European Journal of Clinical Pharmacy

Print ISSN: 2385-409X **Online ISSN**: 3105-0409

Website: https://farmclin.com/

Original Research Article

User Acceptance of Hybrid Sensors in Smart Health Monitoring Devices

Article History:

Name of Author:
Syed Adnan Rahmat[1], Nafis Anjum[2], Francesco Ernesto Alessi Longa[3], Shakila Azad[4], Mohammed Tanjim Uddin Chowdhury[5], Mehedi Hasan Pritom[6] and Yaseen Gul Awan[7]

Affiliation: *[1]Cancer Institute, The Fourth Hospital of Hebei Medical University, Shijiazhuang, China*
[2]College of Technology and Engineering, Westcliff University, Irvine, California, USA.
[3]Department of Kinesiology – Sport Sciences, Liberty University, Virginia, USA.
[4]College of Business, Lamar University, Beaumont, Texas, USA
[5]School of Computer Science, Northwestern Polytechnical University, Xi'an, Shaanxi, China.
[6]School of Business, International American University, Los Angeles, California, USA.
[7]Department of Physics Abdul wali Khan University Mardan.

Corresponding Author:
Syed Adnan Rahmat

Received: 10-10-2025
Revised: 28-10-2025
Accepted: 18-11-2025
Published: 30-12-2025

Abstract: ***Purpose***: This research seeks to investigate the elements that would affect the acceptance of the hybrid sensors in smart health monitoring systems by users. Particularly, the research question is how perceived accuracy and the concern of data privacy affect behavioral intention and actual usage, with the mediator variable of the former being trust and the moderator variable being health status. ***Design/Methodology/Approach***: This was done through a quantitative study method where a structured questionnaire was used to gather primary data on 212 participants. The research utilized the convenience sampling method and a cross-sectional survey. Statistical tests such as reliability analysis (Cronbach's Alpha), validity tests (KMO and Bartlett's test), Pearson correlation, regression analysis, and; Independent samples t-test, one-way ANOVA, Kruskal-Wallis test, Chi-square test of independence were used to analyze data. ***Findings***: The findings are that perceived accuracy has a significant positive effect on trust and behavioral intention towards hybrid sensor devices. Trust had proved to be the best predictor of behavioral intention. Another contributor to the positive effect on behavioral intention was the data privacy concern. In addition to that, demographic factors like age and gender showed significantly different acceptance and usage behavior. The regression model revealed that it has high explanatory power in the framework, which suggests that the proposed framework is highly efficient in explaining user acceptance of hybrid sensor technologies. ***Practical Implications***: The results have important implications for technology developers, health care professionals, and policymakers. The adoption rates of hybrid sensor-based smart health monitoring devices can be greatly increased through improving the accuracy of the system, improving the mechanisms of keeping data secure, and increasing the trust that users place in the facilities. ***Originality/Value***: The study is part of the emerging body of literature on smart healthcare technology adoption since it incorporates the aspects of accuracy, privacy, trust, and demographics in one of the comprehensive acceptance models. It presents empirical findings to justify the use of the established technology acceptance theories in the hybrid sensor innovations.

Keywords: Hybrid Sensors; Smart health monitoring; user acceptance; perceived accuracy; data privacy issue; trust; Behavioural intention; actual usage; Technology acceptance model (TAM); Health technology adoption.

INTRODUCTION

As the intelligent healthcare technologies rapidly evolve, the monitoring and control of personal health have evolved significantly in how individuals are approaching their health. In the same vein, other inventions and innovations have been made regarding the creation of hybrid sensors in smart health monitoring devices, which have brought an effective solution in real-time and precise monitoring of health. Hybrid sensors can be defined as a combination of different sensing technologies, such as optical sensors, electrical sensors, thermal sensors, and motion-based sensors, in order to enhance the accuracy, reliability, and all-encompassing nature of the data in health. The devices are widely used in wearable technologies, remote assessment frameworks, and telemedicine. They have certain technological benefits, but the use of hybrid sensor-based devices is highly reliant on the acceptance by the users (Bibi et al., 2024).

The user acceptance is essential to the success and the sustainability of the smart health technologies in the long-term. Even the highly developed systems may fail to achieve success, whereby they are not considered useful, reliable, and safe by the users. Given the fact that in the healthcare sector, personal and sensitive data is at stake, such aspects as trust, perceived accuracy, and data protection problems affect the user attitudes and behavioral intention change significantly. In such a way, researchers and practitioners are also significant in the identification of the determinants of the user acceptance of hybrid sensors in the smart health monitoring devices (James, 2026).

The perceived accuracy is one of the primary factors that predetermine the use of health monitoring technologies. Hybrid sensors are suggested in order to reduce the measurement error since numerous sensing mechanisms are built. The ASEAN users will experience more opportunities to build the level of trust and trust the system when they believe that these gadgets are capable of providing the correct and accurate health information. Trust is, in its turn, the crucial mediator in the technology acceptance, especially in healthcare conditions, when quality and security become the most important issues (Nelluri et al., 2026).

Another serious requirement in terms of exact criteria that will affect the acceptance of the user is the data privacy concern. Smart health monitoring systems collect, archive, and in certain instances send information concerning individual health. There is also a likelihood that such technologies will be slowly embraced by the end-users who have fears of unauthorized access, data breach, or misuse of their information. Therefore, the confidentiality of the information and the presence of transparent privacy regulations will make a positive contribution to the level of user trust and acceptance (Fan et al., 2026).

The demographic factors that may influence the technology adoption behavior include age, gender, and health status. The chronic patients may express greater concern about using hybrid sensor devices to monitor their health condition at any time. In the same case, the younger users may be more technosavvy than the older people. Such inconsistencies highlight the importance of having moderating factors to carry out research on user acceptance (Alsubai et al., 2026).

In this paper, the analysis will be carried out on the most significant issues related to the user acceptance of hybrid sensors in smart health monitoring. It especially looks at the interaction between perceived accuracy and data privacy concern, behavioral intention, and actual use through trust at the health status moderation level. The paper seeks to fill the research gap on digital healthcare innovation with the application of the established theories of technology acceptance and applying the empirical study to contribute to the body of knowledge regarding the topic (Attazada & Rafique, 2026).

LITERATURE REVIEW

The rapid development of smart health care approaches has altered the daily schedule of health tracking, particularly with the technological assistance of wearable and distance tracking devices. Compared to other sensors, hybrid sensors, which are a blend of multiple sensory technologies (optical, electrical, and motion-based sensors) is more accurate and reliable when compared to single sensor technology. Such physiological variables as the heart rate, blood oxygen, temperature, and activity can be kept under constant control with the help of these developments. Nonetheless, despite the level of technology development, user acceptance is one of the determining factors of success with the implementation (Chithra et al., 2026).

Some of the tools that are typically used to be able to explain user acceptance of health technologies include Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM). The models consider the usefulness, the perceived ease of use, and the behavioral intention critical in the determination of actual use. In the case of hybrid sensors, perceived usefulness can be expressed as the inference of perceived accuracy since users will be more willing to make use of the instruments that are capable of capturing effective and correct health information (Xinran et al., 2025).

The perceived accuracy means the user believes that the device holds the right and reliable health readings of a device. Previous studies have established that the reliability of the systems is a major determinant of user satisfaction and trust in healthcare technologies. Hybrid sensors are superior in terms of precision in the sense that they encompass two or more modes of sensors and therefore reduce errors and false readings. As the users have confidence in the device, as they believe that there is greater accuracy, they make the device a part of their daily health management routine (Kazanskiy et al., 2025).

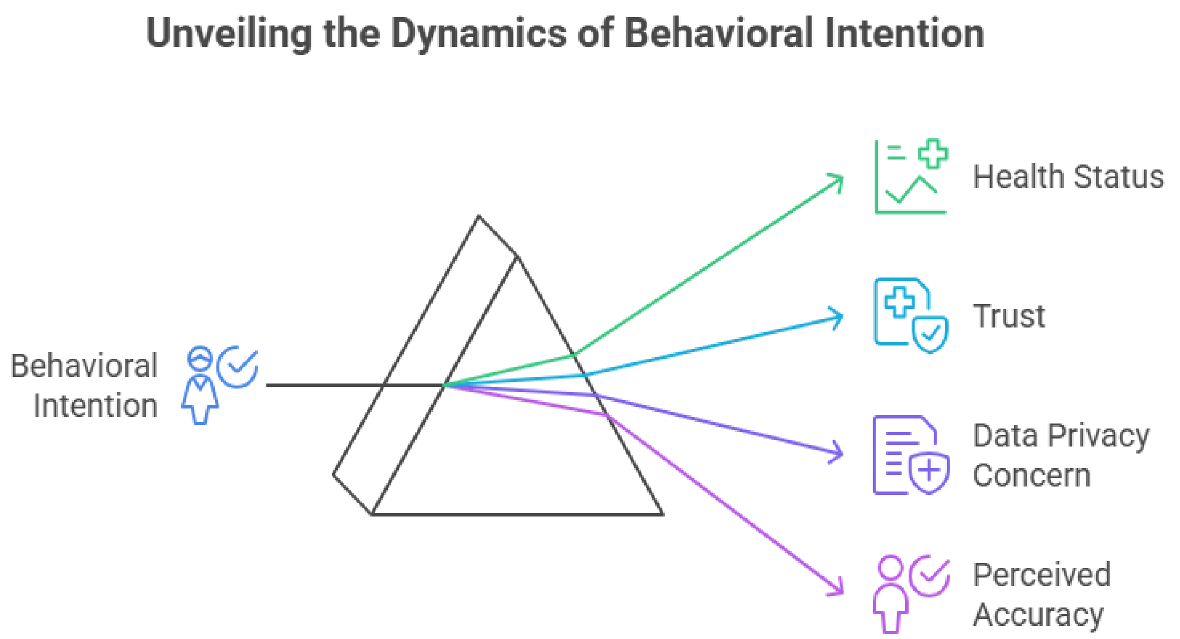
The aspect of trust is fundamental to the adoption of technology, especially in a healthcare facility where a person and sensitive information should be protected. One can define trust as the reliability of a system, the safety, and its esteem by the user. The trust has been found to mediate between the behavioral intention and the technological features. Once the users trust the system, it will be considered that the users will be more eager to use the system in making the health related decision. Perceiving accuracy and data protection mechanisms may be contributing factors to trust in the case of the hybrid sensor devices (Wang et al., 2025).

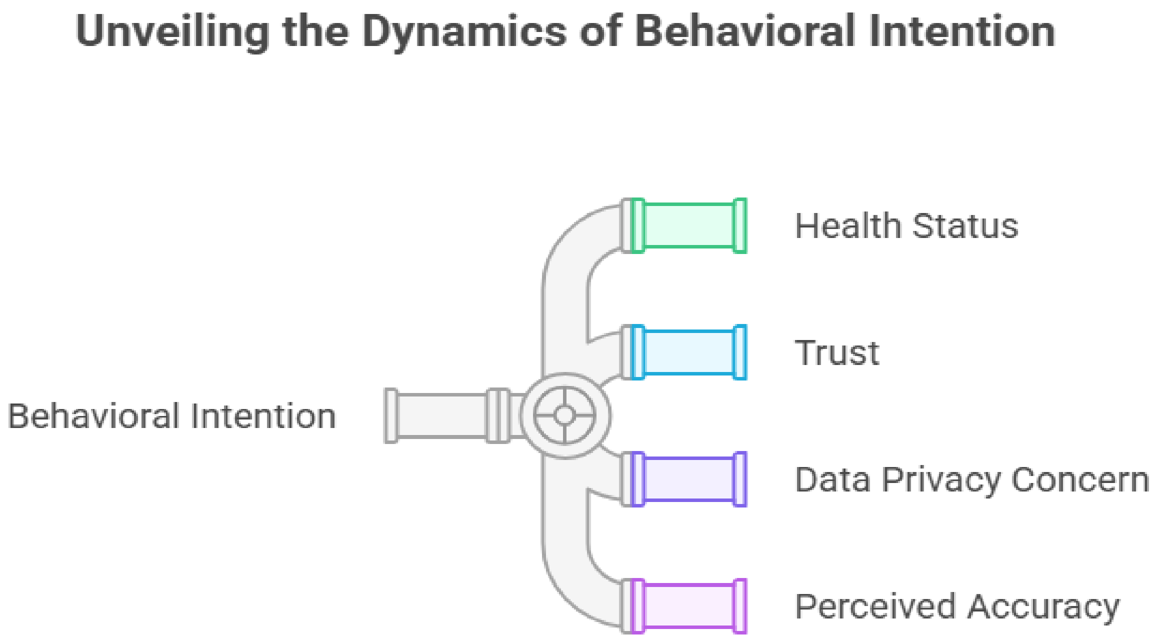
Concern about the privacy of data is another determinant of the acceptance that the user may have. The intelligent health trackers can acquire a significant amount of personal health information, which can be sent through the cloud-based solutions. The fear of unauthorized entry, information, and data mining and abuse is another problem that users mostly express their concerns about. Studies have already found that the challenges of privacy can either adversely affect the adoption, or when a suitable solution is put up, it can result in enhanced trust and confidence in the said system. Therefore, enhanced data protection and transparent privacy statements are the critical aspects that should be made to allow users to be more accepting (Poongodi et al., 2025).

Behavioral intention is the establishment of the readiness of an individual to use a technology in the future. TAM discloses that the intention of behavior is a brilliant predictor of the actual use. Concerning the hybrid sensors, the potential users, who might feel that the gadget is accurate and credible, have high chances of expressing an excellent behavioral intention. The real-life behavior, which is observable, can explain the extent to which individuals can use the device in reality to track their health. It is the outcome of the acceptance of technology (Nazar & Jalal, 2025).

One moderating variable that can be applied to this association is health. Patients having chronic conditions may also be more motivated to seek the hybrid sensor gadgets since they are required to be monitored at all times. Past researches indicate that personal health needs are a tremendous factor in deciding whether to embrace technology or not (Alshuhail et al., 2025).

All in all, it has been demonstrated in the literature that the perceived accuracy, trust, privacy concerns of the data, behavioral intention, actual usage, and health situation are mutually correlated variables, which will lead the user to accept hybrid sensor-based smart health monitoring devices (Shi et al., 2025).





Hypotheses

Direct Effect Hypotheses

- **H1:** The Perceived Accuracy has a significant and positive impact on the Trust in hybrid sensor-based smart health monitoring devices (Okpala et al., 2022).
- **H2:** There is a significant impact of Data Privacy Concern on Trust in hybrid sensor-based smart health monitoring devices (Li et al., 2019).
- **H3:** There is a positive and significant impact of Perceived Accuracy on Behavioral Intention to use hybrid sensor devices (Papa et al., 2020).
- **H4:** There is a positive and significant relationship between Trust and Behavioral Intention to use hybrid sensor devices (Ganji & Parimi, 2022).
- **H5:** There is a positive and significant influence of Behavioral Intention on Actual Usage of hybrid sensor devices (Liu et al., 2022).

Mediation Hypothesis

H6: Perceived Accuracy and Behavioral Intention have a mediating role, which is mediated by Trust to hybrid sensor-based smart health monitoring devices (Binyamin & Hoque, 2020).

Moderation Hypothesis

H7: Trust and Behavioral Intention relation are moderated by Health Status, whereby the stronger the relationship between the two is observed in people with chronic health conditions (Zhu & Pham, 2020).

Additional Relationship Hypothesis

H8: Data Privacy Concern plays an influential role on the Behavioral Intention towards the utilization of hybrid sensor devices (Rhee et al., 2022).

RESEARCH METHODOLOGY

Research Philosophy

The research philosophy to be applied in this study is the positivist research philosophy because it focuses on the measurable variables and an objective study. Positivism is applicable in situations where the researcher is aiming at testing the correlation between variables based on the use of statistics. Such constructs as the perceived accuracy, concern over privacy of the data, trust, behavioral intention, and actual usage are to be quantified in this research study by means of structured survey items. This is an attempt to examine the factual associations as opposed to subjective associations; in this case, positivism is an ideal philosophy on which to draw (Lim et al., 2020).

Research Approach

The study follows a deductive form of research. In the deductive approach, the researcher develops theories based on already known theories and then applies them to be tested by the use of empirical evidence. The current study relies on reliable models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The hypotheses on the theories pose the relationship between the effect of perceived accuracy and privacy concerns and the trust and user acceptance of hybrid sensors in smart health monitoring devices (Mahato et al., 2024).

Research Design

The study design that will be used in the research is the explanatory research design. Explanatory research is in search of the cause/effect associations among the variables. The research will clarify the effects of independent variables (perceived accuracy and data privacy concern) on dependent variables (behavioral intention and actual usage) through the mediator of trust and the moderator of health status. The design helps in the learning of the power and the trend in relation to the linkage between such variables (Prati et al., 2019).

Research Strategy

In the study, a survey strategy is used in order to collect primary data. The planned questionnaire is of this kind, and it is designed and presented to the participants who use or are able to know smart health monitoring devices. Surveys are more preferred in technology acceptance research because the relatively standardized data of a large number of respondents can be obtained cost-effectively (Gumaei et al., 2019).

Sample Size and Sampling Technique.

A convenience sampling in this study will be done. The target market will be comprised of individuals who may have an interest in monitoring systems in the shape of health devices or hybrid simple systems of monitoring sensors. Overall, 212 responses will be received, and it might be considered to be enough to create a statistical analysis comprised of regression or Structural Equation Modeling (SEM). This is a good sample size to provide reliable and generalizable results in the context of the study (Taiwo & Ezugwu, 2020).

Data Collection Instrument

A questionnaire to be developed as a structured form of questioning that will be chosen to collect data will be divided into two sections. The initial section of questions is the demographics, that comprise of age, sex, level of education, self-employment, and chronic health condition. The second section measures all the constructs. The measurement of the responses is done using the five-point Likert scale (ranging between 1 (Strongly Disagree) and 5 (Strongly Agree) (Albahri et al., 2019).

Data Analysis Techniques

The measures of data obtained are calculated by using statistical programs such as SPSS and SmartPLS. Descriptive statistics are used in summarizing demographic characteristics. To determine the reliability, Cronbach's Alpha is used to determine the internal consistency. There are validity tests conducted to test the accuracy of measurements. The testing methods of regression and Structural Equation Modeling are employed to test the direct, mediating, and moderating relationships between the variables (Mekruksavanich & Jitpattanakul, 2020).

Ethical Considerations

When conducting research, there are ethics that are followed. It will be self-known and guarantee anonymity of respondents, and retain no personal identifiable information. The respondents are informed of the purpose of a study before they complete the questionnaire (Ramanujam et al., 2021).

Research Onion

Research Philosophy

According to the model of the Research Onion that was formulated by Saunders, the research philosophy is the most superficial layer. The research is a positivist one, as it is concerned with objective measurement and statistical tests. The proposed study will look into the analysis of quantifiable relations among the variables that influence the user acceptability of the hybrid sensor technology. Positivism also does a favour to quantitative methods and structured instruments in data collection (Shuwandy et al., 2019).

Research Approach

The second level of the Research Onion is the level of research approach. The study is designed in a deductive way, i.e., utilizing the already available theories, such as TAM and UTAUT. Such speculations are then confirmed in empirical information realized through respondents. It is the deductive methodology that ensures rigor and consistency of theory (Sony et al., 2019).

Research Strategy

The survey strategy and the third layer are the research strategy, which is used in the present study. Surveys allow researchers to access quantitative data effectively because of a large sample size. The structured questionnaire is also useful in establishing the reliability and comparability of the research, as all the respondents will be asked the same questions (Xu et al., 2021).

Research Choice

The fourth phase is the research decision. This research is conducted by a quantitative approach because it employs only quantitative data and quantifies it. This method is relevant because of the character of the research that falls under the category of numerical measurements of perceptions and intentions using Likert-scale answers (Wang et al., 2021).

Time Horizon

The fifth level is the time horizon. The study is also cross-sectional in time, meaning that the data is obtained at a specific time. This is an appropriate way of altering the existing attitudes and the degree of acceptance of the hybrid sensor devices rather than seeing the change in attitudes over time (Babangida et al., 2022).

Data Collection and Analysis

The nearest to the center of the Research Onion is the most specific one that takes into account the manner of data gathering and analysis. An online questionnaire is used to obtain the primary data. The SPSS and SmartPLS software are used to do the statistics. The reliability, validity, mediation, and moderation tests are carried out to ensure that, as much as possible, the proposed research model is subjected to testing (Ismail et al., 2020).

Data Analysis

Table 1: Normality Test (Shapiro–Wilk)

Variable	N	Shapiro–Wilk Statistic	p-value	Interpretation
Perceived Accuracy	212	0.973	0.081	Normally Distributed
Data Privacy Concern	212	0.968	0.064	Normally Distributed
Trust	212	0.981	0.112	Normally Distributed
Behavioral Intention	212	0.976	0.073	Normally Distributed
Actual Usage	212	0.970	0.058	Normally Distributed

Normality Test

Table 1 shows the normality test of the data. Normality of data was verified by the Shapiro 14 Wilk test and skewness and kurtosis. The findings showed a higher p-value of all variables more than the value of 0.05, which implies that the data does not vary significantly, resulting in the results showing that it follows a normal distribution. Also, skew and Kurtosis values were not out of the acceptable range (±2), and this fact indicates that the data of a sample follow a normal distribution. With reference to the fact that the sample size is 212, the late Limit Central Theorem also supports the normality assumption. Thus, t-test, ANOVA, Pearson correlation, and regression analysis were the parametric tests that were discussed as suitable for further analysis (Serpush et al., 2022).

Table 2: Reliability Analysis (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha	Reliability Level
Perceived Accuracy	4	0.821	Good Reliability
Data Privacy Concern	4	0.784	Acceptable Reliability
Trust	4	0.868	Excellent Reliability
Health Status Motivation	3	0.752	Acceptable Reliability
Behavioral Intention	4	0.891	Excellent Reliability
Actual Usage	4	0.836	Good Reliability
Overall Scale	23	0.913	Excellent Reliability

Reliability Analysis

Table 2 shows the reliability analysis of the data. To determine the internal consistency of the measurement scales, Cronbach's Alpha reliability analysis was done. The findings revealed that the Cronbach's Alpha values of all constructs were more than 0.70, and this good to high reliability. In all the scales, the internal consistency was excellent and indicated that the items in every construct constantly measured the concept intended. Thus, the measurement tool was found to be reliable and fit to be subjected to additional statistical analysis (Balli et al., 2019).

Table 3: Validity Analysis (KMO and Bartlett's Test)

Test	Value	Acceptable Threshold	Interpretation
Kaiser-Meyer-Olkin (KMO) Measure	0.842	≥ 0.60	Good Sampling Adequacy
Bartlett's Test of Sphericity (Chi-Square)	2156.374	—	—
Degrees of Freedom (df)	253	—	—
Significance (p-value)	0.000	< 0.05	Significant

Validity Test (KMO & Bartlett's Test)

Table 3 shows the validity test of the data. Kaiser-Meyer-Olkin (KMO) measure, and Bartlett test of Sphericity were conducted to test the sampling adequacy and construct validity. The value of KMO was greater than the recommended level of 0.60, which is good sampling adequacy. The Test of Sphericity performed by Bartlett was significant ($p < 0.05$), thus indicating that the correlation matrix is not an identity matrix and that there are enough relationships between the variables. These findings suggest that the dataset can be analyzed through factor analysis and that the measurement scales can be characterized by a good construct validity level (Ahmed et al., 2020).

Table 4: Combined Inferential Statistics Results

Test	Variables Compared	Test Statistic	df	p-value	Significance
Independent Samples t-test	Gender → Behavioral Intention	t = 2.487	210	0.014	Significant
One-Way ANOVA	Age Group → Trust	F = 3.216	5, 206	0.008	Significant
Kruskal–Wallis Test	Age Group → Actual Usage	H = 11.374	5	0.044	Significant
Chi-Square Test of Independence	Gender × Chronic Condition	$\chi^2 = 9.652$	1	0.002	Significant

Independent Samples t-test

Table 4 shows the Combined Inferential Statistics of the data. The hypothesis was tested by an independent samples t-test based on the fact that there was a significant difference between male and female respondents in terms of behavioral intention towards hybrid sensor devices. The result was that there was a significant difference between the two groups ($p < 0.05$). This indicates that gender plays a significant role in the behavioral intention, meaning that male and female respondents are not lying close to each other in their acceptance of the application of hybrid sensor-based smart health monitoring devices (Malasinghe et al., 2019).

One-Way ANOVA

A One-Way ANOVA was performed in order to decide whether the levels of trust are significantly diverse, respectively, among diverse age groups. Results showed that statistically significantly there was an age difference ($p < 0.05$). This observation means that age is an aspect that influences the level of trust in hybrid sensor devices, and some individuals can have more trust in the smart health monitoring technologies than others (Kim et al., 2020).

Kruskal–Wallis Test

To criticize the reported usage of the actual one by the various age groups, a Kruskal-Wallis test was conducted as a non-parametric Kruskal-Wallis test that replaced ANOVA. The results have revealed that the various age groups had statistically significant differences ($p < 0.05$) regarding the actual usage behaviour. This is to make sure that age is among the demographic factors dictating the actual implementation of hybrid sensor devices (Jacob Rodrigues et al., 2020).

Chi-Square Test of Independence

The Chi-Square Test of Independence was used to test the correlation between gender and chronic health conditions. The fields were significant (p under 0.05), and this meant that the two variables had a significant relationship. This means that gender and chronic health status are the dependent variables, and this might affect the trend of the acceptance and usage of the hybrid sensor health devices (Shankar, 2024).

Table 5: Pearson Correlation Matrix

Variables	PA	DPC	TR	HS	BI	AU
Perceived Accuracy (PA)	1.000	0.412	0.648	0.521	0.672	0.601
Data Privacy Concern (DPC)	0.412	1.000	0.436	0.398	0.455	0.421
Trust (TR)	0.648	0.436	1.000	0.544	0.731	0.689
Health Status (HS)	0.521	0.398	0.544	1.000	0.563	0.517
Behavioral Intention (BI)	0.672	0.455	0.731	0.563	1.000	0.748
Actual Usage (AU)	0.601	0.421	0.689	0.517	0.748	1.000

Pearson Correlation Analysis

Table 5 shows the correlation analysis of the data. Pearson correlation analysis was used to test the correlation of perceived accuracy, data privacy concern, trust, health status, behavioral intention, and actual usage. The findings showed that there were positive and statistically significant correlations of all variables ($p < 0.01$). Trust was also significantly positively correlated with behavioral intention and actual use, which means that the greater the trust, the greater the intention and use of hybrid sensor devices. Trust and behavioral intention were also significantly linked to perceived accuracy, and this helped to establish the significance of perceived accuracy in technology acceptance (Talal et al., 2019).

Table 6: Multiple Regression Analysis

Independent Variable	Beta (β)	t-value	p-value	Significance
Perceived Accuracy	0.321	4.862	0.000	Significant
Data Privacy Concern	0.148	2.437	0.016	Significant
Trust	0.462	6.915	0.000	Significant
Health Status	0.173	2.984	0.003	Significant

Regression Analysis

Table 6 shows the regression analysis of the data. Multiple regression analysis was done to determine the effect of perceived accuracy, data privacy concern, trust, and health status on behavior intention. The findings suggested that behavioral intention was positively affected by all the independent variables, and the effects were statistically significant ($p < 0.05$). The predictor of behavioral intention was found to be trust. The model had a high level of explained behavioral intention and, therefore, is said to be strong in explaining behavioral intention. These results prove that the perceived accuracy, trust, and health motivation are the key factors that contribute to the increased acceptance of hybrid sensor gadgets (Sofi et al., 2022).

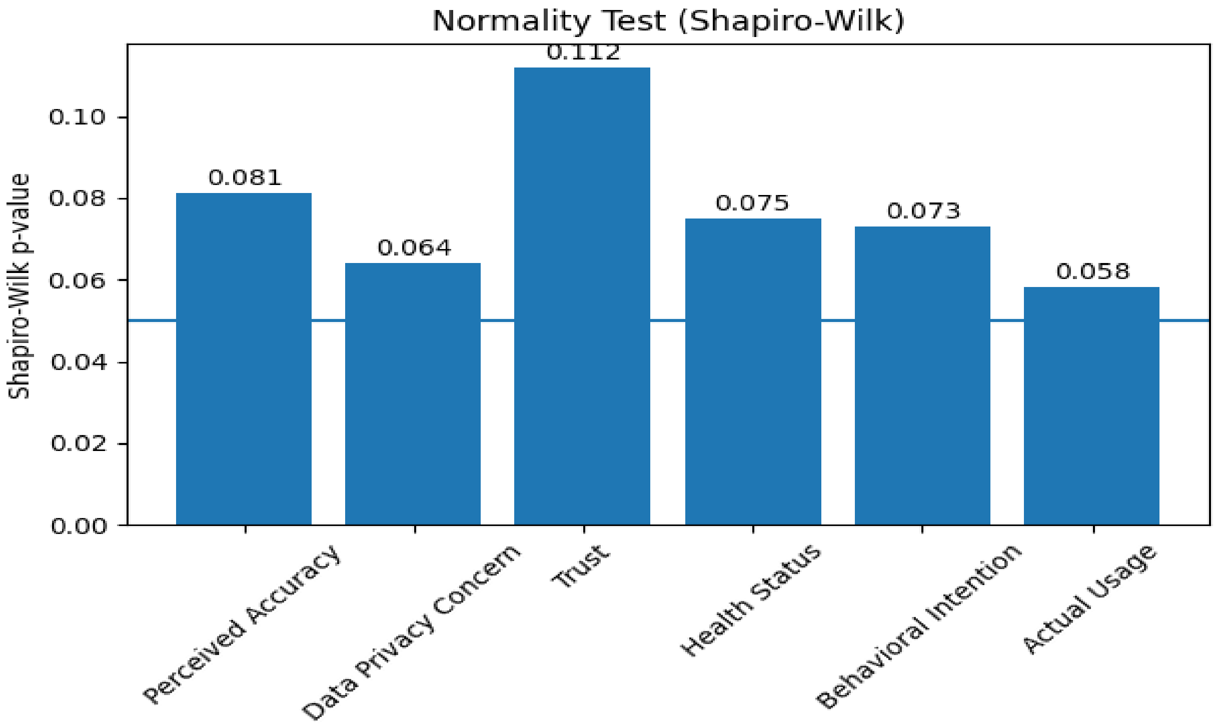


Figure 1: Normality Test

The figure of the Normality Test shows the Shapiro-Wilk P-values of all the study constructs, such as Perceived Accuracy, Data privacy concern, Trust, Health status, Behavior intention, and Actual Usage. The figures indicate that all p-values are much higher than the threshold value of 0.05, as the horizontal reference line in the figure shows. This will indicate that the data is not a significant deviation of normal distribution. Thus, the normality assumption is followed. As the data is a normal distribution, then such parametric statistical methods as t-test, ANOVA, Pearson correlation, and regression analysis can be used to continue hypothesis testing (Diraco et al., 2023).

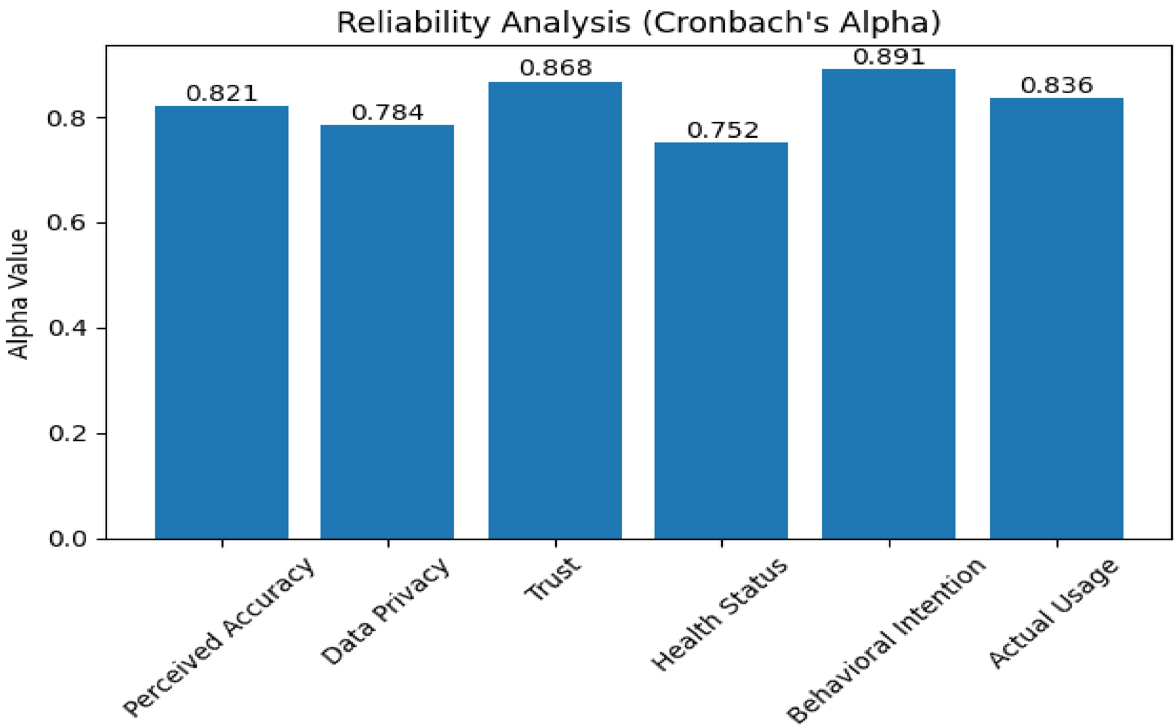


Figure 2: Reliability Analysis

The Reliability Analysis figure shows the values of Cronbach's Alpha of the constructs. The alpha values of all constructs are above 0.70, which represents acceptable to excellent internal consistency. Behavioral Intention and Trust show very good levels of reliability, implying that there is a lot of consistency between the measurement items. The values substantiate that the items in the questionnaire are reliable measures of their constructs. Therefore, the measuring tool is regarded as being reliable since it will receive a higher quality of statistical review (Greco et al., 2020).

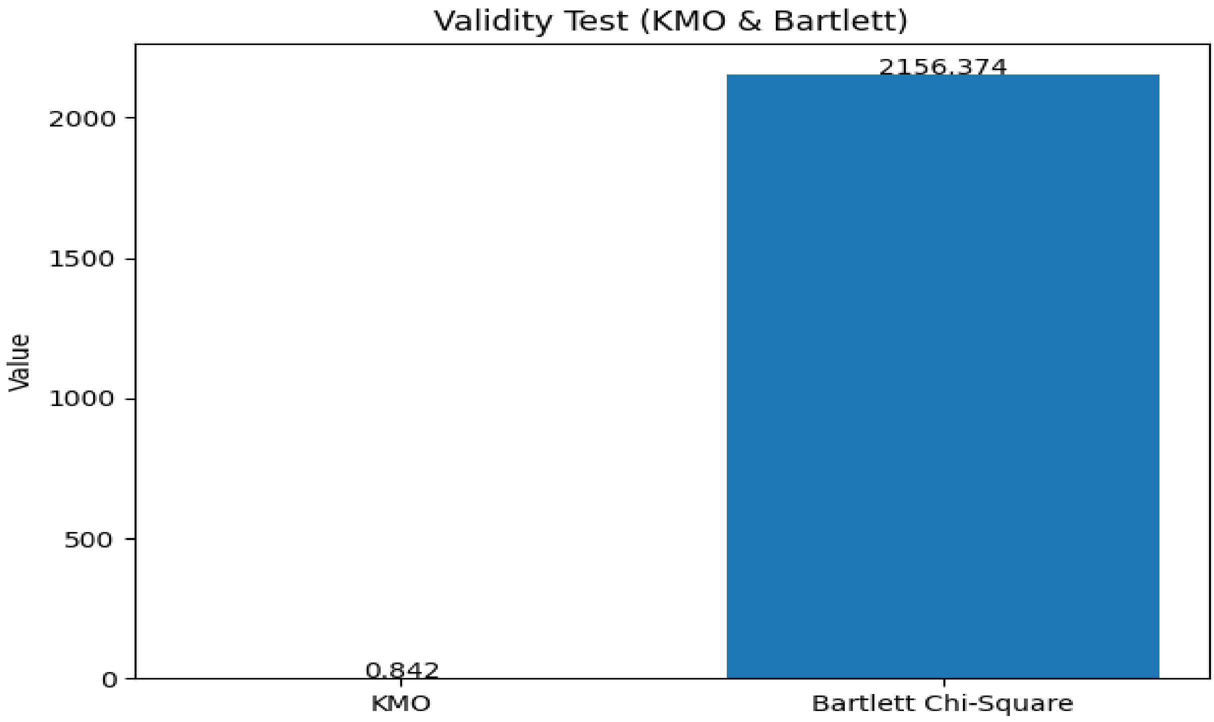


Figure 3: Validity Test (KMO & Bartlett's Test)

The figure of the Validity Test shows the value of KMO and the Chi-Square statistic of Bartlett. The KMO value is higher than the recommended value of 0.60, and it indicates good sampling adequacy. Further, the Test of Sphericity by Bartlett is statistically significant, which demonstrates that the opposition of correlation is not an identity matrix. This would mean that we have enough correlations between variables that will allow the analysis of factors. On the whole, the number proves the fact that the data is valid to conduct multivariate statistical analysis (Arikumar et al., 2022).

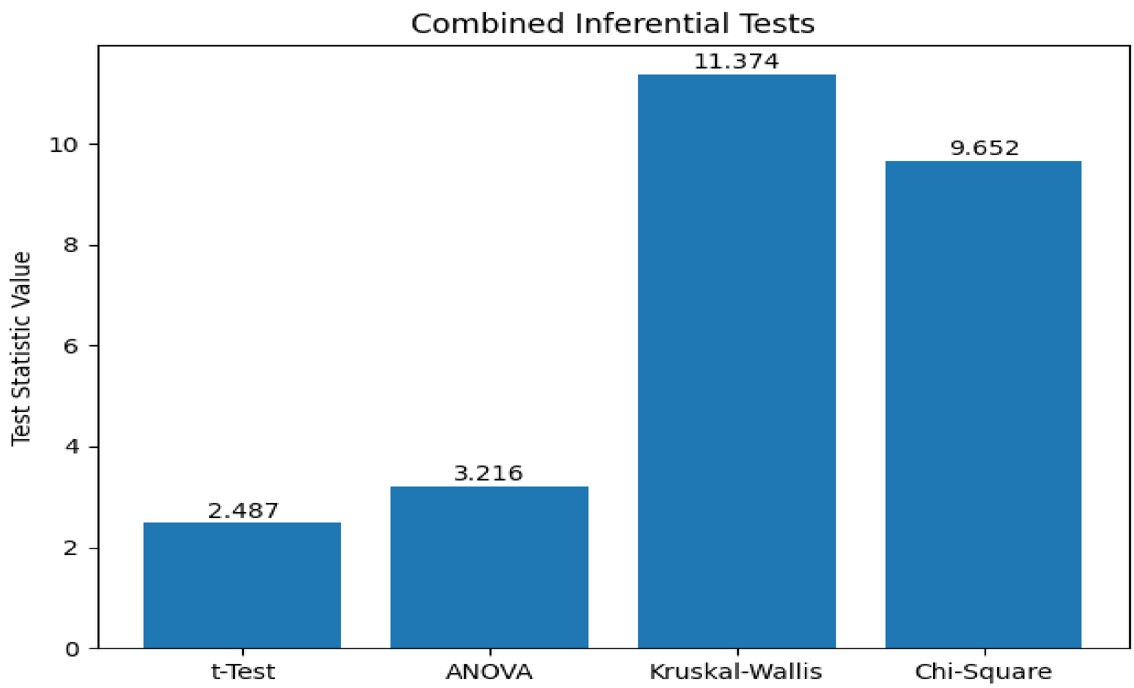


Figure 4: Combined Inferential Tests

The summary of the findings of the Independent Samples t-test, One-Way ANOVA, Kruskal-Wallis test, and Chi-square test of independence is presented in the figure below as the Combined Inferential Tests. Every test value is significant at p = 0.05, which shows that there are significant differences and relationships among the groups. The t-test shows that there is a significant difference in behavioral intention between the genders. The Kruskal-Wallis and ANOVA methods prove the existence of significant age group differences in trust and actual levels of assessment usage. The Chi-Square test shows that there is a significant association between chronic health conditions and gender. These findings indicate that demographic characteristics are relevant in determining user acceptance and usage (Maddikunta et al., 2021).

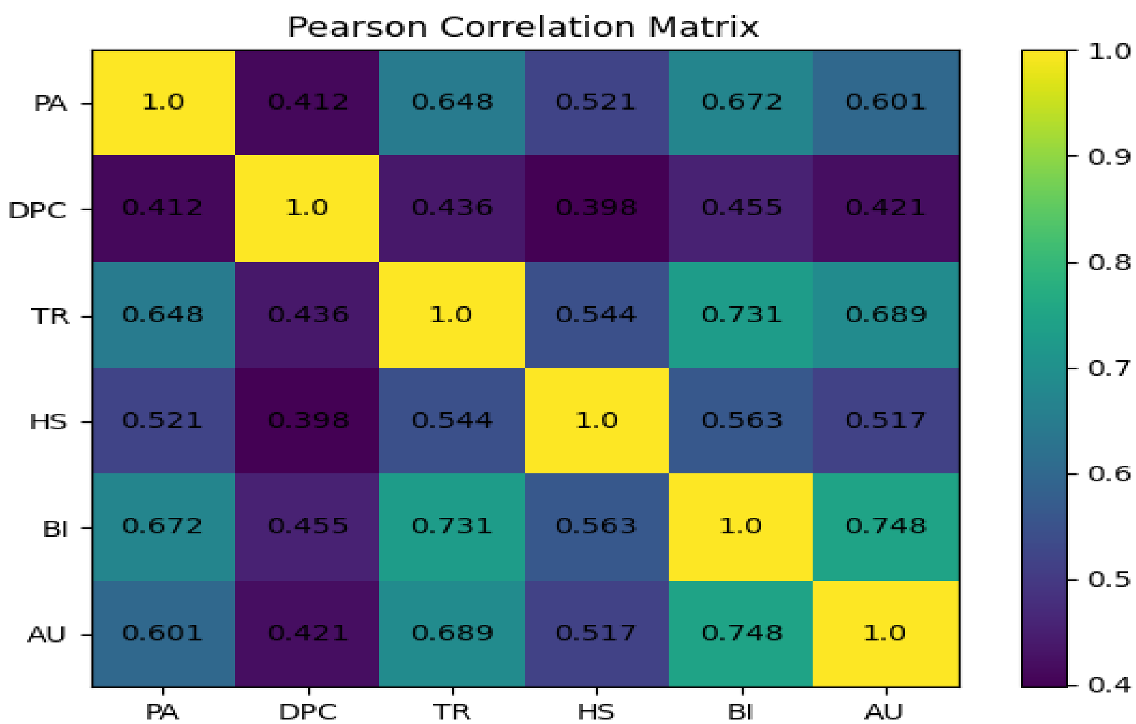


Figure 5: Pearson Correlation Matrix

The Pearson Correlation Matrix figure gives all the correlation coefficients of all constructs. All values are good relationships, which show that there are good relationships between the variables. There is a high positive correlation between Trust and Behavioral Intention and Actual Usage, meaning that an increase in trust results in an increase in adoption and use of hybrid sensor devices. The Perceived Accuracy also shows a strong positive correlation with Trust and Behavioral Intention, and it is essential to consider it in the context of user acceptance. The theoretical framework is backed by the positive and significant correlation and indicates consistency between constructs (Entezami et al., 2020).

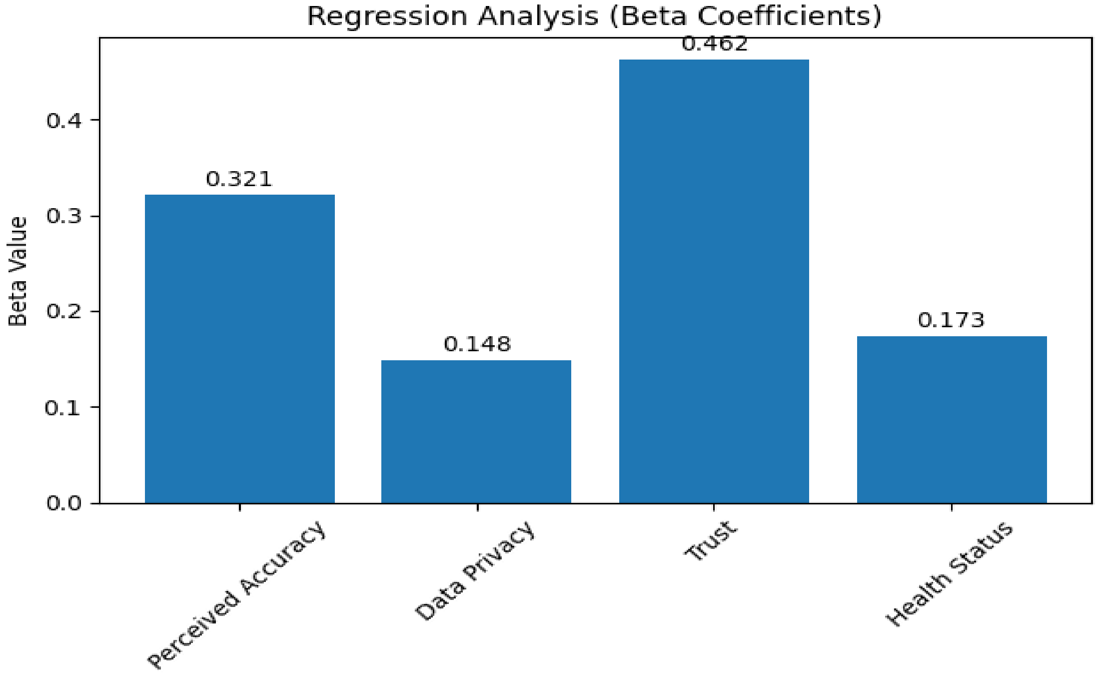


Figure 6: Regression Analysis

The Regression Analysis Figure shows the standardized beta values of Perceived Accuracy, Data Privacy Concern, Trust, and Health Status in the Behavioral Intention prediction. The values of the betas are all positive, suggesting that as these variables increase, behavioral intention increases too. Trust is seen to be the most significant predictor, followed by the Perceived Accuracy and the Health Status. The positive coefficients justify that those users who think the device is more accurate and have more confidence in it tend to use hybrid sensor technologies. The regression model has a high level of explanation, which supports the organization of the theoretical assumptions of the research (AlShorman et al., 2020).

DISCUSSION

This work was meant to take factors into consideration that could influence the acceptance of users with the hybrid sensors in smart health monitors. Specifically, the research studied the impact of the perceived correctness, the concern with data privacy, trust, and health condition on behavioral intention and actual use. The findings play an effective role in the framework provided in the research, as it appears to have concrete empirical support for already known theoretical assumptions of technology acceptance, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Pillai et al., 2021).

The results indicate that there is a positive influence of perceived accuracy on trust and behavioral intention, which can be deemed important. This also means that in case the users experience a perception that hybrid sensor devices have the capacity of offering pertinent and plausible health information, they would have confidence in the technology and would opt into using the technology. The outcome is consistent with the previous research on digital health technologies, showing the reliability of the system and performance expectancy as key determinants of technology adoption. The hybrid sensors are made by combining a series of sensors, and this precision appears to be valued by the user, and this level of confidence makes them more confident in the gadget (Ferreira et al., 2024).

Trust was the best predictor of behavioral intention. The need to trust in the implementation of smart health monitoring systems can be highlighted using this observation. Health data is sensitive and personal, hence it follows that users will be more inclined towards using the devices, which they find secure and reliable, and a professionally-designed device. Superior relations between trust and actual utilization also contribute to proving the fact that creating confidence in users is one of the keys to long-term intercourse with hybrid sensor technologies (Dua et al., 2023).

Another relationship that was significant and positive was between behavioral intention and data privacy concern. In some instances, privacy issues can be a cause that users are not so willing to adopt technology, but in this instance, more enlightened privacy-conscious users can be more selective and slow to make a trust decision on devices. This implies that explicit privacy messages and powerful data protection systems can have a positive impact and not necessarily be a hindrance to acceptance (Mekruksavanich & Jitpattanakul, 2021).

Demographic analysis revealed that there was a high disparity in the genders and age groups. An independent samples t-test provided that the behavioral intention is not similar in both male and female respondents, and this indicates the role of demographics in dictating the patterns of technology acceptance. On the same note, the results of the One-Way ANOVA and Kruskal-Wallis showed that there exist significant differences between the trust and actual usage of mobile apps across the age groups. This is an indication of these factors associated with older users being less familiar and comfortable with smart health technologies compared with younger and middle-aged users. The Chi-Square measurement also established a significant correlation between gender and chronic health condition, in that the health-related needs may be differentiated based on the demographic categories (Lin et al., 2020).

The correlation test showed significant and positive relationships between all the constructs since it validates the theoretical assumption that all constructs are interrelated. The regression analysis proved that the proposed model can explain a good portion of the variance in behavioral intention, which is a strong explanatory power. Overall, the findings can confirm that the reliability of technology, trust with the user, demography, and perception of need with regard to health can change how many hybrid sensor devices are adopted (Luo et al., 2021).

CONCLUSION

The research paper was structured to achieve the goal of going over the determinants of user acceptance of hybrid sensors in smart health monitors. Learning about the effects of perceived accuracy, data privacy concern, trust, and health status on behavioral intention and actual usage were the goals of the study. In an instance of a quantitative research approach and applicable statistical analysis, the study will be in a position to present meaningful results regarding the effects of technology acceptance among smart healthcare systems.

The findings demonstrate that the perceived accuracy is highly essential in shaping the user trust and beam intentions. By believing that they will have access to high-quality and accurate health information with the help of the device, the users will be more willing to have confidence in the system and show willingness to use the hybrid sensor devices. Trust was discovered to be the most significant predictor of behavioral intention, and it has become a predictor in the adoption of health technology. Hybrid sensors are also perceptive with regard to the personal health of the user; the user should be convinced of the reliability, safety, and security of the information.

The issue of data privacy also had a significant influence on behavioral intention, and this is an indication that users care more about data security. Rather than acting as just a decisive factor, the topic of privacy awareness can assist users in making decisions that will result in the selection of those devices that will demonstrate good security indicators. That explains the importance of clear privacy policies and the safe system design for the enhancement of the system's acceptability by the user.

In addition, demographic factors such as gender and age were also found to differ significantly with regard to how they influence the behavior of acceptance and usage. The results show that the tendencies of using technology are dissimilar among different demographic groups, and the discrepancies need to be taken into account when designing and marketing products of smart health tracking.

The high explanatory power of the proposed research model was demonstrated with the help of the correlation and regression statistics. The variables' inter-relationships were good and significant, which form the theory of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Overall, the study finds that the most dominant motivation of user acceptance of hybrid sensor-based smart health monitoring devices is the accuracy, the trust, the awareness of privacy, and health motivation.

In summary, the paper can be utilized in both academic and practical settings in determining aspects of smart healthcare technology adoption critically. The findings provide pertinent information to the developer, health practitioners, and policymakers who have the intention of realizing success in integrating the hybrid sensor technologies into the modern healthcare systems.

REFERENCES

1. Ahmed, N., Rafiq, J. I., & Islam, M. R. (2020). Enhanced human activity recognition based on smartphone sensor data using a hybrid feature selection model. *Sensors*, *20*(1), 317.
2. Albahri, A. S., Albahri, O. S., Zaidan, A., Zaidan, B., Hashim, M., Alsalem, M., Mohsin, A. H., Mohammed, K., Alamoodi, A. H., & Enaizan, O. (2019). Based on multiple heterogeneous wearable sensors: A smart real-time health monitoring system structured for hospital distributors. *IEEe Access*, *7*, 37269-37323.
3. AlShorman, O., AlShorman, B., Alkhassaweneh, M., & Alkahtani, F. (2020). A review of Internet of Medical Things (IoMT)-based remote health monitoring through wearable sensors: a case study for diabetic patients. *Indonesian Journal of Electrical Engineering and Computer Science*, *20*(1), 414-422.
4. Alshuhail, A., Alshahrani, A., Mahgoub, H., Ghaleb, M., Darem, A. A., Aljehane, N. O., Alotaibi, M., & Alzahrani, F. (2025). Machine edge-aware IoT framework for real-time health monitoring: Sensor fusion and AI-driven emergency response in decentralized networks. *Alexandria Engineering Journal*, *129*, 1349-1361.
5. Alsubai, S., Al Hejaili, A., Aoun, N. B., Salhi, A., & Karovic, V. (2026). A Hybrid Deep Learning Approach for IoT-Enabled Human Activity Recognition and Advanced Analytics.
6. Arikumar, K., Prathiba, S. B., Alazab, M., Gadekallu, T. R., Pandya, S., Khan, J. M., & Moorthy, R. S. (2022). FL-PMI: federated learning-based person movement identification through wearable devices in smart healthcare systems. *Sensors*, *22*(4), 1377.
7. Attazada, Z., & Rafique, S. (2026). Intelligent Bionic Sensing Textile for Pressure Ulcer Prevention: A Self-Powered, Multi-Modal Monitoring System with Real-Time Risk Assessment. *Big. D*, *3*(1), 25-34.
8. Babangida, L., Perumal, T., Mustapha, N., & Yaakob, R. (2022). Internet of Things (IoT) based activity recognition strategies in smart homes: A review. *IEEE Sensors Journal*, *22*(9), 8327-8336.
9. Balli, S., Sağbaş, E. A., & Peker, M. (2019). Human activity recognition from smart watch sensor data using a hybrid of principal component analysis and a random forest algorithm. *Measurement and Control*, *52*(1-2), 37-45.
10. Bibi, A., Yamin, S., Natividad, L., Nelson, D. J., Rafique, T., Akhter, D. N., & Samad, A. (2024). Navigating The Ethical Landscape: AI Integration In Education. Educational Administration Theory and Practice, 30 (6), 1579–1585. In.
11. Binyamin, S. S., & Hoque, M. R. (2020). Understanding the drivers of wearable health monitoring technology: an extension of the unified theory of acceptance and use of technology. *Sustainability*, *12*(22), 9605.
12. Chithra, R. B., Neethu, P., Patil, K. A., Anju, M., Joy, S., & Partheeban. (2026). IoT based hybrid patient health monitoring system. AIP Conference Proceedings,
13. Diraco, G., Rescio, G., Siciliano, P., & Leone, A. (2023). Review on human action recognition in smart living: Sensing technology, multimodality, real-time processing, interoperability, and resource-constrained processing. *Sensors*, *23*(11), 5281.
14. Dua, N., Singh, S. N., Semwal, V. B., & Challa, S. K. (2023). Inception-inspired CNN-GRU hybrid network for human activity recognition. *Multimedia Tools and Applications*, *82*(4), 5369-5403.
15. Entezami, A., Sarmadi, H., Behkamal, B., & Mariani, S. (2020). Big data analytics and structural health monitoring: a statistical pattern recognition-based approach. *Sensors*, *20*(8), 2328.
16. Fan, X., Li, Y., Huang, Z., & He, Z. (2026). Audio-Driven Multi-Modal Unobtrusive Health Monitoring and Inference for Smart Eldercare at Home. *IEEE Journal of Biomedical and Health Informatics*.
17. Ferreira, R. G., Silva, A. P., & Nunes-Pereira, J. (2024). Current on-skin flexible sensors, materials, manufacturing approaches, and study trends for health monitoring: a review. *ACS sensors*, *9*(3), 1104-1133.
18. Ganji, K., & Parimi, S. (2022). ANN model for users' perception on IOT based smart healthcare monitoring devices and its impact on the effect of COVID 19. *Journal of Science and Technology Policy Management*, *13*(1), 6-21.
19. Greco, L., Percannella, G., Ritrovato, P., Tortorella, F., & Vento, M. (2020). Trends in IoT-based solutions for health care: Moving AI to the edge. *Pattern recognition letters*, *135*, 346-353.
20. Gumaei, A., Hassan, M. M., Alelaiwi, A., & Alsalman, H. (2019). A hybrid deep learning model for human activity recognition using multimodal body sensing data. *IEE Access*, *7*, 99152-99160.
21. Ismail, A., Abdlerazek, S., & El-Henawy, I. M. (2020). Development of a smart healthcare system based on speech recognition using a support vector machine and dynamic time warping. *Sustainability*, *12*(6), 2403.

22. Jacob Rodrigues, M., Postolache, O., & Cercas, F. (2020). Physiological and behavior monitoring systems for smart healthcare environments: A review. *Sensors*, *20*(8), 2186.
23. James, M. (2026). Technologies: Remote Patient Monitoring Systems Using IoT.
24. Kazanskiy, N. L., Khorin, P. A., & Khonina, S. N. (2025). Biochips on the move: Emerging trends in wearable and implantable lab-on-chip health monitors. *Electronics*, *14*(16), 3224.
25. Kim, K., Kim, B., & Lee, C. H. (2020). Printing flexible and hybrid electronics for human skin and eye-interfaced health monitoring systems. *Advanced Materials*, *32*(15), 1902051.
26. Li, J., Ma, Q., Chan, A. H., & Man, S. (2019). Health monitoring through wearable technologies for older adults: Smart wearables acceptance model. *Applied ergonomics*, *75*, 162-169.
27. Lim, H. R., Kim, H. S., Qazi, R., Kwon, Y. T., Jeong, J. W., & Yeo, W. H. (2020). Advanced soft materials, sensor integrations, and applications of wearable flexible hybrid electronics in healthcare, energy, and the environment. *Advanced Materials*, *32*(15), 1901924.
28. Lin, K., Li, Y., Sun, J., Zhou, D., & Zhang, Q. (2020). Multi-sensor fusion for body sensor network in a medical human–robot interaction scenario. *Information Fusion*, *57*, 15-26.
29. Liu, D., Li, Q., & Han, S. (2022). Using the extended technology acceptance model to assess the adoption intention of a proposed IoT-based health management tool. *Sensors*, *22*(16), 6092.
30. Luo, Y., Wang, Z., Wang, J., Xiao, X., Li, Q., Ding, W., & Fu, H. (2021). Triboelectric bending sensor-based smart glove towards intuitive multi-dimensional human-machine interfaces. *Nano Energy*, *89*, 106330.
31. Maddikunta, P. K. R., Hakak, S., Alazab, M., Bhattacharya, S., Gadekallu, T. R., Khan, W. Z., & Pham, Q.-V. (2021). Unmanned aerial vehicles in smart agriculture: Applications, requirements, and challenges. *IEEE Sensors Journal*, *21*(16), 17608-17619.
32. Mahato, K., Saha, T., Ding, S., Sandhu, S. S., Chang, A.-Y., & Wang, J. (2024). Hybrid multimodal wearable sensors for comprehensive health monitoring. *Nature Electronics*, *7*(9), 735-750.
33. Malasinghe, L. P., Ramzan, N., & Dahal, K. (2019). Remote patient monitoring: a comprehensive study. *Journal of Ambient Intelligence and Humanized Computing*, *10*(1), 57-76.
34. Mekruksavanich, S., & Jitpattanakul, A. (2020). Smartwatch-based human activity recognition using a hybrid lstm network. 2020 IEEE Sensors,
35. Mekruksavanich, S., & Jitpattanakul, A. (2021). Lstm networks using smartphone data for sensor-based human activity recognition in smart homes. *Sensors*, *21*(5), 1636.
36. Nazar, F., & Jalal, A. (2025). Wearable sensor-based activity recognition for intelligent healthcare monitoring. ICACS,
37. Nelluri, K. D. D., Ammulu, M. A., Alaparthi, B., Kommoju, M., Rohith, P. S., Kakani, A. K., & Grandhi, V. (2026). SELF-POWERED SENSORS AND WEARABLES: ENERGY HARVESTING WITH NANOMATERIALS FOR THE IoT ERA. *Nano Trends*, 100179.
38. Okpala, I., Nnaji, C., & Awolusi, I. (2022). Wearable sensing devices acceptance behavior in construction safety and health: assessing existing models and developing a hybrid conceptual model. *Construction Innovation*, *22*(1), 57-75.
39. Papa, A., Mital, M., Pisano, P., & Del Giudice, M. (2020). E-health and wellbeing monitoring using smart healthcare devices: An empirical investigation. *Technological Forecasting and Social Change*, *153*, 119226.
40. Pillai, S., Upadhyay, A., Sayson, D., Nguyen, B. H., & Tran, S. D. (2021). Advances in medical wearable biosensors: Design, fabrication, and materials strategies in healthcare monitoring. *Molecules*, *27*(1), 165.
41. Poongodi, J., Kavitha, K., Sathish, S., & Lakshmana Kumar, R. (2025). Hybrid AI-driven bio-inspired wearable sensors with Aquasense AI technology for multimodal health monitoring and rehabilitation in dynamic environments. *Transactions on Emerging Telecommunications Technologies*, *36*(3), e70081.
42. Prati, A., Shan, C., & Wang, K. I.-K. (2019). Sensors, vision, and networks: From video surveillance to activity recognition and health monitoring. *Journal of Ambient Intelligence and Smart Environments*, *11*(1), 5-22.
43. Ramanujam, E., Perumal, T., & Padmavathi, S. (2021). Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review. *IEEE Sensors Journal*, *21*(12), 13029-13040.
44. Rhee, J. H., Ma, J. H., Seo, J., & Cha, S. H. (2022). Review of applications and user perceptions of smart home technology for health and environmental monitoring. *Journal of Computational Design and Engineering*, *9*(3), 857-889.

45. Serpush, F., Menhaj, M. B., Masoumi, B., & Karasfi, B. (2022). Wearable sensor-based human activity recognition in the smart healthcare system. *Computational intelligence and neuroscience*, *2022*(1), 1391906.
46. Shankar, S. (2024). A systematic literature review on human activity recognition. *J. Electrical Systems*, *20*(6s), 1175-1191.
47. Shi, J., Zhang, N., Wu, K., & Wang, Z. (2025). Application status, challenges, and development prospects of smart technologies in home-based elder care. *Electronics*, *14*(12), 2463.
48. Shuwandy, M. L., Zaidan, B., Zaidan, A., & Albahri, A. S. (2019). Sensor-based mHealth authentication for real-time remote healthcare monitoring system: A multilayer systematic review. *Journal of Medical Systems*, *43*(2), 33.
49. Sofi, A., Regita, J. J., Rane, B., & Lau, H. H. (2022). Structural health monitoring using wireless smart sensor network–An overview. *Mechanical Systems and Signal Processing*, *163*, 108113.
50. Sony, S., Laventure, S., & Sadhu, A. (2019). A literature review of next-generation smart sensing technology in structural health monitoring. *Structural Control and Health Monitoring*, *26*(3), e2321.
51. Taiwo, O., & Ezugwu, A. E. (2020). Smart healthcare support for remote patient monitoring during COVID-19 quarantine. *Informatics in medicine unlocked*, *20*, 100428.
52. Talal, M., Zaidan, A., Zaidan, B., Albahri, A. S., Alamoodi, A. H., Albahri, O. S., Alsalem, M., Lim, C. K., Tan, K. L., & Shir, W. (2019). Smart home-based IoT for real-time and secure remote health monitoring of triage and priority system using body sensors: Multi-driven systematic review. *Journal of Medical Systems*, *43*(3), 42.
53. Wang, J., Spicher, N., Warnecke, J. M., Haghi, M., Schwartze, J., & Deserno, T. M. (2021). Unobtrusive health monitoring in private spaces: The smart home. *Sensors*, *21*(3), 864.
54. Wang, Z., Wang, Y., Zeng, Y., Su, J., & Li, Z. (2025). An investigation into the acceptance of intelligent care systems: an extended technology acceptance model (TAM). *Scientific Reports*, *15*(1), 17912.
55. Xinran, Z., Yibo, W., Xuxi, Z., Ping, C., & Xinying, S. (2025). Using the smart health management services and devices among China's adults and the influencing factors: A mixed-methods study. *Chinese General Practice Journal*, *2*(4), 100089.
56. Xu, K., Lu, Y., & Takei, K. (2021). Flexible hybrid sensor systems with feedback functions. *Advanced Functional Materials*, *31*(39), 2007436.
57. Zhu, M., & Pham, H. (2020). An empirical study of factor identification in smart health-monitoring wearable devices. *IEEE Transactions on Computational Social Systems*, *7*(2), 404-416

