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Exploring factors influencing the adoption of smart elderly care products: An enhanced UTAUT model analysis of smart wearables

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Abstract: This study investigates factors influencing elderly adoption of smart wearables. Using a modified Unified Theory of Acceptance and Use of Technology (UTAUT), it surveyed 395 elders. Structural equation modeling (SEM) analysis reveals positive impacts of facilitation, performance, and social influence on adoption, while cost and risk hinder it. Adoption intention mediates usage. The study emphasizes usability, functionality, social acceptance, and affordability in designing and marketing smart wearables for the elderly, aiming for broader acceptance and usage.

Keywords: *Elderly adoption, Smart wearable technology, Unified theory of acceptance and use of technology (UTAUT), User behavior, Social influence.*

1. Introduction

With the improvement of global medical standards, increased levels of education, and declining birth rates, human lifespan is significantly extending [1]. According to the 'World Social Report 2023,' by 2021, the global population aged 65 and above reached 761 million, and it is expected to increase to 1.6 billion by 2050 [2]. Particularly, the growth rate of the population aged 80 and above is even more rapid, posing significant challenges for global society [2]. As the largest developing country in the world, China also faces severe aging issues. By 2022, the population aged 65 and above accounted for 14.90% of the total population of mainland China, a proportion that is accelerating [3]. This indicates that China has far exceeded the international standards for entering an aging society, namely a population ratio of 10% aged 60 and above or 7% aged 65 and above.

To address the aging issue, the development of smart elderly care products provides a comprehensive and sustainable solution [4]. These products meet the needs of the elderly in terms of health management, social interaction, and convenience in daily life, significantly improving their quality of life. Moreover, the rise of the smart elderly care industry also drives technological innovation and opens new approaches to solving the problems of an aging society. It is expected that China's smart elderly care industry will continue to expand in the future, making a greater contribution to global elderly care services.

The most important civilian product in smart elderly care is wearable technology, which provides scientific health management advice by monitoring health data in real-time (such as heart rate, steps, sleep conditions, etc.), helping the elderly to promptly detect physical abnormalities [5]. These devices also feature emergency call and location functions, providing quick rescue means for elderly living alone, and their life assistance and reminder functions help them regulate their lives and remember daily tasks. Additionally, through built-in social functions, wearable devices can alleviate the loneliness of the elderly, enabling them to easily keep in touch with family and friends.

Since 2013, the rapid development of internet technology and smart sensors has greatly enhanced the performance of wearable technology, which has played a significant role in fields such as medical, healthcare, and sports. Wearable devices like smart bracelets, smart running shoes, smart garments, and

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smart glasses have been widely integrated into daily life [6, 7, 8, 9]. These devices are considered the 'golden key linking the human body to smart devices' [10].

To meet the demands for elderly care and personalized health services, age-appropriate smart wearable products have emerged in the consumer market for the elderly [11]. These products are typically designed to be worn on the wrist, head, glasses, shoes, etc., with sensing and interaction capabilities that can collect, analyze, and transmit data to fulfill various elderly care application scenarios [12]. With the development of big data and the digital economy, it is expected that from 2020 to 2025, the compound growth rate of the market for age-appropriate smart wearable products will reach 20%.

However, despite the huge market potential of age-appropriate smart wearable products, research on the factors influencing consumer adoption is still relatively insufficient. Current studies generally consider product characteristics as the key factor influencing consumer adoption, but further research into other potential influencing factors and mechanisms is needed. Besides, issues like privacy leaks and false alarms may also affect consumers' judgment and trust levels [12, 13]. Although some studies have explored the impact of product characteristics on consumer adoption, the results are relatively limited and lack depth. Furthermore, existing research methods mainly rely on qualitative research or simulated product experiences, which need further validation to guide practical applications [5]. Therefore, this paper is based on exploring the Unified Theory of Acceptance and Use of Technology (UTAUT) to predict and understand the application of elderly people's adoption behavior of smart wearable products and its potential improvements.

2. Literature Review

2.1. Concepts Related to Smart Elderly Care Products and Wearable Technology

Wearable technology (WT) combines artificial intelligence with portable electronic devices, creating an interdisciplinary field that covers electronic information engineering, healthcare, life sciences, and sports, among others. Godfrey et al. [7] define wearable technology as a collection of various devices that include both tightly and loosely worn equipment on the body. These devices can be comfortably worn on the body or clothing and are capable of processing personalized data [14, 15].

Smart wearable products are wearable devices integrated with smart technology, typically including sensors, computing power, and communication functions, capable of monitoring, recording, and analyzing users' physiological states and physical activities [5]. These products are designed to be fashionable and lightweight, such as smart watches, smart glasses, smart bracelets, and smart clothing, all falling within the category of smart wearable products. These products contact the user's body and can be worn on the wrist, head, glasses, shoes, etc. Through their sensing and interactive capabilities, they collect, analyze, and transmit data, enabling various application scenarios [16]. With technological advancements and the pursuit of intelligence, wearable technology products have become one of the commonly used devices in everyday life [17].

2.2. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a comprehensive model proposed by Venkatesh et al. [18] that integrates the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Diffusion of Innovations (DOI), aiming to more comprehensively explain users' acceptance and use of new technologies. The UTAUT model relies on four core variables to predict technology acceptance and use, which include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), and is moderated by variables such as gender, age, experience, and voluntariness. These factors collectively measure users' expectations of technology performance, the effort required to adopt the technology, the technology's impact on users' social status, and the convenience of using the technology [19].

In the field of smart elderly care products, the UTAUT model has shown good applicability and has been widely used to explore the factors of acceptance among the elderly, as indicated by studies such as those by Chen et al. [20] and Wang et al. [5]. However, in the field of smart wearable products, the application of the UTAUT model faces some challenges, mainly due to the special nature of smart wearable products, which require more in-depth consideration of user experience, design factors, and actual convenience of use.

Research indicates that when elderly people adopt smart elderly care products, there is no significant difference in gender and age, thus these two control variables are not included in the model [21]. Besides gender and age, characteristics such as health condition and lifestyle of smart wearable product users are particularly important in the model. Therefore, when applying UTAUT to smart wearable products, further adjustments and enhancements to the model might be necessary to more comprehensively explain users' adoption behavior. By integrating and extending existing theories, researchers can more accurately describe users' behaviors and motivations in real-world contexts, thereby addressing new challenges brought by technological advancements and social development.

2.3. Facilitating Conditions and Actual Use of Smart Wearable Products

Usability, wearing comfort, and the burden of daily use are important factors influencing the adoption of smart wearable products by the elderly [22]. As technology advances and smart products become more common, whether elderly people can easily access the necessary support resources becomes a key factor influencing their willingness to adopt these products [5]. Elderly consumers are more likely to adopt and continue using smart elderly care products and wearable devices if they believe these resources can effectively help them use the products [17]. This not only enhances their quality of life but also optimizes their health management [4]. Therefore, usability and the ease of accessing support resources directly affect the development of the smart elderly care product market and the preference choices of elderly consumers. Thus, the following hypothesis is proposed:

H_1: Facilitating conditions have a positive impact on the actual use of smart wearable products.

2.4. Features of Smart Wearable Products and Actual Use of Smart Wearable Products

The actual use of smart wearable products is influenced by multiple factors related to their features and surrounding elements, including expected performance, perceived cost, and the impact of the social environment. According to the study by Jeng et al. [22], product features play a crucial role in forming user adoption intentions. First, expected performance is an important factor for users, especially for elderly users who expect smart wearable devices to accurately monitor health data and provide timely alerts or suggestions to meet their health management needs [5]. Second, perceived cost is also a key factor influencing user decisions, including the purchase cost, usage cost, and maintenance cost of the devices [23]. If the costs are too high, even if the device performs well, it might suppress users' willingness to adopt, thereby affecting actual use [24]. Lastly, the impact of the social environment cannot be ignored; user adoption behavior is influenced by the surrounding social and cultural atmosphere, the attitudes and behaviors of others, and positive social support can enhance user adoption willingness and vice versa [25]. Therefore, the following hypotheses are proposed:

H_2: Expected performance has a positive impact on the actual use of smart wearable products.

H_3: Perceived cost has a negative impact on the actual use of smart wearable products.

H_4: Social environmental impact has a positive impact on the actual use of smart wearable products.

2.5. Intention to Adopt Smart Wearable Products and Actual Use of Smart Wearable Products

The intention to adopt a device is a prerequisite for truly integrating it into daily life and for its continued use, directly determining the occurrence of actual adoption behavior. When users believe that smart wearable devices meet their expectations, are cost-effective, and are recognized by the social environment, they are more likely to adopt such devices [20]. For example, if a device meets users' health management needs, is easy to operate, has comprehensive functions, and is reasonably priced, and if it is recommended or approved by friends or family, users will be more willing to adopt it [4]. Conversely, if the cost of the device is too high or its functions do not meet users' expectations, users may abandon adoption, affecting the occurrence of actual adoption behavior [5]. Therefore, the following hypothesis is proposed:

H_5: The intention to adopt smart wearable products has a positive impact on the actual use of smart wearable products.

2.6. Characteristics of the Elderly and Actual Use of Smart Wearable Products

When discussing the actual adoption rate of smart wearable products among the elderly, several key factors play a decisive role. Firstly, a high perception of risk may lead to increased concerns among the elderly about smart wearable devices, thereby reducing their actual adoption rate [26]. These concerns mainly stem from unfamiliarity with new technology and fear of potential problems, such as privacy breaches and device malfunctions. Secondly, the physical condition of the elderly directly affects the comfort and convenience of wearing the devices; those in better physical condition may find these devices more comfortable and convenient to wear, and therefore are more likely to adopt such products [27]. Additionally, concerns about health status are also an important factor; elderly individuals who are more concerned about their health may be more inclined to adopt smart wearable devices to better monitor and manage their health [22]. Lastly, the demand for information technology innovation also affects the adoption decisions of the elderly; those who are open to new technology and have a clear need for health management are more likely to actually adopt smart wearable devices [5]. Therefore, the following hypotheses are proposed:

H_6: Perceived risk has a negative impact on the actual use of smart wearable products.

H_7: Physical condition has a positive impact on the actual use of smart wearable products.

H_8: Health anxiety has a positive impact on the actual use of smart wearable products.

H_9: Demand for information technology innovation has a positive impact on the actual adoption of smart wearable products.

2.7. The Impact of Perceived Risk on the Intention to Adopt Smart Wearable Products

As they age and due to limited experience with technology, the elderly often hold a higher perception of risk towards emerging technology products, especially smart wearable devices. This perception mainly stems from concerns about the unknown and doubts about their own ability to operate the devices [23]. On one hand, elderly individuals worry that they cannot adapt to the changes brought by new technology, feeling uneasy about potential technical failures and adverse experiences [24]; on the other hand, they are concerned about privacy breaches, security risks, or information leaks that may occur during use. These factors together reduce their willingness to adopt smart wearable devices.

Furthermore, the complexity and technical nature of smart wearable products may also make them seem difficult to master for older users, further intensifying their hesitation and concerns, leading to a lower acceptance of such emerging technologies [26]. Therefore, the following hypothesis is proposed:

H_{10}: Perceived risk has a negative impact on the intention to adopt smart wearable products.

2.8. Mediating Effects of Intention to Adopt Smart Wearable Products

Users' positive expectations that the device can efficiently and accurately meet their needs for health monitoring can increase their intention to adopt, thereby leading to the actual adoption of the device. Higher perceived costs, such as purchase and maintenance costs, may reduce users' intention to adopt, thus hindering the actual adoption of the product [24]. In other words, if the costs are perceived as too high, even if the product performs well, users' intention to adopt can be negatively affected, ultimately impacting the actual use of the product [25]. When users feel positive support from the social environment, such as recommendations from friends and family, their intention to adopt is enhanced, making it more likely that they will actually adopt these devices [20]. High perceived risk may lead to low adoption intention because users worry about privacy breaches or device malfunctions, and this low intention reduces the likelihood that they will actually adopt such products [26]. These hypotheses collectively demonstrate the bridging role of adoption intention between various motivators and the actual adoption of smart wearable products, highlighting the importance of understanding and increasing the adoption rate of smart wearable products. Therefore, the following hypotheses are proposed:

H_{11}: Intention to adopt smart wearable products mediates between expected performance and actual adoption of smart wearable products.

H_{12}: Intention to adopt smart wearable products mediates between perceived cost and actual adoption of smart wearable products.

H_{13}: Intention to adopt smart wearable products mediates between social environmental impact and actual adoption of smart wearable products.

H_{14}: Intention to adopt smart wearable products mediates between perceived risk and actual adoption of smart wearable products.

2.9. Research Model

This paper is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model and has been modified and expanded for the adoption of smart wearable technology by the elderly. The explanation of each variable is as follows: Product features include facilitating conditions and expected performance, which are traditional factors affecting technology acceptance. Perceived cost refers to the costs perceived by users when adopting technology, including money, time, or effort. Social environmental impact refers to the influence of people around the user, such as the views and attitudes of family, friends, or colleagues towards using the technology. Perceived risk is particularly important among the elderly, referring to concerns about safety and privacy protection that users may have when considering adopting new technology. Elderly characteristics are a special contribution of this model, including physical condition, health anxiety, and the demand for information technology innovation, which are directly related to the likelihood of elderly people accepting and using smart wearable devices. The intention to adopt reflects the user's intrinsic willingness to adopt a certain technology, while actual adoption is the behavior of users actually starting to use the technology. The relationship between these two indicates that intention does not always directly translate into action, and actual use may also be influenced by other factors. As shown in Figure 1.

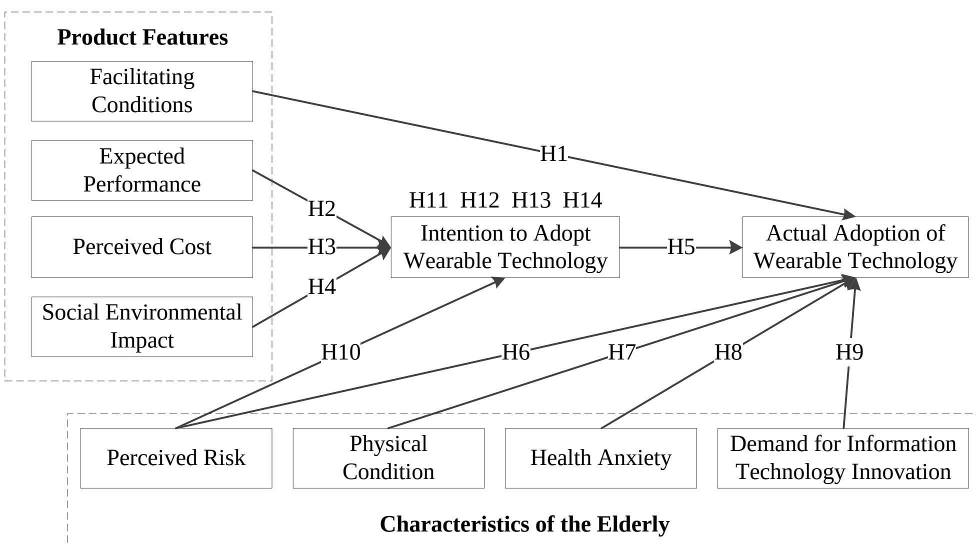

Figure 1.
Research model.

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3. Methodology

3.1. Survey Questionnaire

The Facilitating Conditions scale refers to the scales of Davis [28] and Walczuch et al. [29], consisting of 4 items, for example, 'I have sufficient resources to obtain smart wearable products, such as financial conditions, knowledge level, etc.' The Expected Performance scale also refers to the scales of Davis [28] and Walczuch et al. [29], with 4 items, such as 'Smart wearable products can help me better enjoy elderly care services.' The Perceived Cost scale is based on the scale of Sonderegger and Sauer [30], with 3 items, such as 'I need to spend a lot of time and effort learning to use smart wearable products.' The Social Environmental Impact scale refers to the scales of Davis [28] and Walczuch et al. [29], consisting of 4 items, for example, 'People around me influence my decision to use smart wearable products.' The Perceived Risk scale refers to the scales of Stone and Gr Nhaug [31], Wu and Wang [32], and Zhao and Zhou [33], with 5 items, such as 'Using smart wearable products might cause me financial loss.' The Physical Condition scale refers to the scale of Phang et al. [34], with 3 items, for example, 'Smart wearable devices can meet my health management needs.' The Health Anxiety scale is based on the scale of Compeau and Higgins [35], with 4 items, such as 'I always feel that my health condition is poor.' The Demand for Information Technology Innovation scale refers to the scale of Agarwal and Prasad [36], with 4 items, such as 'I desire to use the latest technology products.' The Intention to Adopt Smart Wearable Products scale refers to the scales of Davis [28] and Walczuch et al. [29], with 4 items, such as 'Having smart wearable products can improve my quality of life.' The Actual Adoption of Smart Wearable Products scale also refers to the scales of Davis [28] and Walczuch et al. [29], with 4 items, such as 'I will continuously use smart wearable products.'

3.2. Sample

As this study will employ AMOS 26.0 for structural equation modeling, the sample size will be determined based on the commonly referenced rule of ten [37]. The questionnaire used in this study includes 39 scales within the conceptual model, and this rule stipulates that the sample size should be at least 390 responses. Therefore, the survey involves an investigation of the factors influencing consumer adoption in the smart wearable product market, targeting both existing elderly consumers who already own smart wearable products and potential elderly consumers. For this purpose, the survey data should be distributed to participants who are at least 60 years old to complete.

Jinan, the capital of Shandong Province and a sub-provincial city, is an ideal location for studying consumer decision-making regarding smart wearable products due to its geographical advantages, abundant resources, active economic and cultural atmosphere, and advanced level of technology. The high degree of aging and large elderly population in Jinan mean that the demand for smart elderly care products is increasing, presenting significant market potential. The elderly population's focus on health management and quality of life, coupled with possible support measures from the Jinan government, provide favorable conditions for research on smart elderly care products. Jinan's moderate level of economic development provides a stable market base and rich human resources, supporting the research and development and promotion of smart elderly care products. In such an economic environment, the elderly are more willing to try new products, which helps expand the market and enhance product competitiveness.

In this study, the survey questionnaires were distributed both online and offline, totaling 420 questionnaires distributed, with 417 returned, yielding a response rate of 99.29%. Among these, 22 questionnaires were invalid, leaving 395 valid questionnaires and an effective recovery rate of 94.72%. Demographic data shows that the gender ratio in Jinan is 52.43% female and 47.57% male. The age distribution is as follows: 25.24% are aged 60 to 65 years, 23.30% are 66 to 70 years, 20.39% are 71 to 75 years, 17.48% are 76 to 80 years, and 13.59% are over 80 years old. Regarding marital status, 57.28% are married, 14.56% are unmarried, and 28.16% have experienced marital changes. In terms of educational level, 47.57% have an education of college level or higher. Economically, over 70% of individuals have a monthly income of less than 5000 yuan. Most residents are distributed in the Lixia

District, Tianqiao District, Licheng District, and Shanghe County. The ownership rate of smart wearable products is 78.64%, with smart bands and smart blood pressure monitors being the most common types.

4. Results

4.1. Common-Method Bias

Common Method Bias (CMB) is a frequently noted issue in social science research, particularly when collecting data using survey methods. In this paper, Harman's single-factor test was used by conducting a factor analysis of all the measured variables. If only one factor emerges or if one factor explains a major portion of the variance (typically more than 50%), then there may be a significant common method bias. The results of Harman's single-factor test revealed that ten factors with eigenvalues greater than 1 were extracted, where the largest cumulative explanatory power was 9.747%, not exceeding 50%. Therefore, it can be determined that the scales used in this study do not suffer from severe common method bias [38].

4.2. Reliability and Validity Analysis

To test the reliability and validity of the scales, AMOS 26 was used to conduct confirmatory factor analysis to test convergent validity, and SPSS 26 was used to verify the scales' Cronbach's alpha coefficients.

First, an oblique rotation was performed on the variables to construct the overall confirmatory factor analysis model. The results showed that $\chi^2/df = 2.884 < 3$, GFI = 0.937 > 0.9, AGFI = 0.919 > 0.9, CFI = 0.935 > 0.9, PCFI = 0.825 > 0.5, RMSEA = 0.049 < 0.08, SRMR = 0.055 < 0.08, indicating that the scale's indices fit ideally [39].

As shown in Table 1, there are three criteria to assess convergent validity: All standardized factor loadings (Standard Regression Weights) must be greater than 0.5 [40, 41]; Composite reliability (CR) must be greater than 0.6 [40, 41]; Average variance extracted (AVE) must be greater than 0.5 [40, 41]. According to Table 1, all items' standardized loadings exceed 0.5, meeting the criteria. The composite reliability values (CR) are all greater than 0.6, and the average variance extracted (AVE) values are all greater than 0.5, indicating that the scales meet the standards for convergent validity [40]. Additionally, the Cronbach's alpha coefficients for each variable are higher than 0.7, indicating good reliability for each variable.

Table 1.
Convergent validity test results.

Variables	Items	λ	CR	AVE	α
Facilitating conditions	FC1	0.742	0.835	0.560	0.822
	FC2	0.690			
	FC3	0.698			
	FC4	0.853			
Expected performance	EP1	0.725	0.850	0.586	0.847
	EP2	0.764			
	EP3	0.814			
	EP4	0.757			
Perceived cost	PC1	0.719	0.876	0.701	0.800
	PC2	0.887			
	PC3	0.894			
Social environmental impact	SEI1	0.734	0.887	0.664	0.841
	SEI2	0.801			
	SEI3	0.877			

Variables	Items	λ	CR	AVE	α
	SEI4	0.840			
Perceived risk	PR1	0.801	0.897	0.636	0.855
	PR2	0.809			
	PR3	0.870			
	PR4	0.811			
	PR5	0.684			
Physical condition	RCO1	0.857	0.882	0.714	0.714
	RCO2	0.884			
	RCO3	0.791			
Health anxiety	HA1	0.614	0.830	0.555	0.780
	HA2	0.692			
	HA3	0.720			
	HA4	0.920			
Demand for information technology innovation	DITI1	0.686	0.845	0.581	0.836
	DITI2	0.850			
	DITI3	0.848			
	DITI4	0.641			
Intention to adopt wearable technology	IAWT1	0.720	0.845	0.581	0.793
	IAWT2	0.805			
	IAWT3	0.733			
	IAWT4	0.779			
Actual adoption of wearable technology	AAWT1	0.688	0.832	0.557	0.765
	AAWT2	0.875			
	AAWT3	0.692			
	AAWT4	0.713			

Table 2.
Correlation matrix and discriminant validity.

Variables	FC	EP	PC	SEI	PR	PCO	HA	DITI	IAWT	AAWT
FC	0.75									
EP	0.41**	0.77								
PC	-0.36**	-0.38**	0.84							
SEI	0.43**	0.39**	-0.49**	0.82						
PR	-0.40**	-0.38**	0.34**	-0.48**	0.80					
PCO	0.37**	0.36**	-0.50**	0.31**	-0.48**	0.85				
HA	0.37**	0.32**	-0.36**	0.34**	-0.48**	0.46**	0.75			
DITI	0.33**	0.36**	-0.37**	0.39**	-0.31**	0.39**	0.32**	0.76		
IAWT	0.45**	0.32**	-0.40**	0.49**	-0.39**	0.36**	0.35**	0.47**	0.76	
AAWT	0.31**	0.37**	-0.47**	0.49**	-0.48**	0.37**	0.37**	0.39**	0.48**	0.75

Note: **p<0.01, FC (Facilitating conditions), EP (Expected performance), PC (Perceived cost), SEI (Social environmental impact), PR (Perceived risk), RCO (Physical condition), HA (Health anxiety), DITI (Demand for information technology innovation), IAWT (Intention to Adopt wearable technology), AAWT (Actual Adoption of wearable technology)

4.3. Correlation Analysis

Table 2 presents the discriminant validity table for the scales, analyzing the degree of differentiation by examining the correlations between each internal variable and others. The correlation structure within each factor scale shows consistency internally and significant differentiation between factors [40]. At the same time, there are significant correlations between each variable, preliminarily validating the hypotheses proposed in this paper.

4.4. Hypothesis Testing

Using AMOS 26.0 software and the maximum likelihood estimation method, structural equation modeling analysis was conducted on the main effect model. The fit indices for the model are as follows: (χ^2/df = 2.947 < 3, GFI = 0.931 > 0.9, AGFI = 0.907 > 0.9, CFI = 0.931 > 0.9, PCFI = 0.824 > 0.9, RMSEA = 0.049 < 0.08, SRMR = 0.055 < 0.08), indicating that the model fits well [39].

The results of the hypothesis tests are shown in Figure 2, revealing the following: Facilitating conditions have a significant positive impact on the actual use of smart wearable products ($\beta = 0.30$, $p < 0.001$), supporting H1. Expected performance has a significant positive impact on the actual use of smart wearable products ($\beta = 0.28$, $p < 0.001$), supporting H2. Perceived cost has a significant negative impact on the actual use of smart wearable products ($\beta = -0.19$, $p < 0.01$), supporting H3. Social environmental impact has a significant positive impact on the actual use of smart wearable products ($\beta = 0.33$, $p < 0.001$), supporting H4. The intention to adopt smart wearable products has a significant positive impact on the actual use of smart wearable products ($\beta = 0.44$, $p < 0.001$), supporting H5. Perceived risk has a significant negative impact on the actual use of smart wearable products ($\beta = -0.08$, $p > 0.05$), not supporting H6. Physical condition has a significant positive impact on the actual use of smart wearable products ($\beta = 0.33$, $p < 0.001$), supporting H7. Health anxiety has a significant positive impact on the actual use of smart wearable products ($\beta = 0.19$, $p < 0.05$), supporting H8. The demand for information technology innovation has a significant positive impact on the actual adoption of smart wearable products ($\beta = 0.15$, $p < 0.05$), supporting H9. Perceived risk has a significant negative impact on the intention to adopt smart wearable products ($\beta = -0.17$, $p < 0.05$), supporting H10.

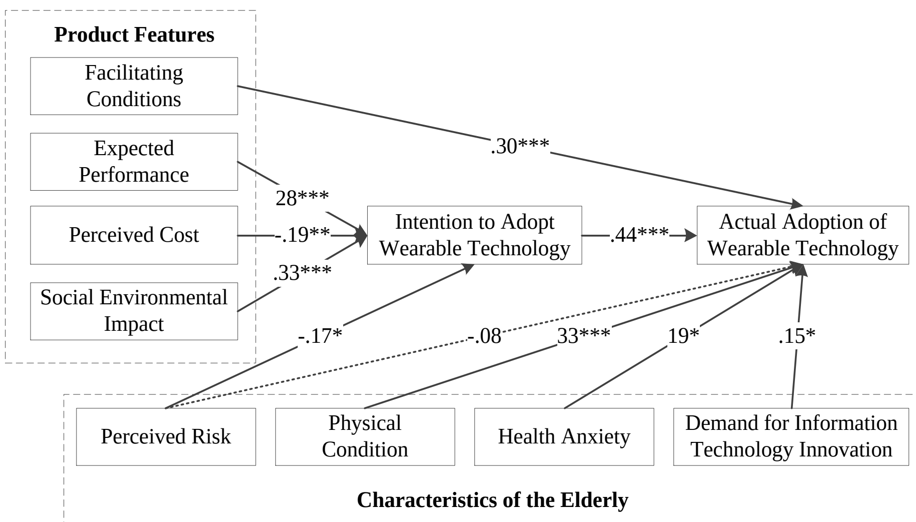

Figure 2.
Results of structural model.
Note: *p<0.05, **p<0.01, ***p<0.001

Bootstrapping can be used to test mediating effects. According to the results of the bootstrapping method, the mediating path from expected performance to the intention to adopt smart wearable products to the actual adoption of smart wearable products ($\beta = 0.12$, $p < 0.01$, CI = [0.003, 0.017]) supports H11. The mediating path from perceived cost to the intention to adopt smart wearable products to the actual adoption of smart wearable products ($\beta = -0.08$, $p > 0.05$, CI = [-0.006, 0.004]) does not support H12. The mediating path from social environmental impact to the intention to adopt smart wearable products to the actual adoption of smart wearable products ($\beta = 0.14$, $p < 0.01$, CI =

[0.005, 0.022]) supports H13. The mediating path from perceived risk to the intention to adopt smart wearable products to the actual adoption of smart wearable products (β = -0.07, p > 0.05, CI = [-0.005, 0.004]) does not support H14.

5. Discussion

This study utilized an improved Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze in detail the factors influencing elderly people's adoption of smart wearable products. The results indicate that facilitating conditions [4, 17], expected performance [5], social environmental impact [25], and the intention to adopt smart wearable products have a significant positive impact on the actual adoption behavior of elderly individuals [5, 20]. These positive effects reflect that elderly people tend to prefer devices that are easy to use, reliable in performance, and widely accepted by society. Additionally, perceived cost and perceived risk negatively impact actual adoption, findings that align with previous research and reemphasize the importance of functionality and cost-effectiveness in the technology adoption decisions of the elderly.

The study also revealed that the intention to adopt smart wearable products mediates between several variables, such as expected performance [25] and social environmental impact [20], and actual adoption. This indicates that once elderly people form an intention to adopt smart wearable products, they are more likely to translate this intention into actual adoption behavior. This finding highlights the importance of enhancing elderly people's recognition and trust in smart wearable products in product design and marketing strategies. By improving user experience design and strengthening the dissemination of positive social influences, the adoption rate among elderly people can be effectively increased.

However, the presence of perceived risk may weaken elderly users' intention to adopt, especially for those concerned about privacy breaches and data security [23, 26]. Therefore, reducing elderly users' perception of risk and increasing their trust in the product is key to the successful promotion of smart wearable products. Manufacturers and designers should focus on the safety design of products, enhance communication with users, and clearly inform users of the security measures in place to alleviate their safety concerns.

Through these strategies, the market acceptance and usage of smart wearable products are expected to significantly increase among the elderly consumer group. Future research could further explore the acceptance of smart wearable technology among elderly people from different cultural backgrounds and how personalized needs influence their adoption decision-making process. Moreover, as technology rapidly advances and the elderly population grows, understanding and addressing the challenges faced by elderly people in adopting new technology will be crucial for promoting social inclusiveness and technological innovation.

6. Conclusion

This study, by meticulously analyzing the motivations and barriers to the adoption of smart wearable products by the elderly, significantly extends our understanding of this field. The research revealed various factors influencing the technology adoption decisions of the elderly, including the usability, functionality, perceived cost, social influence, and personal perception of risk associated with technology. The combined effect of these factors not only influences the elderly's willingness to adopt but also directly impacts their actual adoption behavior.

These findings provide valuable empirical support for the design and market positioning of smart wearable products, guiding companies to focus on balancing functionality and design when developing new products, ensuring that the products are compatible with the operational habits of the elderly while meeting their needs for functions such as health monitoring. Additionally, this study provides a more comprehensive perspective for the further development of technology acceptance models, suggesting that future research could integrate more variables related to personalized needs and psychological perceptions into the model.

When targeting the elderly market, product developers and marketers should consider convenience, safety, cost-effectiveness, and social acceptance as core considerations in design. By doing so, not only can the market competitiveness of the products be enhanced, but it can also better meet the special needs of the elderly population. Governments should create a supportive social and technological environment by enacting favorable policies, such as providing technology training, establishing public access points, and offering discounted purchasing options. These measures can help reduce psychological barriers for the elderly towards new technology, encourage them to actively adopt smart technologies, thereby improving their quality of life and ability to live independently.

Future research should further explore how the attitudes of the elderly towards emerging technologies change with cultural backgrounds and social environments, and how these external factors collectively impact their technology acceptance and usage behaviors. Through these studies, we can gain a deeper understanding of the needs and expectations of the elderly regarding emerging technologies, providing a scientific basis for designing more user-friendly smart products.

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