADOPTION OF WEARABLE HEALTHCARE DEVICES IN HYDERABAD

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ABSTRACT

This study aims to comprehensively examine the key factors influencing the adoption of wearable healthcare devices among individuals in Hyderabad, with a particular focus on understanding whether social, behavioral, economic, or technological elements play a dominant role in shaping user decisions. A quantitative research approach was employed, utilizing primary data collected through a structured questionnaire administered to 254 respondents. The collected data were systematically analyzed using IBM SPSS to ensure statistical rigor and reliability. The study tested four primary hypotheses related to gender differences, the impact of financial subsidies, prior experience with wearable devices, and perceived ease of use. To evaluate these hypotheses, multiple statistical techniques were applied, including Chi-Square tests to assess associations between categorical variables, One-Way ANOVA to examine mean differences across groups, Pearson correlation analysis to identify relationships between continuous variables, and a CHAID decision tree analysis to uncover the most influential predictors of adoption behavior. The findings reveal that gender and prior exposure to wearable healthcare technology significantly influence adoption decisions. Individuals who had previously used or interacted with wearable devices demonstrated a higher likelihood of continued or future usage, highlighting the importance of familiarity and experiential learning in technology adoption. In contrast, factors such as financial subsidies and perceived ease of use were found to be statistically insignificant, suggesting that economic incentives and usability alone are insufficient motivators in this context. One of the most notable insights emerged from the CHAID analysis, which identified the willingness to recommend wearable devices to others as the strongest predictor of adoption. This finding underscores the critical role of social influence, peer recommendations, and word-of-mouth communication in shaping consumer behavior. It suggests that users who perceive value in the technology become advocates, thereby driving adoption within their social networks. Overall, the study concludes that social and behavioral factors outweigh purely technological or economic considerations in influencing wearable healthcare device adoption in Hyderabad. These insights offer valuable implications for marketers, healthcare providers, and policymakers, emphasizing the need for strategies that leverage peer influence, user advocacy, and community engagement to enhance adoption and long-term usage of wearable health technologies.

Keywords: *Wearable Healthcare Devices, Technology Adoption, Consumer Behavior, SPSS, CHAID Analysis, Health Consciousness, Hyderabad*

INTRODUCTION

Wearable healthcare technology can be traced back to the 1960s when the first idea was proposed by an MIT mathematics professor, Edward O. Thorp. Wearable Technology is a term that is considered as a device that is worn in or out of the body. These equipment having sensors integrated to gather behavioral, physiological, or environmental data is known as a healthcare wearable device(Lu et al., 2020). There are two major categories of healthcare wearables that the user can select, one being medical and one being fitness-oriented. While fitness wearables, like the Fitbit, are made to track users' heart rates, sleep patterns, and physical activity in order to provide health and fitness recommendations by syncing with different smartphone apps, medical wearables are able to gather a wide range of personal health data, including blood pressure, blood sugar, and oxygen levels, and remotely provide users with customized medical recommendations(H. Wang et al., 2020).

REVIEW OF LITERATURE

1. **Wearable healthcare devices and their historical perspective:**
   Wearable technology is defined as instruments that may be worn on the body or clothing and have a number of uses (Xie et al., 2020). Early studies have identified three distinct eras in the growth of wearable technology: the 1980s through 1997, 1998 through 2000, and 2001 through 2004 (Ariyatum et al., 2005). First, technology is the prime mover, with wearable computing serving as a point of emphasis; second, the fashion and textiles industry is merged, with increased garment collaboration; and third, the commercial industry is more and more incorporating smart clothing and garments (Ometov et al., 2021).

1.1 **Wearable gadgets come in several types**. Wearable devices can generally be divided into two primary types, which are based on skin and those that are based on biofluids.

1.1.1 **Skin-based gadgets:** As the skin envelops most of the human body, it provides a perfect platform for non-invasive medical devices. Apart from physiological and psychological monitoring, skin-wearable sensors can be employed for the evaluation of the evolution of most diseases, for example, cardiovascular and neuromuscular disorders (Górriz et al., 2023). Other areas of application are investigation of sweat and other glandular secretions for the diagnosis of several diseases. Wearable technology can either be textile- Wearable devices are generally classified as either wearable or epidermal, depending on the nature of skin contact. Textile-based wearables, or e-skin, incorporates necessary sensors into clothing, while epidermal-based wearables is applied directly on the skin, like a tattoo (Iqbal et al., 2021).

1.1.2 **Wearable devices utilizing body fluids:** They operate by analyzing body fluids such as sweat, saliva, tears, and urine.These bodily fluids contain precious biomarkers which are used for diagnosis and observation. Wearable medical technology can either stand alone or be used together with other platforms. For instance, different types of biofluids can have helpful information retrieved from them using a combination of microfluidic devices (Li et al., 2020a).

1.2 **Based on the mode of operation, it is possible to classify wearable sensors into four categories: chemical, optical, electrical and mechanical**.

1.2.1 Wearable mechanical sensors: Wearable mechanical sensors transform mechanical inputs into readable electric signals. Iontronic, capacitive, piezoresistive, and piezoelectric sensors are some types of mechanical sensors. The electrical properties of conductive materials change due to mechanical strain; such a type of electromechanical response is referred to as the piezoresistive effect (Gao et al., 2022). Iontronic sensors react to pressure variations, whereas capacitive detectors register variations in an electrical property called capacitance. The method of detection used by a piezoelectrical sensor is based on the piezoelectric effect used by the materials, which generates electrical charges upon contact with external pressure, strain, and mechanical stress (Park et al., 2014). (B) Wearable electrical sensors: These track variations in the skin's electrical resistance or in the capacitive or conductively coupled charge at the skin surface with capacitive or resistance sensors. These small fluctuations in electrical charge are typically measured by high-input impedance circuits (Sharma et al., 2022).

1.2.2 Wearable optical sensors: Optical sensors worn on the body respond to changes in the environment by producing an optical signal, be it physical, chemical, or biological. There are numerous forms of optical sensor elements that are commonly employed to evaluate chemical or biological alterations in any environment (Zhu et al., 2030). These kinds concerning the elements of optical sensors include colorimetric, plasmonic, and fluorometric perception components. Simply said, colorimetric-based sensing devices use colour changes that occur when an analyte of interest is exposed to them. This can happen through a chemical or biological response (Kim et al., 2012).

1.2.3 Wearable chemical sensors: The two primary components of chemical or biological sensors are typically an identification component (receptor) and a transduction component (conductor). Coupling of bio-fluids to a wearable chemical sensor in successful fashion would allow for conversion of chemical signals into electrical or optical signals. Chemical-to-optical signal transduction employs the use of colorimetric signal detection, which is similar to that of urine-based pregnancy tests (Sempionatto et al., 2022). Chemical-to-optical sensing has the capability to deliver two significant benefits through the elimination of the necessity for localized electronics, detectors, and other parts: (1) it is extremely cheap and straightforward, and (2) it can take advantage of some of the vast library of colorimetric or fluorometric assays that are employed in standard benchtop biofluid analyses (Koh et al., 2016).

2. Global Trends in Wearable Healthcare Devices

2.1 Growth of the Wearable Healthcare Market Individuals are increasingly concerned about their health due to the emerging of sedentary lifestyle disorders like obesity, diabetes, and hypertension (Markets & Markets Report, 2017). Hence, wearable and mobile medical devices are gaining popularity. As more individuals live healthier lifestyles, the healthcare market among the world's most significant sectors will continue to grow. The global market for wearable medical devices is expected to be 27.8 billion dollars in 2022, 87 billion dollars in 2025, and 93.19 billion dollars in 2027 (Grand View Research; ERKILIÇ & YALCIN, 2020).

Currently, India now stands as the third-biggest market for wearables globally technology global market. In order to encourage activity and manage their health, more people are buying wearable products, according to several surveys (Saini et al., 2022). The Indian wearable medical device market was US $922 million in 2023. with a projected 16.70 3,700 million compound yearly growth rate (CAGR). The market is increasing at the national level owing to the rise in health and wellness trends, coupled with increased customers' demand for patient-focused and data-driven approaches (India Wearable Medical Devices Market Overview & Share | 2032, n.d.).

2.2 Technological Advancements in Wearables The advancements in medical health care devices include subcutaneous sensors, smartwatches, Microfluidic Patches, Wearable ECG Monitors, Smart Fabrics and electronic tattoos, but a few of the facts that make them stretchable, thinner than paper, biocompatible, and even self-healing(Yetisen et al., 2018). They accurately dispense drugs, identify chemical constituents in body fluids, including blood, sweat & saliva, and monitor psychological & physiological processes. Integrating wearables with telemedicine and value-based health care reduces illness, offers early diagnosis, and saves expenses. These innovations, bearing the 'quantified self' label, improve the approach to patient care and increase the patient satisfaction level (Sharma et al., 2022).

2.2.1 Glucose Monitoring Devices: The increased interest in the creation of new sensor technologies and capabilities for CGM systems is to a great extent facilitated by the large body of clinical evidence illustrating the advantages of blood glucose control through the use of these systems. Clinically, (CGM) demonstrated significant reductions in glycated haemoglobin and reductions in hypoglycemia. In addition, it was shown that the employment of CGM sensors was cost-beneficial in long-term predictions and improved quality of life, such as lowering apprehension regarding hypoglycemia (Cappon et al., 2017). Biosensing technologies utilizing different body fluids, including sweat and tear fluid, have gained considerable attention. These can be configured to accurately determine blood glucose level. Studying different fluids as testing media is critical to improve the wearability of these devices and lead to many other wearables and implants that will likely be less constrictive to the users. Some recent inventions include: mouthguards, contact lenses, etc. There are various glucose monitoring devices like FreeStyle Libre 3 by Abbott, Dexcom G7, Eversense E3 (Senseonics), etc. (Johnston et al., 2021). Today, sweat measurement finds applications for sports training and recovery monitoring, illness management, and alcoholism prevention. For the managing athletes fatigue monitoring blood sugar is important. High-end fitness wearables featuring integrated sweat sensors are broadly used for determining the body's water levels as well as dehydration. (Zafar et al., 2022).

2.2.2 Fitness and Activity Tracker: One of the most viewed wearable technology categories is fitness and activity-related wear, and it also attracts a lot of research and development. For instance, a Fitbit tracker would calculate an individual's steps, sail lengths, calories burned, active minutes, hourly movement, and immobile time (Cilliers, 2020). Furthermore, this tracker notifies the user's sleeping patterns and allows them to wander about. Every one of these is made feasible by its many sensors, including 3-axis, GPS, gyroscopes with three axes, digital compass, and optical features integrated into the tracker, such as an altimeter, vibration motor, ambient light sensor, and heart rate monitor (Wright & Keith, 2014).

2.2.3 Blood Pressure Monitoring Devices: For diagnosing and treating hypertension, measurement of blood pressure is crucial. Patients are able to take their blood pressure routinely—preferably continuously, beat by beat—without concern using wearable blood pressure monitors. Wearable technology is expected to significantly improve the quality of hypertension detection and care by gathering more readings in a range of environments. This will enable it to identify accurately characteristics like masked hypertension and abnormal blood pressure variability that have a harmful impact on cardiovascular prognoses (Kario, 2020).

2.2.4 Wearable Sleep-Tracking Devices: In circadian rhythm domains, and in a wide range of other arenas, such as various states of illness, the use of wearable sleep monitors is expanding. Due to increasing availability of commercial products and next-generation research/clinical instruments, and because patients are increasingly sharing sleep information from their wearables with their physicians, wearables have become broadly used in research (de Zambotti et al., 2024).

2.2.5 Wearable oxygen monitors: Pulse oximeters, another name for wearable oxygen monitors, track heart rate and blood oxygen (SpO2) levels to deliver important information about respiratory health. Continuous blood oxygen level monitoring is made possible by wearable oxygen monitors, which is especially helpful for people with respiratory disorders or those recuperating from diseases. Real-time blood oxygen level data is provided by wearable oxygen monitors, which can aid in the early identification of conditions like hypoxemia (low blood oxygen levels), which may be a sign of more serious health issues (Takahashi et al., 2022).

3. Key Factors Affecting the Uptake of Wearable Health Devices: A variety of factors, including technological, social, economic, and user experience aspects influence the cceptance of wearable health technology devices:

3.1 Technological Factors: In wearable healthcare technology gadgets, sensors are applied to improve the monitoring of a number of factors such as pulse rate, oxygen level in the blood, and even quality of sleep. These sensors consist of optical sensors which uses light to measure the physiological parameters, electro chemical sensors, which are used to measure some of the bodies chemistries and accelerometers and gyroscopes which are used to measures movements and orientation of an object. Bioimpedance sensors record electrical conductivity in order to identify the distribution of weight in the body, while temperature sensors are used to measure body temperature. These sensors give stable information and such stable information will serve to make health check-ups earlier and also determine our health status through predictive algorithms (Pancar & Ozkan Yildirim, 2023). It is useful in chronic disease, preventive and Wearable Healthcare so that the client‘s total health record and care well-being influence of an individual patient can be enhanced to improve a patient's health. Even in health, superior sensors allow people or healthcare specialists to make the right choices that will affect health and sickness through offering real time accurate information about the health condition (Li et al., 2020b).

3.2 Social and Cultural Influences: Wearable medical technology consumers are fundamentally influenced by social and culture. This can be seen as knowledge, especially as more persons are getting conscious on the need to be fit and healthy. This awareness has created demand for stylish wearable gadgets for tracking multiple parameters such as, and heart rate, sleep quality, and physical activity, so individuals could take necessary steps to improve their health (Y.-S. Kao et al., 2019). Officially, people may still make such kinds of purchases because they require specific items, but social media and friends and family recommendations are also important. Social influence can have an impact by Recommendations from trustworthy individuals, friends and other influential persons Hairstyles Musician are easily influenced by recommendations from other individuals. In addition, the attitudes, views, and tendencies of the so-called powerful friends and members of families contribute to acquiring similar technologies (Kyytsönen et al., 2023). All of these social and cultural factors work together to create an enabling backdrop that would increase the adoption of wearable health-care devices. The use of health-centric wearables is also much stronger in societies that are open to new technologies, and wearables today require more innovative technologies due to the constantly growing trends of healthy initiatives like wellness programs or fitness challenges (Pancar & Ozkan Yildirim, 2023). Most purchasing decisions about devices are impacted by the peer group, particularly if the purchaser is young (Chatterjee & Gupta, 2017).

3.3 Economic Factors: The acceptability of wearing medical technologies is highly dependent with the economic value of the technology. Since these gadgets' prices can be unreasonably high, particularly for the relativity poor, affordability is necessarily a major factor. This is somehow true because expensive costs of health monitoring may prove a hurdle to the wider population from fully capitalizing on the improvement brought about by advanced technologies (Patil et al., 2022a). However, the perceived gain does not fully eradicate all of the financial problems. Thus, once consumers see additional health benefits they can get and notice the difference firsthand, they are willing to make the investment in wearable technology. The time at which customers will accept new technologies is therefore determined by their perception of the value of those new technologies ("An Analysis on Customer Perception towards Fintech Adoption," 2022). In addition, saturation and reduction of prices because of economic growth, and appearance of free money may make wearables cheaper. To this, people would rather purchase health conscious technologies during optimistic economies whenever their income is available. When coupled with wearables perceived benefits and value, therefore the increase in purchasing powers, the adoption rates of wearables can be significantly boosted (Wearable Technology Market Size, Share, Industry Growth 2032, n.d.).

3.4 Health Perception and Awareness in Hyderabad: Over time, Hyderabad has shifted its perception and understanding of health, owing to a number of factors that include agenda for growth in economy, increased disposable income and easier access to education in health (The Trends Defining the $1.8 Trillion Global Wellness Market in 2024, n.d.). More people of this city have grown more health conscious and thus more fitness centres, yoga classes, self-therapy programs and awareness of mental health has escalated. Also, patients' engagement and interactivity with the technology such as tele care services and digital health care applications have also made it easier for people to managing their own health(Wellness Trends around You in 2024, n.d.).

3.5 User Experience and Usability: The adoption of these devices is however higher within scenarios where these devices are easy to use and understand. The most common factors that have been mentioned are comfort, in the sense that the wearable technology needs to be comfortable enough for a person to wear while going about their daily business. Consumer experience is enhanced and adoption encouraged every time smart mobile devices are compatible(Caporusso et al., 2020).

3.6 Consumer Behaviour and Adoption Models: UTAUT (Unified Theory of Acceptance and Use of Technology) and TAM (Technology Acceptance Model) are two commonly applied models popular technology acceptance that can be traced in information systems adoption literature. Technology Adoption Models – Technology Acceptance Model (TAM) Overview of the TAM Framework is developed by Fred Davis. Davis (1989). People's intentions can be measured and the influencing factors on users' acceptance of information systems and technology can be described with the help of this model. It can be used to describe the users' motivation with respect to users' own standards, beliefs, and perceptions of extrinsic aspects, utility, and usability (Y. Wang, 2016). The TAM model identifies perceived usefulness (PU) and perceived ease of use (PEOU) as the two primary factors influencing an effect on consumers' acceptance of new technology. "The extent to which an individual feels that using a specific system would improve their performance on multiple aspects of their job" is what PU signifies. PEOU also refers to "the degree to which a person feels that using a particular system would be easy." Both, as per Patil et al. (2022b), have an influence on individuals' attitudes (A) towards using the technology, and that also impacts BI, which determines how much is actually used. Unified Theory of Acceptance and Use of Technology (UTAUT) Venkatesh et al. brought out the Unified Theory of Acceptance and Use of Technology (UTAUT) in 2003 (Lee & Lee, 2020). By integrating concepts that define how individuals adopt IT autonomously, it offers a simple conceptual framework. (Yanartaş & Ayaz, 2020) Performance expectancy, effort expectancy, social influence, and enabling conditions are the four basic intention and usage behaviour components explained by UTAUT. (Du Plessis & Bayaga, 2024) As stated by Venkatesh et al. (2016), performance expectation is the level of confidence that an employee has regarding the likelihood that technology would enable him or her to perform more effectively at work. The effort perceptions to use the device, however, are referred to as effort expectations (Tamilmani et al., 2017). The facilitation condition is the perceived organisational and technological support to employ the available technology, while social influence is the level to which an individual perceives that his or her important others expect him or her to use the new technology (Xue et al., 2024).

4. Benefits of Wearable Devices

Wearable Technology Devices encourage walking and exercise and are preventative against chronic illnesses. They are frequently used to reduce weight, boost productivity, and enhance sleep. Manufacturers of Wearable Technology Devices use a variety of strategies to increase user engagement, such as gamifying physical exercise with challenges and tournaments and sharing performance feedback on social media. Wearable Technology Devices (ex. FitBit) offer a platform where people can compete against their friends (Sergueeva & Shaw, 2017).

Wearables are also able to monitor vital signs, such as blood pressure, heart rate and glucose levels, providing real-time data to patients and healthcare professionals.

Wearable technology works with the purpose of being able to identify early warning signs for medical issues by constantly monitoring health metrics, this can be helpful so an intervention or treatment can be taken (Page, 2015).

Wearable devices can help in the early detection of diseases by tracking changes in health metrics, enabling timely intervention and treatment. These devices can provide personalized health insights and recommendations based on individual data, helping users make informed decisions about their health (Masoumian Hosseini et al., 2023).

5. Obstacles to Wearable Healthcare Adoption:

5.1 Perceived Inaccuracy of Data:
Ensuring wearable gadgets gather accurate and trustworthy data is a major challenge. Incorrect diagnosis and treatment recommendations may result from imprecise data. To promote mass adoption, wearable technology needs to be easy to use. Devices that are hard to operate or have complicated interfaces might turn off users, especially those who are not tech-savvy (Cheung et al., 2019).

5.2 **High cost of products:** The expense of wearable medical technology may put off numerous prospective consumers. Accessibility may be restricted by high costs, especially for those with lower incomes. Electronic Health Records (EHRs) and other healthcare systems must frequently be integrated with wearable technology. A lack of compatibility and standards may hamper this integration (Y. S. Kao et al., 2019).

5.3 **User Compliance:** Over time, if users misplace devices, forget to use them, or even get bored, the uniformity and reliability of the data that is collected could be influenced. Wearable tech needs to be in your face and pleasing to go along with. If they aren't, users may stop wearing them, leading to inconsistent data collecting (Canali et al., 2022).

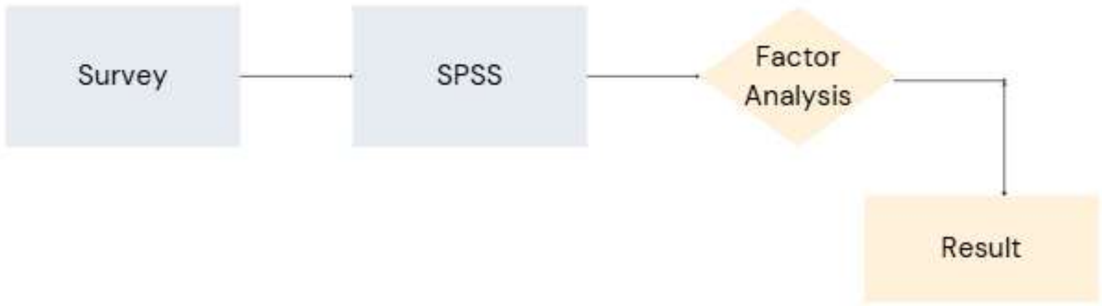
5.4 **Data Security Concerns:** User data needs to be protected from breaches, and privacy should be ensured. Wearable technology could be prone to cyberattacks because it collects sensitive health data. For wearable medical devices, navigating the regulatory environment can be challenging. Obtaining market acceptance requires adherence to healthcare laws and guidelines (Cheung et al., 2019).

6. Opportunities in Adoption of Wearable Devices:

Wearable technology can assist people in taking preventive measures to preserve their health and delay the onset of diseases by giving them access to real-time data on health parameters. This ongoing monitoring may result in better chronic disease management and early intervention (Luo et al., 2024). This may result in lower medical expenses and better general health. By providing access to the health data, wearable technology promotes active involvement in healthcare. Wearable technology allows medical professionals to monitor patients from distance, eliminating the need for frequent hospital stays and permitting prompt action when required. Wearable technology can assist global health initiatives by offering information on health patterns and outcomes across many locations (Kasoju et al., 2023).

Methodology

The study was a quantitative study that was undertaken to study the determinants of wearable healthcare device adoption within Hyderabad. A structured survey was used to collect data on 254 participants who were interviewed based on demographics, health-related behaviors, and perceptions of wearable technology.



Analysis And Results

Research Design and Sample

This study employed a quantitative, cross-sectional research design to examine factors influencing adoption within the target population. Data were collected using a structured questionnaire, which was distributed online via Google Forms to efficiently reach a diverse and digitally engaged audience in Hyderabad. The data collection process yielded 254 complete and valid responses, which constituted the final sample for statistical analysis.

Analytical Strategy

The analysis of the data was carried out with the help of IBM SPSS (Version 25). It was done in several steps that included the descriptive statistics to summarize and profile the characteristics of the sample. Next, inferential statistical tests were performed to evaluate the hypotheses: a Chi-Square Test of Independence for H1 and H3, a One-Way ANOVA for H2, and a Pearson Correlation for H4. Finally, to identify the most powerful predictors and understand their interaction, a Decision Tree Analysis was conducted using the CHAID algorithm. This exploratory technique is adept at segmenting a population into subgroups that share similar characteristics with respect to a target variable, in this case, adoption preference.

Results and Findings

1. **Inferential Analysis and Hypothesis Testing**

The hypothesis testing results provided a distinct idea of what factors were the major drivers of adoption and they can be seen below and tabulated in the table below.

1.1 **Hypothesis 1 (Gender):** The Results from the Chi-Square test showed a significant relationship between gender and willingness to use wearable healthcare devices (Pearson $\chi^2 = 21.679$, $p < 0.001$), supporting the rejection of H_01.

Summary of Cases Processed

	Valid Cases	Valid Percent	Missing Cases	Total Cases	Total Percent
Gender * Would you be willing to use wearable healthcare devices in the future?	254	100.0%	0	0.0%	254 (100.0%)

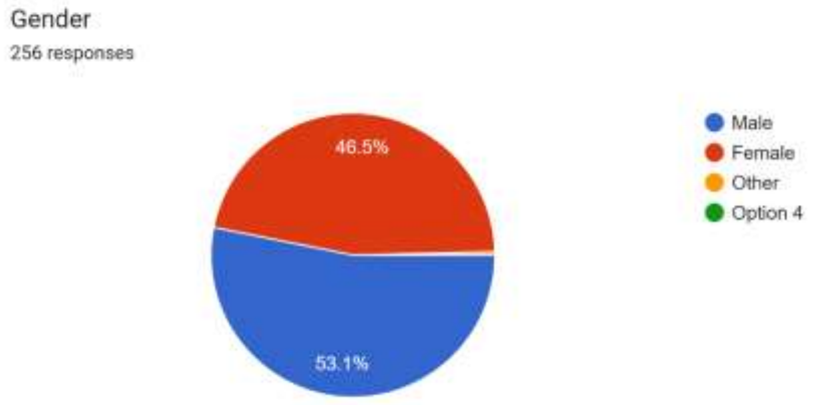
Gender * Would you be willing to use wearable healthcare devices in the future? Crosstabulation

Gender	Definitely	Maybe	No	Total
Female	53	62	3	118

Male	69	53	13	135
Other	0	0	1	1
Total	122	115	17	254

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Notes
Pearson Chi-Square	21.679	4	<.001	3 cells (33.3%) have expected count less than 5; minimum expected count = 0.07
Likelihood Ratio	13.869	4	.008	
N of Valid Cases	254			254

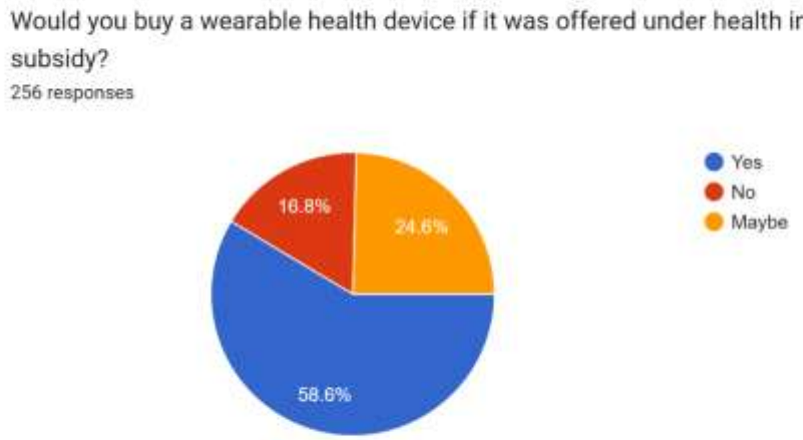


1.2 **Hypothesis 2 (Subsidy):** The ANOVA test showed no statistically significant difference in purchase willingness based on a subsidy ($F = 0.612$, $p = 0.655$). We therefore **fail to reject the null hypothesis (H_02)**.

ANOVA Effect Sizes

	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper	Notes
Eta-squared	.010	.000	.030	Based on fixed-effect model
Epsilon-squared	-.006	-.016	.014	Estimated from fixed-effect model
Omega-squared Fixed-effect	-.006	-.016	.014	Negative but less biased

				estimates retained
Omega-squared Random-effect	-.002	-.004	.004	

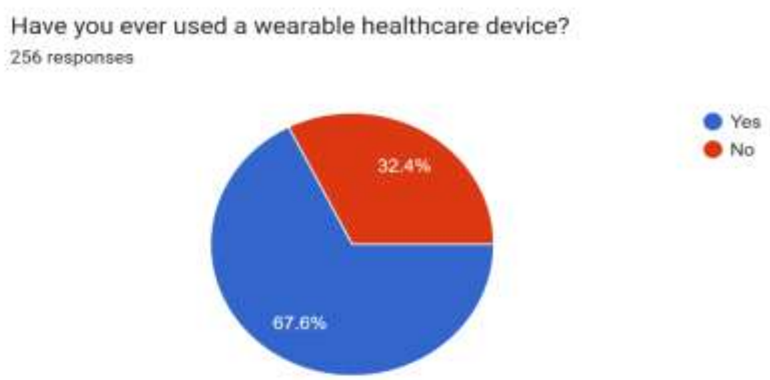


1.3 **Hypothesis 3 (Prior Usage):** A significant association was found between prior use of an HWD and the frequency of visits to healthcare professionals (Pearson $\chi^2 = 26.882$, $p < 0.001$). This result leads to the **rejection of the null hypothesis ($H_0 3$)**.

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	26.682	3	<.001
Likelihood Ratio	25.413	3	<.001
Linear-by-Linear Association	1.235	1	.267
N of Valid Cases	254		

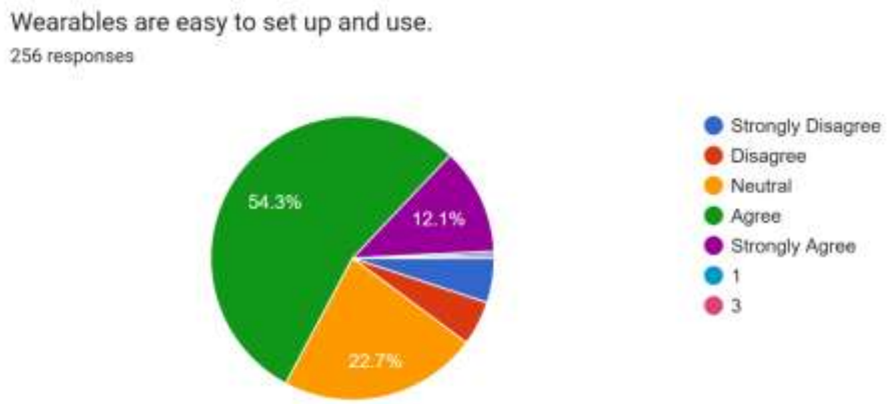
a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 7.52.



1.4 **Hypothesis 4 (Ease of Use):** The correlation analysis did not find a significant relationship between perceived ease of use and future adoption intention (p = 0.601). Consequently, we **fail to reject the null hypothesis (H_04).**

Correlations

	Wearables are easy to set up and use.	Would you be willing to use wearable healthcare devices in the future?
Wearables are easy to set up and use.	Pearson Correlation Sig. (2-tailed) N	1 254
Would you be willing to use wearable healthcare devices in the future?	Pearson Correlation Sig. (2-tailed) N	-.033 .601 254
	-.033 .601 254	1 254



1.5 **Summary of Hypotheses Results:**

Hypothesis	**Statistical Test**	**p-value**	**Decision**	**Accepted?**
H1: **Gender** influences willingness to use wearables	Chi-Square Test	< 0.001	Reject H_0	**Accepted**
H2: **Subsidy/Insurance** influences purchase decision	One-Way ANOVA	0.655	Fail to Reject H_0	Not Accepted
H3: **Prior usage** affects check-up frequency	Chi-Square Test	< 0.001	Reject H_0	**Accepted**
H4: **Ease of use** impacts intention to use	Pearson Correlation	0.601	Fail to Reject H_0	Not Accepted

2. Predictive Modeling: The Decision Tree Analysis

The CHAID decision tree analysis provided a hierarchical model of the most influential factors, achieving an overall classification accuracy of 66.9%.

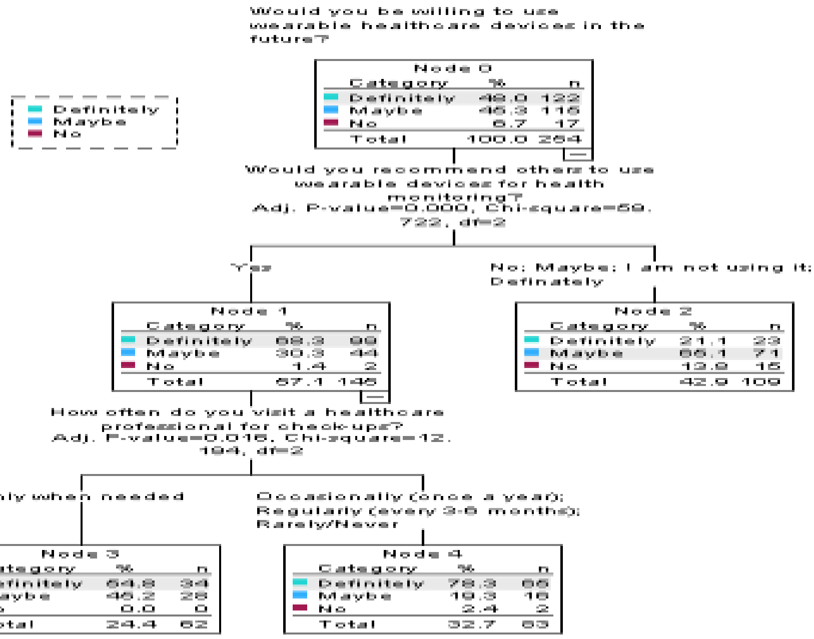
2.1 **Primary Predictor:** The analysis identified the variable **"Would you recommend wearable devices to others?"** as the most powerful predictor of adoption intention ($p < 0.001$).

2.2 **User Segmentation:** Based on this primary predictor, the model partitioned the sample into two distinct segments:

2.2.1 **Segment 1 -** The Advocates (Strong Adopters): Comprising individuals who would recommend HWDs. A decisive 68.3% of this group expressed a definite intention to use the technology in the future.

2.2.2 **Segment** 2 - The Hesitants: Composed of individuals who would "Maybe" or "No" recommend the devices, with only 21.1% expressing definite future intent.

2.2 **Secondary Predictor:** For "The Advocates" segment, the model identified the frequency of health check-ups as a secondary significant predictor ($p = 0.016$). Advocates who engage in regular health monitoring were the most likely future users (78.3% definite intent).



Discussion

This study shows that social influence and individual health engagement drive wearable healthcare adoption in Hyderabad more than usability or cost. The rejection of H1 and H3 indicates that adoption varies across segments, with higher usage among individuals already proactive about their health. The failure to reject H2 and H4 suggests that financial subsidies and ease of use do not significantly affect purchase intent, implying that users value perceived health benefits over price and consider modern wearables sufficiently user-friendly. The CHAID analysis reinforces these findings by identifying peer recommendation as the strongest predictor of adoption, highlighting social proof and user advocacy as key growth drivers—consistent with prior research on technology adoption.

Conclusion

The research highlights a clear ranking of the factors that influence the adoption of wearable healthcare devices in Hyderabad.

1. Recommending wearables to others is the strongest predictor of adoption, signifying that peer influence and personal conviction are critical.

2. Regular health check-ups and prior usage are strongly associated with a higher willingness to adopt, linking adoption to pre-existing health consciousness.

3. Gender significantly influences adoption, while factors like financial subsidies and ease of use do not appear to be primary drivers.

4. The predictive model achieved an overall accuracy of 66.9%, validating the importance of these key influencing factors.

These results can guide wearable tech developers, healthcare providers, and public health departments in tailoring marketing and educational strategies to foster wider adoption.

Limitations and Future Scope

One of the limitations of the study is its geographic scope since it was conducted among the urban population in Hyderabad hence the findings might not be applicable to other regions. To get a larger picture of the usage of wearable technologies in India, it is possible to expand the research further and incorporate the use of tier-2 cities, semi-urban, and rural areas, which might reveal region-specific factors of adoption.

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