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Research Article

Exploring the Factors Influencing Continuance Intention to Use AI-enabled Smart Wearable Devices: A Stimulus-Organism-Response Perspective with Moderating Role of Technology Anxiety

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ABSTRACT

With the rapid development of artificial intelligence (AI) technology, users' continuance intention to use AI-enabled smart wearable devices (AIWDs) has become an important research topic. This study, based on the Stimulus-Organism-Response (S-O-R) framework, constructs and validates a comprehensive model aimed at exploring the impact mechanism of the intelligent characteristics of AIWDs on users' continuance intention. The study focuses on analyzing the complex relationships between perceived intelligence, trust, attitude, satisfaction, and technology anxiety. By conducting partial least squares (PLS) structural equation modeling analysis on data from 562 respondents, the study tests the research hypotheses. The results show that perceived intelligence significantly enhances users' trust, satisfaction, and attitude, which play important mediating roles in the effect of perceived intelligence on continuance intention. At the same time, technology anxiety has a significant negative moderating effect on the relationship between satisfaction and continuance intention. This research not only expands the theoretical understanding of user behavior with AI-driven smart wearable devices but also provides practical guidance for developers and marketers on optimizing user experience, improving user engagement, and refining marketing strategies.

Keywords: AI characteristics; Wearable device; Stimulus-organism-response model; Continuance intention.

1. Introduction

Smart wearable devices, such as smartwatches and fitness trackers, have emerged as the next generation of technology following smartphones, with widespread applications across various fields such as daily life, healthcare, fitness, and security (Niknejad et al., 2020). In recent years, their role in clinical disease diagnosis and treatment has been particularly prominent, such as in the management of anxiety and depression (Abd-Alrazaq et al., 2023) and the diagnosis and prediction of cardiovascular diseases (Huang et al., 2022), significantly enhancing clinical efficiency and accuracy. Moreover, with the growing consumer awareness of health, particularly influenced by the

COVID-19 pandemic (Das et al., 2022), and the increasing demand for personal health data monitoring and management, the market penetration of smart wearable devices outside healthcare institutions has also rapidly increased (Talukder et al., 2019).

With the growing market demand, technological innovations continue to drive the development of smart wearable devices. From the introduction of Wearable 3.0 five years ago to the current AI-enabled smart wearable devices (AIWDs), the level of intelligence in these devices has significantly advanced (Yang et al., 2019; Nahavandi et al., 2022). AIWDs collect real-time physiological and behavioral data through sensors, analyze and provide feedback using machine learning algorithms, thereby enabling more intelligent health management, disease monitoring, and remote healthcare support (Junaid et al., 2022). For instance, AI-based ECG wearable devices have become widely used in fields such as cardiovascular diseases, sleep apnea, mental health, blood glucose monitoring, and exercise evaluation (Neri et al., 2023).

Early research primarily focused on users' initial adoption intentions of smart wearable devices, examining attitudes and motivations when users first encounter or adopt the product (Felea et al., 2021; Cheung et al., 2021; Bianchi et al., 2023). While these studies have provided valuable insights for product design and marketing strategies, with the evolution of the market, companies are increasingly focusing on enhancing user retention, reducing attrition rates, and strengthening the long-term competitiveness of their products. As a result, researchers have shifted their focus to continuance intention to use (Wang et al., 2022; Luo et al., 2023; Sun and Gu, 2024). They have employed frameworks such as the Expectation Confirmation Model (ECM) (Sun and Gu, 2024; El-Gayar and Elnoshokaty, 2023) and the Technology Acceptance Model (TAM) (Ahmad et al., 2020; Salhieh, 2024) to explore the relationships between traditional variables (such as perceived usefulness, perceived ease of use, and satisfaction) and continuance usage intention, providing a theoretical foundation for subsequent research.

Research indicates that users' adoption decisions for AI-based applications and systems are significantly influenced by the functionality of the artificial intelligence features (Balakrishnan and Dwivedi, 2021; Moussawi et al., 2022). AI technology enhances the intelligence level of smart wearable devices (AIWDs) through real-time data analysis, adaptive learning, and lightweight algorithms, achieving comprehensive optimization from data collection to decision support (Das et al., 2018; Janarthanan et al., 2020). This intelligent functionality provides users with a smarter, more personalized, efficient, and convenient experience, while also influencing their trust, satisfaction, and continuance intention to use (Nahavandi et al., 2022). Therefore, exploring how AI features affect users' adoption of AIWDs is of significant theoretical and practical importance.

In this context, it is particularly important to study the relationship between user satisfaction and continuance intention to use, especially focusing on the role of intelligent features in enhancing user trust and reliance (Nahavandi et al., 2022). Unveiling the relationship between intelligent features, user satisfaction, and continuance intention to use not only deepens the understanding of user needs and behavior patterns but also provides a theoretical basis for optimizing device design and enhancing functionalities. Such research can help drive innovation in AIWDs in areas such as health monitoring, activity tracking, and personalized services, while also evaluating their long-term market potential (Zhang and Liang, 2024).

Therefore, AIWDs, unlike traditional smart wearable devices, require a more comprehensive framework to explore their adoption mechanisms. The Stimulus-Organism-Response (SOR) model offers a dynamic framework for depicting the complex relationships between multiple factors, and can effectively analyze the key drivers behind the adoption of innovative technologies (Nieves et al., 2023; Pham et al., 2024). Based on this, this study uses the SOR paradigm to explore the mechanisms through which the intelligent features of AIWDs influence continuance intention, and proposes the following research questions:

RQ1: How does the intelligent feature of AIWDs, as a stimulus, affect users' cognitive systems (trust and attitude) when they consider using these devices?

RQ2: How do users' cognitive systems (trust and attitude) drive satisfaction and further influence continuance intention?

RQ3: How does technology anxiety negatively moderate the relationship between satisfaction and continuance intention?

To address these questions, this study surveyed 562 valid questionnaires and applied the Partial Least Squares (PLS) method to test the model. The contributions of this research are primarily threefold: First, it is the first study to apply the SOR paradigm to clarify the relationship between intelligent features and the continuance intention to use AIWDs; second, it focuses on the intelligent features of AIWDs and reveals their influence on users' cognitive systems; third, it explores the moderating role of technology anxiety in the relationship between satisfaction and continuance intention. From a practical perspective, the findings of this study provide valuable guidance for developers and marketers to optimize user experience, enhance user satisfaction, and promote the long-term use of AIWDs.

2. Literature Review and Hypotheses Development

2.1 General overview of AIWDs

In recent years, the integration of artificial intelligence (AI) and wearable devices has given rise to the rapid development of AI-enabled smart wearable devices (AIWDs), which have demonstrated immense application potential and value across various sectors such as healthcare, industry, and sports. AIWDs collect and analyze real-time data to provide personalized health monitoring and management solutions (Nahavandi et al., 2022). For instance, the “Wall-less Hospital” project developed by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) in Australia uses wearable devices to continuously monitor patients' vital signs and transmits the data via 5G networks to medical professionals, enabling remote healthcare services (Ometov et al., 2021). In the healthcare field, AIWDs not only monitor physiological parameters but also employ deep learning algorithms for early disease prediction and intervention. Research has demonstrated the development of an epilepsy prediction system based on deep learning, which can distinguish between electroencephalogram signals before and between seizures, offering timely alerts to patients (Ometov et al., 2021). Moreover, AIWDs have found increasing applications in sports, where they help athletes optimize training plans and reduce the risk of injuries (Athavale & Krishnan, 2017). For example, certain wearable devices assess athletes' heatstroke risks by collecting exercise data and utilizing fuzzy logic reasoning systems to issue timely alerts.However, despite the promising applications of AIWDs in various fields, literature highlights challenges in their development, such as issues with data accuracy, processing limitations, and security concerns (Acharya et al., 2017). Future research needs to further explore the applications of AI technology in wearable devices to improve their effectiveness and reliability in health monitoring and disease prevention (Banerjee et al., 2020). As a crucial component of future information and communication technology (ICT) systems, AIWDs are steadily maturing and revealing vast potential for a wide range of applications. With continuous technological advancements, AIWDs are expected to play an increasingly significant role in enhancing human life quality and health management.

2.2 SOR in continuance intention

Currently, research on the continued usage intention of wearable devices is predominantly based on traditional frameworks such as the Expectation Confirmation Model (ECM) (Nascimento et al., 2018; El-Gayar & Elnoshokaty, 2023; Sun & Gu, 2024). While these models have demonstrated robustness in studying continuance usage intention, they have been widely discussed and applied, necessitating innovation in this area (Wang et al., 2022). Despite considerable efforts made by scholars, a key issue remains insufficiently addressed—namely, the application of the Stimulus-Organism-Response (SOR) theory. The SOR theory has shown unique advantages in studying continued usage intention and has gained broad recognition and validation (Pham et al., 2024; Lee & Chen, 2022; Vafaei et al., 2024). This model originates from the Stimulus-Response theory, first proposed by Mehrabian and Russell (1974) in the field of environmental psychology, and is also known as the Mehrabian-Russell model. The SOR paradigm outlines how environmental stimuli affect individuals' cognition, emotions, and behaviors (Liu & Huang, 2023). Specifically, the SOR model focuses on how external and internal stimuli influence individuals' emotional and cognitive processes, thereby shaping their behavioral responses (Xie et al., 2023). In the SOR model, "Stimulus" (S) encompasses various external and internal environmental factors that drive changes in individuals' emotional states; "Organism" (O) refers to the individual's internal perceptions and reactions to these stimuli; and "Response" (R) represents the natural reactions of the individual after perceiving the stimulus (Duong, 2023). Previous studies have validated the effectiveness of using AI features as "stimuli," trust, attitude, and satisfaction as "organisms," and continuance usage intention as "responses" in other fields, confirming the robustness of the model structure (Pham et al., 2024; Lee & Chen, 2022; Vafaei et al., 2024). Building on these findings, we aim to apply the SOR model to study the continuance usage intention of AI-enabled wearable devices (AIWDs) and further explore its applicability and value.

2.3 AI Characteristics

Perceived intelligence of AI-enabled wearable devices (AIWDs) is one of the most prominent characteristics of artificial intelligence technology. It refers to the degree to which users perceive the device's technology and its intelligent capabilities during interactions with the device (Balakrishnan & Dwivedi, 2021). This concept has been widely studied across various fields and plays a crucial role in AIWDs as well (Moussawi et al., 2020, 2022; Nahavandi et al., 2022). By integrating functions such as voice recognition, text recognition, sensor data collection, and intelligent analytics, AIWDs allow devices to interact with users in an easily understandable manner, enabling them to quickly and accurately identify user needs and assist in efficiently completing tasks (Marikyan et al., 2022; Moussawi et al., 2022). For example, AI-enabled wearable devices can automatically adjust health management strategies based on the user's physiological data and behavioral habits, providing personalized exercise recommendations or promptly identifying and alerting users to potential health risks.The manifestation of perceived intelligence in AIWDs relies not only on the technical capabilities of the device but also on the user's perception of the device's level of intelligence. When users perceive the device as highly intelligent, they are more likely to trust its capabilities and continue using it. For instance, AIWDs can provide real-time feedback based on the user's physical condition, helping them adjust exercise intensity or monitor health metrics. This intelligent characteristic enables users to perceive the device's practicality in improving health management efficiency, thereby enhancing their trust and satisfaction with the device (Nahavandi et al., 2022). Specifically, when users engage in health monitoring or activity tracking with AIWDs, the device can analyze user data in real time and offer personalized recommendations. This intelligent operation enhances the user experience and increases their reliance on the device's functions. For example, when AIWDs detect abnormal heart rates or blood sugar levels, they can send timely alerts to the user and provide appropriate action suggestions. This not only meets users' expectations for device intelligence but also strengthens their trust in the device, promoting continued usage (Ahmed et al., 2022). Furthermore, the intelligent capabilities of AIWDs enhance their utility in specific contexts, such as real-time health monitoring and exercise performance evaluation, thus increasing users' perception of the device's usefulness and driving long-term adoption (Shajari et al., 2023). Based on this, we propose the following hypotheses:

H1a: Perceived intelligence significantly influences trust in AI wearable products.

H1b: Perceived intelligence significantly influences satisfaction.

H1c: Perceived intelligence significantly influences attitude towards AI wearable products.

2.4 Trust

Trust, as a psychological state, is typically defined as an individual's belief that others or technology will act in ways that align with their expectations, especially in situations involving risk or uncertainty (Wang et al., 2023). In the context of AI-enabled wearable devices (AIWDs), trust encompasses not only confidence in the device's functionality but also trust in its intelligence, data processing capabilities, and privacy protection measures. This trust is based on users' perceptions of the device's intelligent features and its potential benefits, such as whether the smart device can meet users' needs through real-time data analysis, accurate health monitoring, and personalized recommendations. For example, the application of AIWDs in health monitoring, activity tracking, and sleep monitoring requires users to have a high level of trust in the device’s intelligent algorithms and decision support systems (Pal et al., 2019).Research has shown that there is a significant positive relationship between trust and user satisfaction (Hsiao et al., 2022; Jiang & Lau, 2021). In the context of AIWDs, when users trust that the device can perform its expected functions and provide personalized, precise health management services, they are likely to experience higher satisfaction with the device. Specifically, trust enhances users' expectations regarding the device's performance, which, in turn, influences their attitudes and overall user experience. This satisfaction not only serves as immediate feedback on the user's experience but also lays the foundation for continued use of the device. Furthermore, trust can directly impact users' intentions to continue using the device (Meng et al., 2022; Xia et al., 2023; Li et al., 2022), a conclusion that has been validated in other devices and systems. Based on this, we propose the following hypotheses:

H2a: Trust in AI wearable products significantly influences satisfaction.

H2b: Trust in AI wearable products significantly influences continued use intention.

2.5 Attitude

Attitude is typically defined as a positive or negative evaluation of a person, object, or situation (Balakrishnan et al., 2022). According to Davis (1989), attitude refers to an individual’s emotional response to a specific behavior or action, which can be either positive or negative. In the context of AI-driven smart wearable devices (AIWDs), user attitude plays a critical role in shaping their interactions with the device and determining their level of satisfaction. For example, if users have a positive attitude towards AIWDs as health monitoring tools and personalized recommendation systems, they are more likely to have higher satisfaction with the device’s performance and capabilities (Benbunan, 2020).Moreover, existing research has indicated a direct relationship between an individual’s attitude and their intention to continue using a product or service. When users hold a positive attitude towards a product or service, they are more likely to continue using it (Foroughi et al., 2024). Specifically, users who hold a positive attitude towards the intelligence and usability of AIWDs are more inclined to experience higher satisfaction and are more willing to continue using the device. Based on this, we propose the following hypotheses:

H3a: Attitude towards AI wearable products significantly influences satisfaction.

H3b: Attitude towards AI wearable products significantly influences continued use intention.

2.6 Satisfaction

In the field of AI-enabled smart wearable devices (AIWDs), user satisfaction has been widely recognized as a key factor influencing continued use intention. User satisfaction refers to the overall evaluation of the device’s performance, functionality, and experience during its use (Kim, 2021). With the rapid development of AI technology, AIWDs have evolved beyond basic health monitoring tools to highly intelligent devices capable of providing personalized health management, disease early warning, exercise tracking, and other services (Saygılı & Yalçıntekin, 2021). The relationship between user satisfaction and continued use intention has been validated in numerous studies (Nascimento et al., 2018; Zhang & Mao, 2022; Gupta et al., 2021). Specifically, when users can access the expected functionalities and convenient services from AIWDs, they tend to express higher satisfaction with the device. This satisfaction not only strengthens the user's trust and sense of identification with the device but also stimulates their intention to continue using it (Uzir et al., 2021). Research has shown that the intelligent features of AIWDs, such as health data analysis and personalized recommendations provided through AI, are critical factors in enhancing user satisfaction (Nahavandi et al., 2022). When users find that AIWDs effectively meet their personalized needs and improve health management efficiency, their satisfaction increases, thereby boosting their long-term intention to use the device. Based on this, we propose the following hypothesis:

H4: Satisfaction significantly influences the continuance intention of smart wearable products.

2.7 Moderator

Technical anxiety refers to the negative emotions, such as fear, worry, and nervousness, that individuals experience when confronted with emerging or complex technologies (Maduku et al., 2023). These emotions typically arise from a user's unfamiliarity with the technology or the increased complexity of its operation, especially for emerging technologies like AI-enabled wearable devices (AIWDs) (Li et al., 2021). In this study, we propose that the level of technical anxiety significantly affects the relationship between user satisfaction and continued use intention. With the integration of AI technology (e.g., AIWDs) into traditional wearable devices, technical anxiety has become a critical variable, particularly when users transition from traditional devices to those with more advanced intelligent features (Nahavandi et al., 2022).When users interact with AIWDs, understanding how they perceive technical anxiety and how it influences their usage intentions is crucial to a comprehensive exploration of their acceptance of AIWDs. The decision to treat technical anxiety as a moderating variable is based on the idea that it may affect users' interaction experience with AIWDs on both cognitive and emotional levels. Previous studies have shown that anxiety or discomfort with technology tends to intensify during the decision-making and cognitive processes, rather than at the initial encounter (Maduku et al., 2023; Pham et al., 2024). Therefore, technical anxiety is considered a moderating factor in the relationship between user satisfaction and continued use intention.For users with low technical anxiety, the relationship between satisfaction and continued use intention is typically more direct and straightforward when using AIWDs. In contrast, for users with high technical anxiety, there may be a weaker relationship between satisfaction and continued use intention. These users might adopt a more cautious or skeptical attitude towards the operation and functions of AIWDs, which would weaken their intention to continue using the devices. In contrast, users with lower levels of technical anxiety are more likely to embrace the convenience and innovation brought by AIWDs, and they are less likely to be affected by minor issues. This creates a stronger positive relationship between their satisfaction and continued use intention. Based on this, we hypothesize:

H5: Technology anxiety negatively moderates the effect of satisfaction on continuance usage intention

The hypothesized model is demonstrated in Fig. 1.

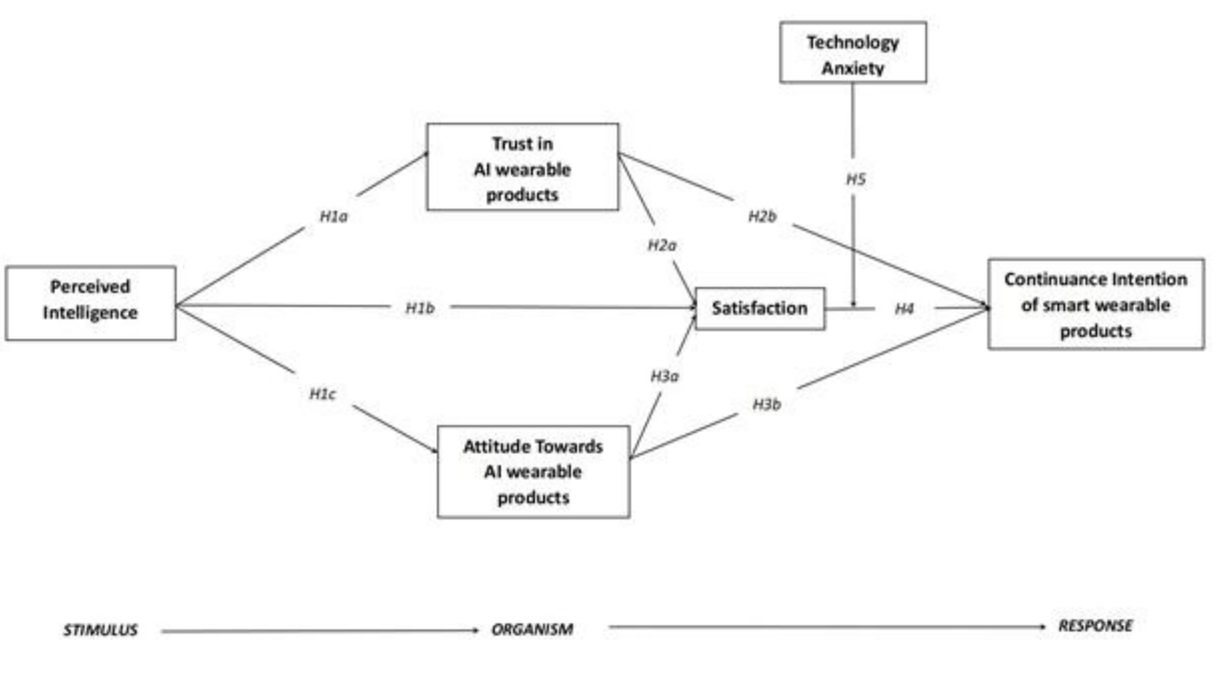

Figure 1 Conceptual Framework

3. Methods

3.1. Survey instruments

The measurement scales used in this study are based on previously validated, mature, and reliable scales from prior research. The first part of the survey includes measurement scales for six construct variables. These scales were designed with reference to the studies of Moussawi et al. (2023) and Lin et al. (2023), with slight modifications. For the measurement of trust in AIWDs (Artificial Intelligence-Driven Devices), a scale integrating items from Liu et al. (2022) and Hsiao and Chen (2022) was used, consisting of five items. The attitude towards AIWDs (five items) was constructed based on the works of Foroughi et al. (2019), Khayer and Bao (2019), and Jeng et al. (2022). The measurement of satisfaction was adapted from the scales of El-Gayar and Elnoshokaty (2023) and Bölen (2020), with five items. Willingness to continue using AIWDs was measured using a scale derived from the studies of Wang et al. (2022) and Bölen (2020), also consisting of five items. The scale for technology anxiety (five items) was designed based on the research of Jeng et al. (2022) and Pham et al. (2024). All scales were evaluated using a seven-point Likert scale, ranging from "strongly disagree" to "strongly agree."In the second part of the survey, demographic data including gender, age, and educational background were collected. During the development of the questionnaire, all measurement items underwent repeated review, modification, and optimization to ensure the clarity, readability, and reliability of the survey.

3.2. Sampling and data collection

This research employed a systematic sampling method to collect data. Specifically, the research team recruited respondents over a six-week period (from June 15 to July 30, 2024) through on-site questionnaires. The team consisted of trained assistants who engaged potential participants in public and commercial areas (such as shopping malls, parks, gyms, etc.). The target population for this study consisted of users who had previously used AI wearable devices (such as smartwatches and fitness trackers). The questionnaire was designed to include six core variables (willingness to continue using, satisfaction, attitude, trust, perceived intelligence, and technology anxiety) as well as demographic information, with all measurement items based on a 7-point Likert scale.

The data collection process was conducted using paper questionnaires, with on-site implementation starting at

9:00 AM each day. To ensure sample diversity, the research team utilized a systematic sampling method. A random number (denoted as "n") between 1 and 10 was generated using mobile applications (e.g., "Random Balls" or "Randomizer"), and the "n-th" person to pass by was selected as the first respondent. Then, every tenth individual in the target population passing by was invited to participate in the survey. The research assistants first asked respondents if they had used AI wearable devices and confirmed their willingness to participate in the questionnaire. For those who agreed, the research team briefly explained the purpose of the study and provided the questionnaire. If the potential participant had not used AI wearable devices or refused to participate, the assistant patiently waited for the next tenth person to arrive.

It is important to note that this study strictly adhered to ethical guidelines, ensuring that participation was entirely voluntary. Prior to completing the questionnaire, all respondents were informed about the basic nature and purpose of the study and were made aware of the background, methodology, and objectives of the research. Participants had the freedom to choose whether to participate. Only those who explicitly agreed to participate were included in the study. This study fully upheld the principles of informed consent and ethical transparency. However, this meticulous process slightly reduced the efficiency of data collection. Over the six-week period, a total of 649 questionnaires were distributed. After excluding incomplete questionnaires and invalid data (such as duplicate responses or missing information), 562 valid questionnaires were retained for subsequent analysis. The demographic information of the respondents is summarized in Table 1.

Table 1. Demographic profile

Variabl	**Characteristics**	**Freque**	%
Experien	Yes	562	100
	Never	0	0
Gender	Male	171	30.4
	Female	202	35.9
	Prefer not to say	189	33.6
Age	Below 18	115	20.5
	18-30	99	17.6
	30-40	117	20.8
	40-50	105	18.7
	Above 50	126	22.4
Educatio	High school or	127	22.6
	Bachelor	163	29.0
	Master	123	21.9
	Doctorate	149	26.5
Frequen	Daily	119	21.2
	Weekly	138	24.6
	Occasionally	155	27.6
	Rarely	150	26.7
Type	Smartwatch	180	32.0
	Fitness tracker	200	35.6
	Others	182	32.4

Note(s): N = 562;

Source(s): Created by authors

3.3. Common method bias

To address the issue of common method bias (CMB) that may arise from systematic biases, preventive measures were taken during both the data collection and analysis phases. Initially, the study was carefully designed to ensure a well-balanced questionnaire layout and distribution, including intentional mixed measurement item sequences and the use of systematic sampling methods (Podsakoff et al., 2003). In accordance with the recommendations of MacKenzie and Podsakoff (2012), several preventative measures were implemented at the onset of the study to mitigate the impact of CMB. These measures included optimizing the structure of the questionnaire, randomizing the item order, adjusting scale types and anchor labels, and informing respondents that, although some items might appear similar, each question addressed distinct aspects and encouraging careful responses. Additionally, three post hoc statistical tests were conducted to further assess the presence of CMB.

First, Harman's single-factor test was performed, revealing that the first factor explained only 35.23% of the total variance, which is below the 50% threshold. This suggests that CMB is unlikely to be a significant issue in this study. Second, following the guidance of Lee et al. (2022), a collinearity assessment using variance inflation factors (VIF) was conducted. The results showed that all VIF values were below the recommended threshold of 3.3 (see Table 2), further supporting the conclusion that CMB is not a significant concern in this study. Finally, a marker variable technique (Simmering et al., 2015) was employed, using respondents' educational level as the marker variable (following Cao et al., 2021), as it is theoretically unrelated to artificial intelligence traits. The analysis revealed no statistically significant correlation between educational level and any of the variables in the model. In conclusion, CMB does not have a significant impact on the results of this study.

Table 2. The collinearity test for CMB.

	ATT	CI	PI	SAT	TA	TR	TA x SAT
ATT		1.219		1.167			
CI							
PI	1			1.19		1	
SAT		1.305					
TA		1.091					
TR		1.212		1.151			
TA x SAT		1.017					

Note(s): N = 562; ATT:Attitude; CI:Continuance Intention; PI:Perceived Intelligence; SAT:Satisfaction; TA:Technology Anxiety; TR:Trust.

Source(s): Created by authors.

4. Results

This research employs Structural Equation Modeling (SEM) to estimate the paths within a multivariate model involving latent structures, based on empirical data collected from the questionnaire (Hair et al., 2020; Tran and Huang, 2021). Given the presence of formative constructs, the nature of the collected data, and the complexity of the hypothesized model, Partial Least Squares Structural Equation Modeling (PLS-SEM) was chosen to test the hypothesized model (Hair et al., 2020). Data analysis was conducted using SmartPLS 4.0 software.

PLS-SEM, combined with Confirmatory Composite Analysis (CCA), was used to examine the proposed model structure, following the recommendations of Hair et al. (2020) and Cuesta-Valino et al. (2022). The choice of PLS-SEM was based on several advantages, including robustness against distributional assumptions, its ability to handle model complexity, small sample sizes, and non-normal data, while effectively mitigating multicollinearity issues (Hair et al., 2013; Lee et al., 2018). Unlike Covariance-Based SEM (CB-SEM), the reasons for choosing PLS as the analysis method are as follows: First, the model in this study involves ten hypotheses and multiple latent mediation paths, making PLS more suitable for handling complex modeling scenarios compared to CB-SEM (Hair et al., 2017; Ringle et al., 2012). Second, this study is exploratory in nature, as the current literature lacks a clear understanding of the potential impact of AI features (such as intelligence) on the SOR, which makes PLS an ideal choice for exploratory research (Hair et al., 2017; Ringle et al., 2012). Considering these factors, data analysis was performed using SmartPLS 4.0 software (Ringle et al., 2015; Hair et al., 2020). The PLS-SEM analysis followed a two-stage approach: first, a measurement model analysis was conducted to assess the reliability and validity of the latent constructs; then, in the structural model phase, the paths within the latent variable model were estimated using the empirical data collected from the questionnaire (Hair et al., 2020).

4.1. Measurement model testing

First, we assessed the reliability and validity of the model to ensure data consistency and measurement reliability. Reliability analysis was conducted based on Cronbach's alpha, while validity and internal consistency were examined using Confirmatory Factor Analysis (CFA). The results of the measurement model are presented in Table 3. Cronbach's alpha values ranged from 0.918 to 0.934, exceeding the commonly accepted threshold of 0.7 (Hair et al., 2013), indicating high reliability. Additionally, to establish convergent validity, Hair et al. (2020) recommend that outer loadings should exceed 0.7, the Average Variance Extracted (AVE) should be greater than 0.5, and Composite Reliability (CR) should be above 0.7. The results showed that all outer loadings exceeded 0.7, AVE values ranged from 0.753 to 0.791, and CR values ranged from 0.938 to 0.946, all above the recommended thresholds (see Table 3), demonstrating good convergent validity for the model.

Table 3. Measurement model results.

Construct	Items	M	S.D.	λ	α	CR	AVE
Attitude	ATT1	5.098	1.427	0.868	0.924	0.943	0.767
	ATT2	5.125	1.48	0.87			
	ATT3	5.078	1.48	0.893			
	ATT4	5.117	1.447	0.886			
	ATT5	5.133	1.421	0.861			
Continuance Intention	CI1	5.306	1.368	0.863	0.92	0.94	0.757
	CI2	5.32	1.351	0.876			
	CI3	5.228	1.345	0.865			
	CI4	5.315	1.357	0.879			
	CI5	5.189	1.381	0.867			
Perceived Intelligence	PI1	5.26	1.388	0.894	0.927	0.945	0.773
	PI2	5.203	1.431	0.865			
	PI3	5.205	1.46	0.87			
	PI4	5.21	1.462	0.875			
	PI5	5.249	1.415	0.893			
Satisfaction	SAT1	5.205	1.406	0.872	0.928	0.946	0.777
	SAT2	5.285	1.446	0.89			
	SAT3	5.196	1.481	0.877			
	SAT4	5.183	1.448	0.884			
	SAT5	5.176	1.446	0.884			
Technology Anxiety	TA1	4.888	1.561	0.884	0.934	0.95	0.791
	TA2	4.936	1.523	0.885			
	TA3	4.877	1.563	0.898			
	TA4	4.849	1.545	0.886			
	TA5	4.859	1.569	0.893			
Trust	TR1	5.274	1.378	0.872	0.918	0.938	0.753
	TR2	5.27	1.358	0.86			

TR3	5.345	1.362	0.854
TR4	5.32	1.404	0.885
TR5	5.295	1.378	0.867

Note(s): N = 562; M: Mean; S.D.: Standard deviation; λ: Outer loadings; α: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted.The average variance extracted (AVE) of each construct should exceed the threshold value of 0.5 (Hair et al., 2013). The acceptable level of factor loading, composite reliability,and Cronbach's α is 0.7 (Hair et al., 2013).

Source(s): Created by authors

Second, to examine discriminant validity, the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT) were applied. According to the Fornell-Larcker criterion, the square root of each construct's AVE should be greater than its correlations with other constructs. Table 4 presents the results of the Fornell-Larcker analysis, showing that the square root of the AVE for each construct (highlighted in bold) was greater than its correlations with other constructs, meeting the requirements for discriminant validity. Furthermore, the HTMT ratio is widely recognized as a reliable method for assessing discriminant validity, with HTMT values below the threshold of 0.85 indicating strong discriminant validity (Hair et al., 2020). As shown in Table 5, all HTMT values were below 0.85, further confirming the model's discriminant validity.the measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity, providing a solid foundation for subsequent structural model analysis.

Table 4. Discriminant validity: Fornell-Larcker criterion.

	ATT	CI	PI	SAT	TA	TR
ATT	0.876					
CI	0.276	0.87				
PI	0.329	0.273	0.879			
SAT	0.368	0.356	0.41	0.881		
TA	-0.233	-0.204	-0.116	-0.215	0.889	
TR	0.279	0.298	0.309	0.376	-0.173	0.868

Note(s): N = 562; ATT:Attitude; CI:Continuance Intention; PI:Perceived Intelligence; SAT:Satisfaction; TA:Technology Anxiety; TR:Trust.

Source(s): Created by authors.

Table 5. HTMT analysis results.

	ATT	CI	PI	SAT	TA	TR
ATT						
CI	0.296					
PI	0.353	0.294				
SAT	0.396	0.384	0.441			
TA	0.251	0.217	0.125	0.231		
TR	0.299	0.321	0.332	0.405	0.187	
TA x SAT	0.036	0.266	0.025	0.048	0.071	0.074

Note(s): N = 562; ATT:Attitude; CI:Continuance Intention; PI:Perceived Intelligence; SAT:Satisfaction; TA:Technology Anxiety; TR:Trust.

Source(s): Created by authors.

4.2. Testing the research hypotheses

We assessed the hypothesized relationships using SEM. To evaluate the significance of the path coefficients, a bootstrapping test with 5000 subsamples was conducted. The R^2 value for the endogenous variable, Continuance Intention (CI), was 0.244, exceeding the threshold of 0.10 suggested by Falk and Miller (1992). This indicates that the conceptual model explains a substantial proportion of the variance in the continuance intention of AI wearable devices (AIWDs). The results of the hypothesis testing are summarized in Table 6, with the structural model shown in Figure 2.

Table 6. Hypothetical relationship test results.

Hypothesis	Path	β	S.D.	T-Value	P-Value	f²	Supported [Yes/No]
H1a	PI→TR	0.309	0.04	7.671	0	0.106	Yes
H1b	PI→SAT	0.267	0.04	6.699	0	0.083	Yes
H1c	PI→ATT	0.329	0.037	8.774	0	0.121	Yes
H2a	TR→SAT	0.234	0.041	5.747	0	0.066	Yes
H2b	TR→CI	0.138	0.041	3.344	0.001	0.021	Yes
H3a	ATT→SAT	0.215	0.039	5.5	0	0.055	Yes
H3b	ATT→CI	0.117	0.04	2.93	0.003	0.015	Yes
H4	SAT→CI	0.255	0.043	5.984	0	0.066	Yes
H5	TA x SAT→CI	-0.25	0.041	6.044	0	0.08	Yes

Note(s): N = 562; S.D.:Standard deviation; ATT:Attitude; CI:Continuance Intention; PI:Perceived Intelligence; SAT:Satisfaction; TA:Technology Anxiety; TR:Trust.
Source(s): Created by authors.

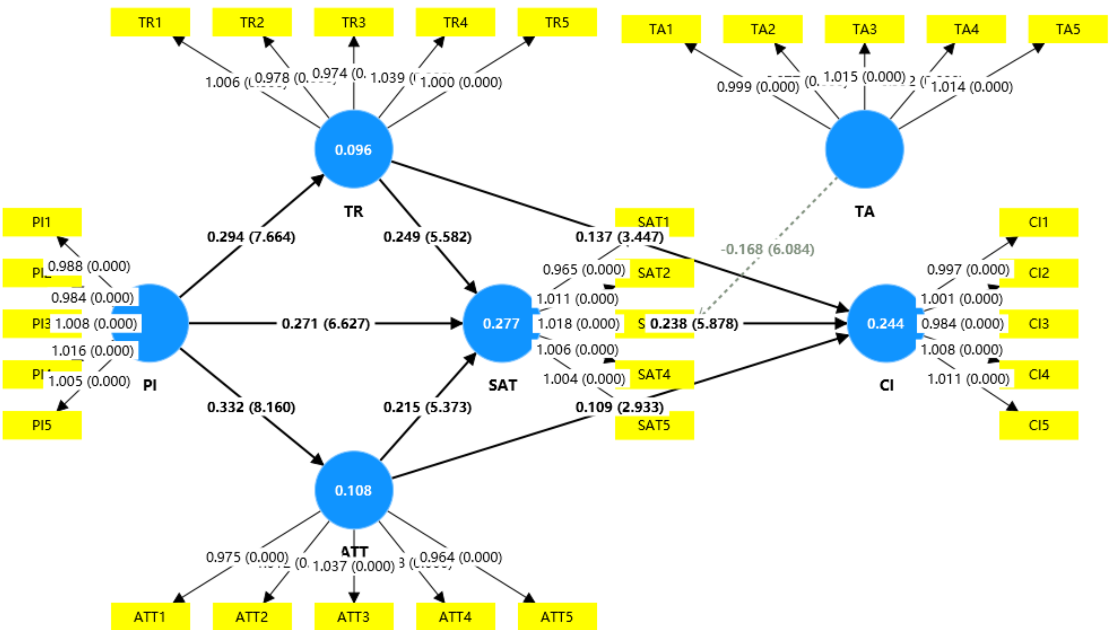

Figure 2 Structural model results.

The results reveal that Perceived Intelligence (PI) is positively and significantly associated with Trust (TR) (β=0.309, p<0.001), Satisfaction (SAT) (β=0.267, p<0.001), and Attitude (ATT) (β=0.329, p<0.001), supporting H1a, H1b, and H1c. Similarly, Trust (TR) positively and significantly influences both Satisfaction (SAT) (β=0.234, p<0.001) and Continuance Intention (CI) (β=0.138, p=0.001), supporting H2a and H2b. Additionally, Attitude (ATT) significantly affects Satisfaction (SAT) (β=0.215, p<0.001) and Continuance Intention (CI) (β=0.117, p=0.003), providing support for H3a and H3b.Further analysis reveals that Satisfaction (SAT) is positively and significantly associated with Continuance Intention (CI) (β=0.255, $p<0.001$), supporting H4. Moreover, Technology Anxiety (TA) negatively moderates the relationship between Satisfaction (SAT) and Continuance Intention (CI) (β=−0.25, $p<0.001$), supporting H5. This moderation effect is visually depicted in Figure 3, demonstrating how technology anxiety weakens the positive impact of satisfaction on continuance intention.

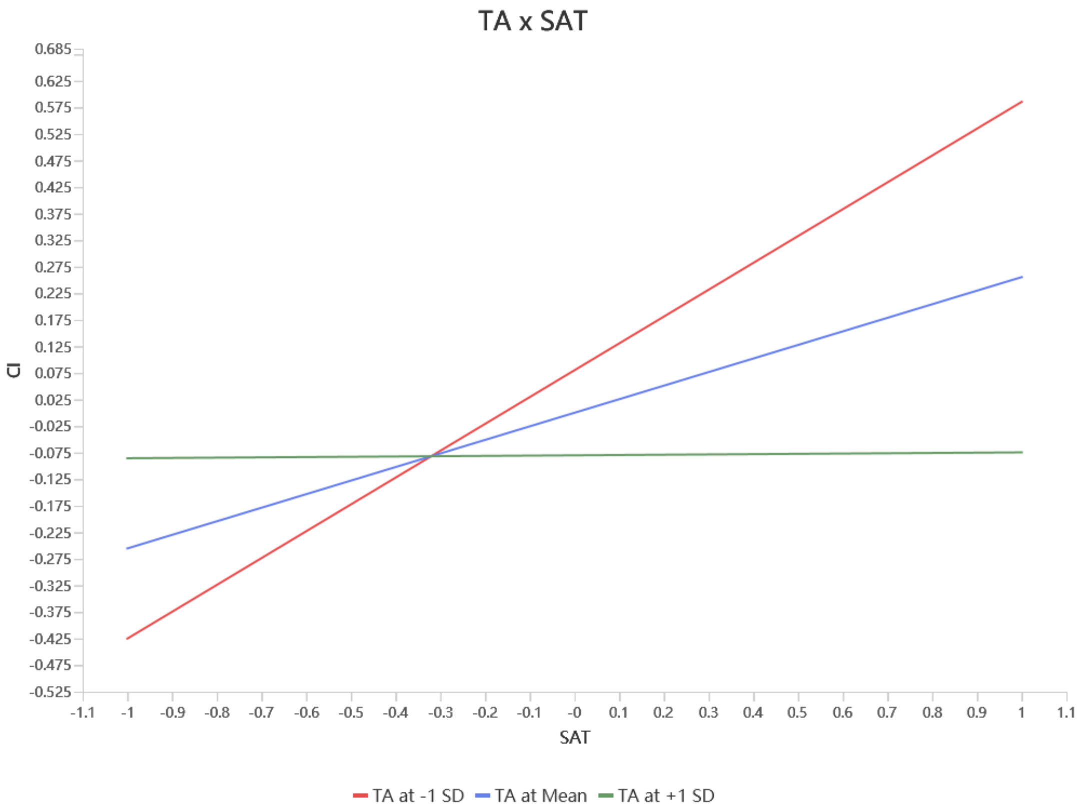

Figure 3 Moderation effect of technology anxiety on the relationship between satisfaction and continuance usage intention.

The results of the indirect effect analysis are summarized in Table 7. The findings indicate that Perceived Intelligence (PI) indirectly influences both Satisfaction (SAT) and Continuance Intention (CI) through Trust (TR) and Attitude (ATT). Specifically, PI indirectly impacts Satisfaction (SAT) via Trust (TR) (β=0.073, $p<0.001$) and Attitude (ATT) (β=0.071, $p<0.001$). Additionally, PI indirectly affects Continuance Intention (CI) through Trust (TR) (β=0.04, $p=0.003$) and Attitude (ATT) (β=0.036, $p=0.007$).Similarly, Trust (TR) indirectly influences Continuance Intention (CI) via Satisfaction (SAT) (β=0.059, $p<0.001$), and Attitude (ATT) also indirectly affects Continuance Intention (CI) via Satisfaction (SAT) (β=0.051, $p<0.001$). These findings highlight the critical mediating roles of trust, attitude, and satisfaction in shaping the continuance intention of AI wearable devices.

Table 7. Indirect effects.

No	Mediation regression coefficient Path	Indirect effects	S.D.	T-Value	P-Value	95% CIs	
						LL	UL
1	PI→TR→SAT	0.073	0.016	4.599	0	0.045	0.108
2	PI→TR→CI	0.04	0.013	2.989	0.003	0.016	0.069
3	PI→ATT→SAT	0.071	0.016	4.389	0	0.043	0.107
4	PI→ATT→CI	0.036	0.013	2.709	0.007	0.012	0.065
5	PI→SAT→CI	0.064	0.015	4.303	0	0.038	0.098

6	TR→SAT→CI	0.059	0.015	3.936	0	0.034	0.094
7	ATT→SAT→CI	0.051	0.013	3.946	0	0.03	0.081

Note(s): N = 562; S.D.:Standard deviation; ATT:Attitude; CI:Continuance Intention; PI:Perceived Intelligence; SAT:Satisfaction; TA:Technology Anxiety; TR:Trust.; CIs:Confidence intervals; LL:Low limit; UL:Upper limit. Source(s): Created by authors.

In summary, all hypothesized relationships were supported (see Table 6), demonstrating the robustness of the conceptual model. The results emphasize the importance of perceived intelligence, trust, and attitude in driving user satisfaction and continuance intention, while also highlighting the negative moderating effect of technology anxiety on the satisfaction-continuance intention relationship. Indirect effects further underscore the mediating roles of trust and attitude, providing a comprehensive understanding of the factors influencing continuance intention for AI wearable devices.

5. Discussion and conclusion

5.1. Key findings and theoretical contributions

With the increasing prevalence of AI-driven wearable devices in daily life, there has been a significant rise in public attention towards these devices (Tran et al., 2019). AI-powered wearable devices not only provide functions such as health monitoring, information alerts, and entertainment, but also attract a large number of users due to their constantly evolving AI capabilities (Hijazi et al., 2021; El-Gayar et al., 2020). These devices are now widely applied in various fields, including health management, sports tracking, and real-time communication, with their service functions gradually becoming more intelligent and personalized (Nahavandi et al., 2022). However, existing research on the factors that drive users' continued use of these devices is still relatively limited. This paper adopts the SOR model to explore the role of perceived intelligence in triggering users' cognitive responses (such as trust and attitude towards wearable devices), which in turn influence users' behavioral responses (e.g., satisfaction and continuance usage intention). Additionally, this study investigates the moderating effect of technology anxiety on the relationship between satisfaction and continuance usage intention, providing new theoretical insights into the field of AI-powered wearable devices.

Firstly, the empirical results of this study indicate that perceived intelligence plays a crucial role in triggering users' cognitive responses, such as trust and attitude. Specifically, perceived intelligence significantly and positively influences users' trust and attitude. This suggests that when users believe that AI wearable devices can provide personalized, thoughtful services and possess strong technological capabilities, their trust and attitude toward the device are enhanced (Kaplan et al., 2023; Sindermann et al., 2021), which aligns with our predictions.

Secondly, this study further validates the important role of trust and attitude in users' continuance usage intention towards AI wearable devices. Previous studies have shown that trust and attitude significantly affect the use behavior of technological systems (Bergmann et al., 2023; Foroughi et al., 2024). Our research provides empirical evidence that users' trust and attitude towards AI wearable devices can significantly predict their continuance usage intention. In this process, cognitive responses serve as an important mediating mechanism. In other words, when users have higher trust and a more positive attitude towards the device, they are more likely to continue using it. This finding suggests that designers of AI wearable devices should focus on enhancing the device's credibility and improving the user experience to promote long-term use.

Thirdly, although trust and attitude play a central role in continuance usage intention, technology anxiety serves as a significant moderating factor in this relationship. The study finds that technology anxiety negatively moderates the relationship between user satisfaction and continuance usage intention. Specifically, when users experience higher levels of technology anxiety while using AI wearable devices, the relationship between their satisfaction and continuance usage intention weakens. This finding suggests that technology anxiety may influence users' perceptions of the device, thereby reducing their intent to continue using it. To alleviate technology anxiety, designers of AI wearable devices could optimize the user interface, provide more user-friendly operation tips, and enhance users' sense of control over the device, which would reduce anxiety and strengthen their intention to use the device.

Finally, this study not only provides new insights into the continuance usage intention of AI wearable devices but also expands and validates the application of the SOR theory. There is relatively little research applying the SOR model to explore user behavior, especially in the context of AI wearable devices (Chakraborty et al., 2023; Nieves et al., 2023). By treating perceived intelligence as an important external stimulus factor, this study explores how it indirectly influences users' behavioral responses (i.e., satisfaction and continuance usage intention) through their cognitive responses (i.e., trust and attitude). Specifically, we demonstrate that perceived intelligence not only directly affects users' cognitive responses but also indirectly enhances users' satisfaction and continuance usage intention through these cognitive responses. This finding provides a theoretical basis for the design and optimization of AI wearable devices, particularly in terms of how intelligent design can enhance users' intention to continue using the devices, which has important practical implications.

5.2. Practical and managerial implications

With the rapid development of AI technology, the applications of AI-driven wearable devices are expanding across various domains, including health management, personal assistance, and entertainment, offering users rich personalized experiences (Huang et al., 2022; Ye et al., 2024). These devices not only enable real-time health monitoring but also provide intelligent reminders and customized life suggestions based on users' needs (Nahavandi et al., 2022). This study, based on the Stimulus-Organism-Response (SOR) model, explores the impact of perceived intelligence on user behavior and further analyzes the moderating role of technology anxiety in users' continuance usage intention. The findings offer valuable practical and managerial insights for the wearable device industry, particularly regarding how to enhance user experience and optimize device design.

Firstly, the study reveals that perceived intelligence, as a key stimulus factor, influences users' cognitive processes (such as trust and attitude), which in turn affects their behavioral responses (e.g., satisfaction and continuance usage intention). Specifically, the intelligence level, responsiveness, and personalized services of AI wearable devices are key decision-making factors for users (Bruine et al., 2020; Araujo et al., 2020). For example, to improve user experience, device manufacturers can enhance the natural language processing algorithms to increase response speed and accuracy (Liang et al., 2022). In addition, the appearance design, user interface friendliness, and interaction functions of the device should focus on conveying the device's intelligence and capability. By enhancing the perception of intelligence, manufacturers can trigger users' trust and positive attitudes, thereby increasing their intention to continue using the device (Lee et al., 2023). Therefore, brands and marketing strategies for AI wearable devices should emphasize the device's intelligence and efficiency, highlighting personalized services and round-the-clock availability to attract and retain more users.

Secondly, this study highlights the core role of satisfaction in users' continuance usage intention. For the AI wearable device industry, this finding underscores the necessity of improving user satisfaction. Device manufacturers need to continually optimize user experience, particularly in terms of the device's level of intelligence and functional reliability. Collecting continuous user feedback, especially related to device performance, comfort, and personalized services, will help further enhance device design and functionality (Gupta et al., 2021). Moreover, AI wearable devices should possess the ability to predict user needs and respond instantly. By integrating predictive analytics, devices can anticipate changes in users' health or exercise needs and provide personalized suggestions or reminders, thereby enhancing user satisfaction and increasing their continuance usage intention (Prentice et al., 2020). For example, the device can predict the user's next exercise plan or health status

based on their activity trajectory, prompting users to rely more on the device.
Finally, technology anxiety was found to significantly moderate the relationship between satisfaction and continuance usage intention. When users experience anxiety regarding the technological complexity of AI wearable devices, it may affect their user experience and intentions to continue using the device (Pham et al., 2024). Therefore, device manufacturers should pay particular attention to designing more intuitive and user-friendly interfaces, providing clear usage instructions and technical support options to reduce users' technology anxiety (Tsai et al., 2020). Additionally, providing human-assisted services or virtual assistant functions can help users who feel uneasy about AI technology gain more trust, thereby alleviating their anxiety (AlQudah et al., 2021). By optimizing these factors, device manufacturers can improve user satisfaction and promote the intention to continue using the device.

5.3. Limitations and avenue for further research

Although this study provides innovative findings and significant contributions to both theory and practice regarding the continuance usage intention of AI-driven wearable devices, it also has some limitations and offers potential directions for future research. First, this study was conducted in China, with data collected from 562 respondents. While this sample size is sufficient for many studies, it may limit the generalizability of the findings. The conclusions of this research are primarily applicable to Chinese users and may not fully represent users from different countries or regions. Future research could expand the sample size to include users from diverse countries, regions, and backgrounds, which would enhance the external validity of the study and make the conclusions more universal, thus contributing to a broader understanding of wearable device user behavior globally.Second, the data collection period for this study was only six weeks. Although this time frame provided valuable preliminary data, it may not have captured the changes in long-term usage experiences and outcomes. Long-term usage experiences and outcomes could influence users' adoption behaviors, such as the effectiveness of chronic disease management or treatment. Therefore, future studies could adopt a more extended observation period to comprehensively understand how users' behaviors, satisfaction, and continuance usage intentions evolve over time.Finally, given the rapid advancements in AI and natural language processing technologies, future research should focus on exploring the impact of improvements in wearable device functionality on user adoption and satisfaction. Specifically, as AI technologies and device functionalities continue to evolve, understanding how these advancements change users' perceptions, usage experiences, and continuance usage intentions will provide more forward-looking insights for the industry. For example, improvements in AI-driven technological tools may directly influence user engagement and usage intentions. Therefore, research on how to optimize these technological features to meet users' ever-changing needs will offer valuable guidance for the promotion and optimization of AI-powered wearable devices.

Author Contributions

In this study, the first author, Gao Feng, conducted the entire research under the guidance of the corresponding author, Edwin Ng Siew Kten. Specifically, Edwin Ng Siew Kten was responsible for the study design, the development of the theoretical model, and the data analysis, providing crucial guidance on the overall direction and methodology of the research. Meanwhile, Gao Feng primarily managed data collection and was actively involved in data analysis, manuscript drafting, and other related tasks throughout the research process. All authors contributed to the discussion, review, and final approval of the manuscript.

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Appendix

Variable	Item	Reference
Perceived Intelligence	AI-based wearable products understand my needs and preferences well.	(Moussawi et al.,2023), (Lin et al.,2023)
	I find AI-based wearable products to be highly intelligent.	
	AI-based wearable products provide me with personalized recommendations.	
	I believe AI-based wearable products can handle complex tasks in a smart way.	
	While using AI-based wearable products, I feel like they act as a smart assistant.	
Trust	I trust AI-based wearable products to protect my personal information.	(Liu et al.,2022), (Hsiao and Chen,2022)
	I believe the features of AI-based wearable products are reliable.	
	I think AI-based wearable products work as expected.	
	I trust the manufacturers of AI-based wearable products.	
	I am confident that AI-based wearable products will not misuse my personal data.	
Attitude	Using AI-based wearable products is a good idea.	(Foroughi et al.,2019), (Khayer and Bao,2019), (Jeng et al.,2022)
	I think AI-based wearable products are useful tools.	
	I have a positive attitude toward using AI-based wearable products.	
	I believe using AI-based wearable products improves the quality of my life.	
	I think using AI-based wearable products is an enjoyable experience.	
Satisfaction	Overall, I am satisfied with my experience of using AI-based wearable products.	(El-Gayar and Elnoshokaty,2023), (Bölen,2020)
	Using AI-based wearable products has been a pleasant experience for me.	
	AI-based wearable products have met my needs and expectations.	
	I am satisfied with the quality of services provided by AI-based wearable products.	
	Compared to other similar products, I feel more satisfied with AI-based wearable products.	
Continuance Intention	I intend to continue using AI-based wearable products in the future.	(Wang et al.,2022),

	Even if I have other options, I will still choose to use AI-based wearable products.	(Bölen,2020)
	I will prioritize AI-based wearable products for my future needs.	
	I am willing to recommend AI-based wearable products to my friends or family.	
	AI-based wearable products are important to me, and I plan to keep using them.	
Technology Anxiety	I feel nervous when I need to use AI-based wearable products.	(Jeng et al.,2022)， (Pham et al.,2024)
	I worry that I might make mistakes while using AI-based wearable products.	
	AI-based wearable products make me feel anxious because they seem too complex.	
	I am afraid I might not fully understand how to operate AI-based wearable products.	
	I am concerned that AI-based wearable products might malfunction or fail.	