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# Dual Drivers of Experience and Trust: Exploring the Mechanisms of Elderly User Adoption of AI-HVAs from a UTAUT Perspective

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## Abstract

INTRODUCTION: With the accelerating aging of the population and the integrated development of artificial intelligence (AI) technology, AI health voice assistants (AI-HVAs) present a novel approach for enhancing health management among older adults. However, the adoption of this technology by the elderly population still faces multiple barriers, including cognition, trust, and user experience, and its adoption mechanisms have yet to be fully elucidated.
OBJECTIVES: This study aims to construct an AI-HVA adoption model applicable to China's elderly population, focusing on revealing the dual driving role of “experience (experiential rationality)” and “trust (relational rationality)” in the decision-making process of elderly users.
METHODS: Integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) model, this study introduces two key variables—"Perceived AI Experience (PAIE)" and "Perceived AI Trust (PAIT)"—to form a dual-path hypothesis of "internal experience-external influence." Through a questionnaire survey of 413 elderly users, structural equation modeling (SEM) was employed to analyze the data and examine the influence relationships among variables.
RESULTS: (1)Internal Experience Path:PAIE significantly and positively influenced Performance Expectancy (PE) and Effort Expectancy (EE), and also directly promoted Behavioral Intention (BI). This indicates that the quality of the interaction experience is a key antecedent for elderly users forming perceptions of usefulness and ease of use . (2) External Influence Path:Social Influence (SI) did not exert a direct effect on BI but required mediation through PAIT, highlighting the pivotal bridging role of trust in the adoption decision . (3) BI and Facilitating Conditions (FC) jointly significantly promoted Usage Behavior (UB), supporting the applicability of the UTAUT model in the context of AI technology adoption among the elderly.
CONCLUSION: This study extends the explanatory boundaries of the UTAUT model in the field of digital technology adoption by older adults, revealing the complex psychological processes underlying their acceptance of AI-HVAs. On a practical level, the findings provide important insights for the age-friendly design, trust-building, and promotion strategies of AI health products.

**Keywords:** AI-HVAs, elderly users, UTAUT, PAIE, PAIT, dual perspective

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## 1. Introduction

The world is undergoing an unprecedented demographic transformation, characterized by continuously accelerating global aging. Projections indicate that the global population

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aged 65 and above will surge from 761 million in 2022 to 1.6 billion by 2050, while the number of those aged 80 and above is expected to grow from 143 million to 426 million [1]. This profound shift poses significant challenges to socioeconomic systems and healthcare infrastructure. A core issue lies in effectively supporting seniors who are aging at home to maintain independent living capabilities and enjoy a high quality of life in their later years. Digital technology is widely recognized as a key enabler for elderly users to achieve independent living and effective health management [2]. Various intelligent terminals—from smartphones and wearable devices to smart home systems—create extensive opportunities for enhancing elderly health through functions such as health monitoring, remote communication, and assistance with daily tasks [3]. These technologies are designed to provide self-management tools and visualize health data, thereby empowering elderly users and improving their overall quality of life.

Breakthroughs in AI, particularly the maturation of AI-HVAs, offer an innovative pathway to overcome the aforementioned "usage barriers." Unlike earlier voice assistants, which were often limited in functionality and featured rigid interactions [4], modern AI voice assistants integrated with large language models demonstrate unique value in elderly health services due to their natural language interaction capabilities, low operational barriers, and age-friendly design[5]. Their core advantage lies in establishing an "experience-oriented" interaction paradigm: the use of voice commands to replace complex physical operations can effectively assist users with mobility or visual impairments[6,7].

Despite the significant technological advantages and application potential of AI-HVAs, their actual adoption among the elderly population remains relatively low. The Statistical Report on China's Internet Development (2025) [8] indicates that China's elderly non-internet user population remains substantial, with AI-HVAs usage rates being even lower . This stark contradiction between "high potential" and "low adoption" raises the core research question: what key factors hinder the transition among elderly users from "perceiving the technology as useful" to "forming a BI" to use it?

Existing research on the adoption of AI-HVAs by elderly users often focuses narrowly on technical functional attributes or relies on single-model theoretical perspectives. For instance, UTAUT emphasizes utilitarian drivers such as PE and EE, failing to fully reveal the complex decision-making psychology exhibited by elderly users when encountering AI technology.

The adoption decision of elderly users is not a simple process of "use it if it's useful." Rather, it constitutes a dual psychological process jointly constructed by internal perceptions and external influences. Internally, users place high value on the intuitive feelings experienced during interactions with AI-HVAs (i.e., "experiential rationality"), emphasizing "my direct relationship with the technology." Externally, they rely heavily on evaluations of the technology's safety and reliability within their social networks (i.e., "relational rationality"), using these perceptions as crucial foundations for building personal trust . Therefore, a comprehensive understanding of their adoption behavior requires simultaneous attention to the synergistic effects of both 'experiential' and 'trust-based' rational factors.

To address this theoretical gap and practical contradiction, this study innovatively integrates the dual factors of "PAIE" and "PAIT" into the UTAUT model, constructing a dual-path theoretical model of "Internal Experience-External Influence." This model aims to systematically reveal the key factors influencing elderly users' adoption decisions and their underlying mechanisms. The research findings are intended to provide a robust theoretical foundation and practical pathways for bridging the digital divide among seniors, thereby advancing the precise design and effective promotion of age-friendly AI-HVAs. This holds significant practical implications for addressing the challenges of technological integration in an aging society .

## 2. Literature review

### 2.1 UTAUT Model

The UTAUT model, proposed by Venkatesh et al. (2003) [9], was developed to establish a universal technology acceptance framework. It categorizes the key antecedents influencing user adoption behavior into four core constructs:

- PE: The degree to which users perceive that using the new technology will enhance their work or task performance;
- EE: The perceived ease associated with learning and operating the new technology.;
- SI: The degree to which users perceive that important others (e.g., family, friends) or their social environment believe they should use the new technology;
- FC: The extent to which users believe that an organizational and technical infrastructure exists to support the use of the new technology, including available resources and knowledge.

As shown in Figure 1, the structural relationships within the UTAUT model posit that PE, EE, and SI directly and positively influence the user's BI. In contrast, FC is theorized to have a direct impact on the user's UB, by passing BI in its influence on actual use .

Substantial empirical evidence demonstrates the UTAUT model's effectiveness in explaining user adoption behaviors toward various new technologies, including AI-HVAs [10], which strongly supports its applicability in AIGC-related research. Consequently, this study proposes to systematically examine the factors influencing Chinese elderly (with a sample from East China) users' acceptance of AI-HVAs applications based on the UTAUT model.

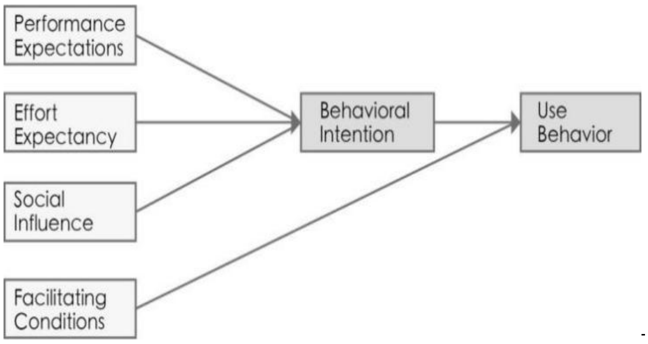


**Figure 1.** UTAUT Model

## 2.2 PAIE

User experience refers to the overall sum of subjective feelings that users develop when interacting with a product [11]. Traditional voice assistants often suffer from limited user experience due to their one-dimensional and static interaction logic [12]. In contrast, health voice assistants powered by large AI models achieve breakthrough improvements in recognition accuracy, depth of semantic understanding, and interaction fluency. This fundamentally reconstructs the human-computer interaction paradigm, resulting in services that are more human-like, efficient, and contextually adaptive [13].

In this study, PAIE denotes the overall subjective assessment formed by elderly users regarding the intelligent service capability and interaction convenience of AI-HVAs. Distinct from constructs commonly examined in prior research such as perceived enjoyment or hedonic motivation PAIE focuses more on the functional efficacy of the AI technology itself, rather than on emotional gratification. The construct introduces conceptual innovation in three key aspects: PAIE moves beyond emotion-centric evaluations to underscore technology-grounded experiential attributes. It is tailored to the specific demands of elderly users for highly reliable and adaptable interactions within health-management scenarios. It addresses a gap in extended UTAUT models by introducing a dedicated metric for capturing functional technology experiences.

## 2.3 PAIT

PAIT reflects an individual's subjective assessment of the reliability of others or objects [14]. In human–AI interaction, it denotes a psychological state in which users, despite uncertainties, believe an AI system will dependably help achieve their goals [15]. This is especially critical for elderly users interacting with AI-HVAs, which often function as "black boxes" due to complex deep learning algorithms. Cognitive or technological barriers may make it harder for this group to interpret AI behavior, thus making trust a prerequisite for adoption [16]. In health-management settings—where interactions involve personal health data and physical well-being-establishing and sustaining user trust becomes essential.

Within this study, PAIT is defined as the multidimensional psychological assessment made by elderly users regarding an AI-HVA's competence, sincerity, security, and behavioral predictability. It captures their holistic judgment of whether the system is trustworthy enough to be integrated into personal health management.

Unlike the "general trust" commonly used in UTAUT-extended studies, PAIT emphasizes risk perception and functional dependence specific to AI technology. Compared to institutional trust (e.g., Structural Assurance), it focuses on direct user evaluations of the credibility of AI system behaviors. The construct offers conceptual innovation in three key aspects: It clarifies PAIT's multidimensional structure within AI-enabled wellness scenarios, differentiating it from generalized trust constructs. It establishes PAIT as a mediator between social influence and usage intention, addressing the UTAUT model's under representation of trust pathways in high-risk contexts. It helps fill gaps in understanding trust formation mechanisms specific to elderly AI users.

## 2.4 Research Status of AI-HVAs: Evolution, Focus Areas, and Limitations

As a cutting-edge application of AI technology in health management, AI-HVAs have evolved from early rule-driven simple conversational agents to the current generation of intelligent agents deeply integrated with large language models [17,18]. Research in this field has coalesced around three dominant trajectories shaping their technological development .

Firstly, technology- and effectiveness-driven studies focus on achieving breakthroughs in foundational capabilities. This line of inquiry prioritizes enhancing the robustness of speech recognition, the depth of semantic understanding, and the naturalness of output, which collectively provide the fundamental guarantee for fluent and reliable human-computer interaction [19].

Secondly, user experience-driven research investigates how qualitative dimensions of the interaction influence user engagement. This stream examines the impact of factors such as response speed, execution accuracy, and conversational fluency on the overall user experience and sustained usage [20].

Thirdly, user adoption-driven research explores the motivations and barriers influencing the acceptance of AI-HVAs across different user groups, emphasizing the role of individual differences. This trajectory seeks to understand the psychological and social factors that determine whether a technology is embraced, moving beyond technical feasibility to the complexities of real-world adoption [21] .

In recent years, academic attention has increasingly turned toward elderly user groups, focusing on their technology acceptance factors and emotional needs [22]. However, systematic reviews of the literature reveal significant theoretical limitations in existing research.

Firstly, there is a lack of in-depth exploration from the perspective of the AI technology experience itself. Most studies continue to rely on conventional constructs like "usability" and "usefulness," failing to adequately analyze how the PAIE, particularly when enhanced by large models, translates into genuine perceived value for elderly users. A critical gap exists in understanding the specific interaction barriers, such as those related to speech recognition for users with cognitive decline or dialect usage, which creates a disconnect between the proposed experiential advantages of AI and the actual adoption mechanisms.

Secondly, the mechanisms underlying PAIT remain inadequately explained. While existing research often addresses the concept of “reliability,” it lacks a thorough investigation into the pivotal role of PAIT in the decision-making processes of elderly users, who typically exhibit heightened sensitivity regarding data privacy and a lack of confidence in controlling technology. Consequently, the pathway through which SI enhances behavioral intention by building trust lacks robust empirical validation.

These limitations collectively highlight that prevailing technology acceptance models overemphasize “instrumental rationality” while largely overlooking the “experiential rationality” and “relational rationality” unique to elderly users. To address these gaps, this study constructs an extended UTAUT model, proposing a dual-pathway framework. The internal experience-driven pathway elucidates how PAIE fosters BI by enhancing PE and EE. The external influence-driven pathway demonstrates that SI indirectly promotes intention by strengthening PAIT as a critical mediator. This integrated model provides a more comprehensive framework for understanding the complex decision-making psychology of elderly users toward AI health technologies.

## 3. Research hypotheses and methods

### 3.1 Research hypotheses

#### 3.1.1 The Impact of PAIE on PE and EE

As a core dimension of user-technology interaction, PAIE serves as a key antecedent shaping subsequent cognition and BI. Research by Faraon et al. (2025) [23] confirms that AI tools significantly enhance learning efficiency by enabling rapid knowledge acquisition and providing personalized tutoring, thereby fostering positive PE. Similarly, Hou & Li (2021) [24] found that a high-quality reading experience can effectively enhance older adults' perceived usefulness in information-seeking behaviors. In health contexts, when elderly users perceive that AI-HVAs simplify health management processes, deliver accurate feedback, or improve decision quality, their belief in the technology’s ability to enhance life efficacy is reinforced, promoting sustained BI. Accordingly, the following hypothesis is proposed:

- H1a: PAIE positively influences PE.

The interaction optimization enabled by AI technology can significantly reduce users’ cognitive load and operational difficulty. For example, Zhang (2023) [25] demonstrated that the application of WPS AI significantly reduces operational complexity in scientific journal editing, thereby effectively enhancing overall editorial efficiency. Cai & Zhu (2025) [26] demonstrate that AI-assisted design cloud platforms, as critical enabling tools, not only optimize workflows and reduce non-creative operations but also provide a viable pathway for simultaneously achieving efficiency gains and innovation breakthroughs. This study argues that if elderly users recognize the practicality and convenience of AI voice assistants through interaction, their EE will improve. Thus, we hypothesize:

- H1b: PAIE positively influences EE.

#### 3.1.2 The Impact of PE and EE on BI

As core constructs of the UTAUT model, PE and EE have been empirically validated as significant drivers of BI among older adults. Wang et al. (2023) [27] found that both factors significantly enhance older users’ intention to adopt smart elderly care products, a conclusion further supported by Chen (2023) [28] in the context of “Internet + Nursing Services.” In this study, positive perceptions of PE and EE among elderly users are regarded as key mechanisms stimulating their willingness to use AI-HVAs. The following hypotheses are proposed:

- H2: PE positively influences BI.
- H3: EE positively influences BI.

#### 3.1.3 The Influence Mechanisms of SI, PAIT, and BI

SI denotes the degree to which older adults are affected by the views, evaluations, or usage behaviors of important reference groups when deciding whether to adopt AI health assistants. Within the adoption context of the UTAUT, prior studies [29,30] have confirmed that SI exerts a direct impact on BI.

However, in scenarios involving AI-HVAs where personal sensitive health data and high-stakes technological decisions are involved the decision-making logic of elderly users extends beyond mere conformity. The mechanism of social influence undergoes a significant transformation, centering on an indirect pathway that can be described as “information transmission → risk assessment → trust building.” Specifically, SI offers social proof and collective experience concerning the performance, safety, and utility of the technology, thereby assisting older users in reducing uncertainties and alleviating perceived risks. This is particularly critical in high-uncertainty domains like health, where the experiences of others serve as a form of social learning, compensating for individual cognitive limitations and strengthening judgments about the reliability of the technology. As information accumulates and risk perceptions are adjusted, users progressively develop trust in the technology a process that culminates in PAIT. Empirical research [31,32] corroborates that SI significantly enhances trust; moreover, trust in AI systems is a key predictor of adoption and has a positive effect on BI [33,34]. Thus, the effect of SI on BI is more likely to be mediated meaning SI must first be translated into user trust in the technology before it can effectively promote BI.

Although traditional UTAUT models posit that SI directly and positively influences BI, the underlying mechanism may prove more complex in high-risk AI technology scenarios involving personal health data. Therefore, we simultaneously propose the following hypotheses for verification:

- H4: SI positively affects the BI.
- H5:PAIT mediates the relationship between SI and BI.

#### 3.1.4 The Impact of FC and BI on UB

The adoption of technology is also contingent upon external environmental and resource support. Research indicates that factors such as accessible technical support and relevant training affect elderly users' willingness to adopt smart elderly care products, and enabling conditions like reliable internet access directly impact actual UB [35,36]. According to the UTAUT model, BI is a direct antecedent of UB, while FC can directly promote UB without necessarily being mediated by BI [9]. This direct impact of BI on usage behavior has been validated among elderly populations [37]. Therefore, the study proposes the following final hypotheses:

- H6: FC positively influences UB.
- H7: BI positively influences UB.

### 3.2 Research Framework

Building upon prior research, this study integrates the UTAUT model, PAIE, PAIT, and other theories to construct a dual-perspective research model driven by internal and external pathways (as shown in Figure 2)..

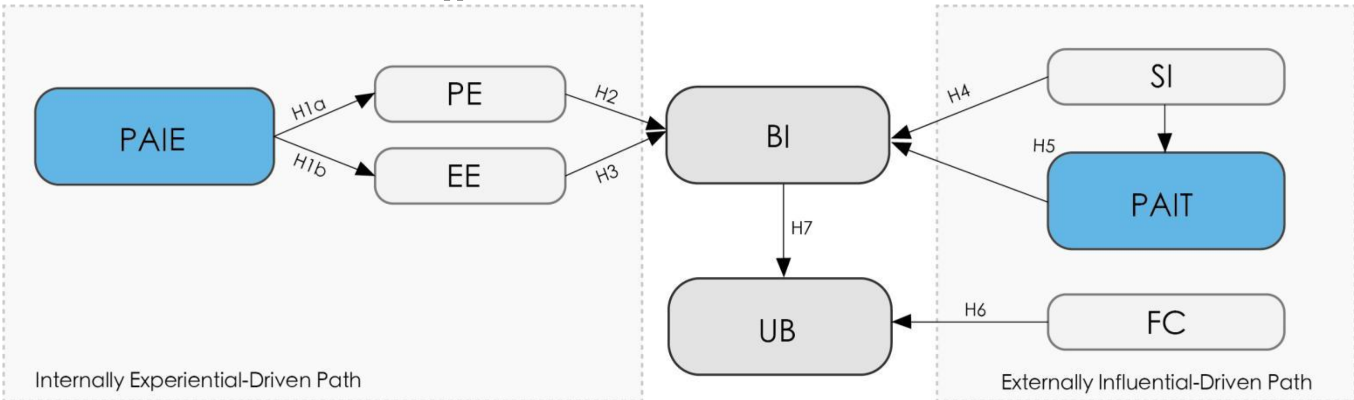


**Figure 2.** Hypothetical Model

### 3.3 Variable Definitions and Measurements

The core variables involved in this study's model include eight primary variables: PAIE, PAIT, PE, EE, SI, FC, BI, and UB. The specific measurement indicators for each variable are shown in Table 1.

## 4. Data and Methods

### 4.1 Questionnaire Survey

All variables in this study were measured using established scales, with item wording adapted to fit the specific context of AI-HVAs, thereby ensuring the validity and reliability of the measurement instrument. A systematic pre-survey was conducted prior to the main data collection to optimize the scale quality. The pre-survey was administered offline between February 25 and March 3, 2025, and targeted individuals who had prior experience using AI-HVAs (e.g., "Xiao Ai"). Responses were collected using a 7-point Likert scale (1= Strongly Disagree, 7 = Strongly Agree). A total of 80 volunteers were recruited, resulting in 69 valid responses. Reliability analysis and item analysis were performed on the pre-survey data; items with low factor loadings or significant cross-loadings were excluded, leading to a final formal questionnaire containing 40 items.

The formal questionnaire consisted of three sections:

- an introduction that defined AI-HVAs and illustrated application scenarios (e.g., built-in mobile assistants, applications from internet companies, and third-party tools);
- demographic information, including gender, age, education level, usage experience, and monthly income;
- item measurement, which included 35 questions assessing the core constructs.

Table 1. Variable Definitions and Measurements

| | | | |
|---|---|---|---|
| PAIE | Elderly users' subjective overall assessment of the interaction quality, functional value, and emotional connection with AI-HVAs. | PAIE1:Do you feel that conversing with the AI health voice assistant is similar to talking with a real person? | [11,13,36,38] |
| | | PAIE2:When asking consecutive questions, can the AI understand the context and respond accordingly? | |
| | | PAIE3:When issuing complex commands, can the AI accurately comprehend and successfully execute them? | |
| | | PAIE4:Can the AI gradually learn your habits and preferences to provide personalized services? | |
| | | PAIE5:Can the AI recognize your emotions and give appropriate responses? | |
| PAIT | Psychological Assessment of Elderly Users Regarding the Reliability, Safety, and Ethical Compliance of AI-HVAs. | PAIT1:This AI application rarely malfunctions, making me feel it's reliable. | [15,34,39] |
| | | PAIT2:I believe this AI application accurately understands my commands and completes tasks. | |
| | | PAIT3:I trust the suggestions/recommendations provided by AI-HVAs. | |
| | | PAIT4:When conversing with it, I feel reassured and willing to confide. | |
| | | PAIT5:I have no concerns about personal privacy leaks when using it. | |
| FC | Environmental and infrastructure factors supporting elderly users in utilizing AI-HVAs. | FC1:Sufficient network, hardware, and other infrastructure support my use of this application. | [11,40] |
| | | FC2:I can conveniently obtain, install, and maintain this application. | |
| | | FC3:I have access to sufficient technical support (e.g., customer service, training) to use the application. | |
| | | FC4:Family, friends, or community workers assist me in using the application more effectively. | |
| PE | Users' perception that using AI-HVAs can help improve quality of life. | PE1:Using it helps me better complete daily tasks. | [11,40] |
| | | PE2:Using it helps me access needed information more quickly. | |
| | | PE3:Using it helps me stay connected with loved ones more conveniently. | |
| | | PE4:Using it helps me better manage my health. | |
| | | PE5:Using it provides me with more entertainment and leisure options. | |
| EE | Users' perception of the difficulty level required to learn how to use an AI health voice assistant. | EE1:I find it easy to learn how to use the AI health voice assistant. | [11,40] |
| | | EE2:I find its operation process simple and straightforward. | |
| | | EE3:I possess the necessary skills or knowledge to use it. | |
| | | EE4:Using it is not a challenge for me. | |
| SI | The extent to which users' decisions to use AI-HVAs are influenced by others. | SI1:People around me influence my decision to use it. | [11,40] |
| | | SI2:Users appear more capable than non-users. | |
| | | SI3:I am influenced by media and advertising. | |
| | | SI4:Using it is trendy, and I want to keep up with the times. | |
| BI | The willingness and attitude intensity of elderly users toward using AI-HVAs. | BI1:I think using it is a good idea. | [11,40] |
| | | BI2:I believe it makes my life more convenient. | |
| | | BI3:I find it highly valuable. | |
| | | BI4:I will use this type of AI application in the future. | |
| UB | The actual behavior of elderly users in utilizing AI health voice assistant applications. | UB1:My actual usage experience is positive, and I'm willing to keep learning new features. | [11,40] |
| | | UB2:Each session lasts for a considerable amount of time. | |
| | | UB3:I use it to complete various types of tasks. | |
| | | UB4:After using it, I achieved the desired results and improved my quality of life. | |

The formal survey was carried out from March 14 to April 17, 2025, with approval from the Ethics Committee of the School of Art and Design at Nanjing Institute of Technology (Approval No.: NJIT-SADE-20250224-12). Convenience sampling was used, primarily covering the East China region. Data were collected from venues such as senior activity centers, community nursing homes, and smart senior living communities, focusing on users aged 60 and above who had prior experience with smart elderly care products. To minimize recruitment bias, the following measures were implemented after ethics approval:

- randomization procedures within selected venues;
- on-site guidance from researchers to reduce completion errors;
- clear recruitment criteria to prevent selection bias.

A total of 450 questionnaires were distributed. Invalid responses were excluded based on criteria such as more than 20% missing answers, logical inconsistencies, uniform responses across all items, or repetitive response patterns. Ultimately, 413 valid questionnaires were retained, yielding a valid response rate of 91.78%.

Table 2. Reliability Analysis

| Dimension | Item | CITC | α coefficients after item deletion | Dimensional Reliability |
|---|---|---|---|---|
| PAIT | PAIT 1 | 0.71 | 0.79 | 0.840 |
| | PAIT 2 | 0.617 | 0.815 | |
| | PAIT 3 | 0.625 | 0.813 | |
| | PAIT 4 | 0.604 | 0.819 | |
| | PAIT 5 | 0.668 | 0.802 | |
| PAIE | PAIE 1 | 0.654 | 0.853 | 0.87 |
| | PAIE 2 | 0.738 | 0.832 | |
| | PAIE 3 | 0.673 | 0.849 | |
| | PAIE 4 | 0.712 | 0.839 | |
| | PAIE 5 | 0.702 | 0.842 | |
| FC | FC1 | 0.718 | 0.854 | 0.88 |
| | FC2 | 0.722 | 0.853 | |
| | FC3 | 0.767 | 0.835 | |
| | FC4 | 0.754 | 0.84 | |
| PE | PE1 | 0.752 | 0.84 | 0.877 |
| | PE2 | 0.697 | 0.853 | |
| | PE3 | 0.671 | 0.86 | |
| | PE4 | 0.713 | 0.85 | |
| | PE5 | 0.712 | 0.85 | |
| EE | EE1 | 0.685 | 0.791 | 0.839 |
| | EE2 | 0.669 | 0.797 | |
| | EE3 | 0.678 | 0.793 | |
| | EE4 | 0.654 | 0.804 | |
| SI | SI1 | 0.711 | 0.813 | 0.857 |
| | SI2 | 0.664 | 0.832 | |
| | SI3 | 0.688 | 0.823 | |
| | SI4 | 0.739 | 0.801 | |
| BI | BI1 | 0.745 | 0.807 | 0.861 |
| | BI2 | 0.695 | 0.829 | |
| | BI3 | 0.71 | 0.822 | |
| | BI4 | 0.686 | 0.833 | |
| UB | UB1 | 0.803 | 0.851 | 0.895 |
| | UB2 | 0.737 | 0.877 | |
| | UB3 | 0.761 | 0.867 | |
| | UB4 | 0.772 | 0.863 | |

In the structural equation modeling analysis, the ratio of sample size (n=413) to the number of estimated parameters (p= 35) was 11.8:1, meeting the recommended standard of n:p ≥ 10:1 proposed by Jackson (2003) [41], thus indicating an adequate sample size. Data cleaning and descriptive statistics were performed using SPSS 23.0, while confirmatory factor analysis and path modeling were conducted using AMOS 17.0.

## 4.2 Reliability Analysis

Reliability analysis results indicate that Cronbach's α coefficients for all dimensions of the scale exceed 0.8, and CITC values for each item surpass 0.4 (as shown in Table 2). Removing any single item did not significantly improve the α coefficient, demonstrating both excellent item design and reliability performance. Data reliability meets research requirements.

## 4.3 Descriptive Statistics

### 4.3.1 Basic Information of Respondents

Based on data collected from the questionnaire survey, the basic characteristics of the study sample are distributed as shown in Table 3.

Table 3. Basic Information of Respondents

| Name | Option | Frequency | Percentage (%) | Cumulative Percentage (%) |
|---|---|---|---|---|
| Gender | Male | 221 | 53.51 | 53.51 |
| | Female | 192 | 46.49 | 100 |
| Age | 60-65 years old | 231 | 55.93 | 55.93 |
| | 66-70 years old | 104 | 25.18 | 81.11 |
| | 71-75 years old | 52 | 12.59 | 93.7 |
| | 76 years old and above | 26 | 6.3 | 100 |
| Education Level | Junior high school and below | 278 | 67.31 | 67.31 |
| | High school | 85 | 20.58 | 87.89 |
| | College and above | 50 | 12.11 | 100 |
| Monthly Income | Below ¥2,000 | 115 | 27.85 | 27.85 |
| | ¥2,001-3,500 | 149 | 36.08 | 63.93 |
| | ¥3,501–5,000 | 107 | 25.91 | 89.84 |
| | ¥5,000+ | 42 | 10.16 | 100 |
| Experience | 6 months or less | 98 | 23.72 | 23.72 |
| | 7–12 months | 132 | 31.96 | 55.68 |
| | 13–18 months | 116 | 28.09 | 83.77 |
| | 19 months or more | 67 | 16.23 | 100 |
| Total | | 413 | 100 | 100 |

In terms of gender, male respondents predominated, totaling 221 individuals, accounting for 53.51% of the total sample; female respondents numbered 192, representing 46.49%. Regarding age distribution, the 60–65 age group was the largest, comprising 231 individuals, or 55.93% of the total; cumulatively, 81.11% of respondents were aged 70 or younger.

Regarding educational attainment, the largest group had a junior high school education or below, totaling 278 individuals, accounting for 67.31%. This was followed by high school/vocational school graduates (20.58%) and college graduates or above (12.11%). Monthly income distribution showed the highest proportion (36.08%) in the 2001–3500 yuan bracket, followed by those earning below 2000 yuan (27.85%) and 3501–5000 yuan (25.91%). Only 42 respondents (10.16%) reported monthly incomes exceeding 5000 yuan.

Regarding AI-HVA usage experience, the largest group (31.96%) had used them for 7–12 months, followed by 13–

18 months (28.09%). Those using them for 6 months or less and over 19 months accounted for 23.72% and 16.23%, respectively.

## 4.4 Validity and Exploratory Factor Analysis

### 4.4.1 KMO and Bartlett's Test

In order to carry out an effective analysis, the sample data (N=413) of this study were divided into two parts. Half of the samples were used for exploratory factor analysis (n=206), and the other half were used for confirmatory factor analysis (n=207). The factor analysis suitability test results (as shown in Table 4) show a KMO value of 0.903 (>0.9), indicating the data are highly suitable for factor analysis. Bartlett's sphericity test also reached statistical significance ($p < 0.05$), confirming that the inter-variable correlations meet the requirements for factor analysis.

### 4.4.2 Total Variance Explained

The results of principal component analysis (as shown in Table 5) indicate that the cumulative variance explained by the eight common factors of the scale is 69.284% (>60%), demonstrating effective factor extraction. Furthermore, Harman's single-factor test shows that the first principal component explains 27.587% of the variance (<40%), indicating that common method bias remains within a controllable range.

Table 4. KMO and Bartlett's Test

| | | |
|---|---|---|
| KMO sampling adequacy measure | | 0.903 |
| Bartlett test of sphericity | Approximate Chi-Square | 7545.594 |
| | Degrees of Freedom | 595 |
| | p value | 0.000 |

Table 5. Total Variance Explained

| Term | Initial Eigenvalue | | | Extraction Sums of Squared Loadings | | | Sum of Squared Rotational Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | Variance percentage | Accumulated % | Total | Variance percentage | Accumulated % | Total | Variance percentage | Accumulated % |
| 1 | 9.655 | 27.587 | 27.587 | 9.655 | 27.587 | 27.587 | 3.445 | 9.842 | 9.842 |
| 2 | 2.675 | 7.643 | 35.231 | 2.675 | 7.643 | 35.231 | 3.36 | 9.6 | 19.442 |
| 3 | 2.306 | 6.588 | 41.819 | 2.306 | 6.588 | 41.819 | 3.153 | 9.007 | 28.449 |
| 4 | 2.137 | 6.105 | 47.924 | 2.137 | 6.105 | 47.924 | 3.01 | 8.6 | 37.049 |
| 5 | 2.046 | 5.845 | 53.769 | 2.046 | 5.845 | 53.769 | 2.941 | 8.403 | 45.452 |
| 6 | 1.878 | 5.364 | 59.134 | 1.878 | 5.364 | 59.134 | 2.819 | 8.056 | 53.508 |
| 7 | 1.86 | 5.315 | 64.448 | 1.86 | 5.315 | 64.448 | 2.799 | 7.996 | 61.504 |
| 8 | 1.693 | 4.836 | 69.284 | 1.693 | 4.836 | 69.284 | 2.723 | 7.78 | 69.284 |
| 9 | 0.667 | 1.907 | 71.191 | | | | | | |
| 10 | 0.629 | 1.798 | 72.989 | | | | | | |
| 11 | 0.606 | 1.731 | 74.72 | | | | | | |
| 12 | 0.549 | 1.57 | 76.29 | | | | | | |
| 13 | 0.543 | 1.553 | 77.843 | | | | | | |
| 14 | 0.514 | 1.469 | 79.312 | | | | | | |
| 15 | 0.495 | 1.415 | 80.727 | | | | | | |
| 16 | 0.462 | 1.32 | 82.047 | | | | | | |
| 17 | 0.46 | 1.315 | 83.362 | | | | | | |
| 18 | 0.445 | 1.271 | 84.632 | | | | | | |
| 19 | 0.432 | 1.233 | 85.866 | | | | | | |
| 20 | 0.42 | 1.2 | 87.066 | | | | | | |
| 21 | 0.394 | 1.125 | 88.19 | | | | | | |
| 22 | 0.378 | 1.081 | 89.271 | | | | | | |
| 23 | 0.359 | 1.026 | 90.297 | | | | | | |
| 24 | 0.359 | 1.025 | 91.322 | | | | | | |
| 25 | 0.334 | 0.954 | 92.276 | | | | | | |
| 26 | 0.323 | 0.923 | 93.199 | | | | | | |
| 27 | 0.311 | 0.889 | 94.088 | | | | | | |
| 28 | 0.299 | 0.855 | 94.944 | | | | | | |
| 29 | 0.286 | 0.817 | 95.76 | | | | | | |
| 30 | 0.275 | 0.786 | 96.547 | | | | | | |
| 31 | 0.27 | 0.77 | 97.317 | | | | | | |
| 32 | 0.262 | 0.748 | 98.065 | | | | | | |
| 33 | 0.239 | 0.684 | 98.749 | | | | | | |
| 34 | 0.222 | 0.635 | 99.384 | | | | | | |
| 35 | 0.216 | 0.616 | 100 | | | | | | |

## 4.5 Confirmatory Factor Analysis

### 4.5.1 Convergent Validity

The confirmatory factor analysis revealed that all standardized loadings exceeded 0.6 ($p < 0.001$).

Furthermore, the composite reliability (CR > 0.7) and average variance extracted (AVE > 0.5) for each latent variable met the established criteria (see Table 6). This indicates that the measurement model possesses ideal convergent validity.

### 4.5.2 Discriminant Validity

Discriminant validity was assessed according to the criteria proposed by Fornell & Larcker (1981) [42]. As shown in Table 7, the square root of the AVE for each latent variable (bolded diagonal values) exceeded its correlation coefficients with other variables, indicating that the model possesses good Discriminant Validity.

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Table 6. Explanation of Total Variance

| Latent variable | Measurement Item | Standardized Factor Loadings | Standard Error | z | p | Standard Load Factor | CR | AVE |
|---|---|---|---|---|---|---|---|---|
| PAIT | PAIT1 | 1.000 | | | | 0.792 | 0.842 | 0.517 |
| | PAIT2 | 0.875 | 0.066 | 13.346 | *** | 0.672 | | |
| | PAIT3 | 0.948 | 0.067 | 14.184 | *** | 0.710 | | |
| | PAIT4 | 0.880 | 0.065 | 13.455 | *** | 0.677 | | |
| | PAIT5 | 0.907 | 0.061 | 14.769 | *** | 0.738 | | |
| PAIE | PAIE1 | 1.000 | | | | 0.701 | 0.871 | 0.574 |
| | PAIE2 | 1.268 | 0.085 | 14.860 | *** | 0.816 | | |
| | PAIE3 | 1.054 | 0.078 | 13.508 | *** | 0.732 | | |
| | PAIE4 | 1.221 | 0.086 | 14.199 | *** | 0.774 | | |
| | PAIE5 | 1.163 | 0.083 | 13.992 | *** | 0.761 | | |
| FC | FC1 | 1.000 | | | | 0.768 | 0.880 | 0.648 |
| | FC2 | 1.111 | 0.069 | 16.174 | *** | 0.787 | | |
| | FC3 | 1.209 | 0.070 | 17.310 | *** | 0.840 | | |
| | FC4 | 1.105 | 0.065 | 16.966 | *** | 0.823 | | |
| PE | PE1 | 1.000 | | | | 0.818 | 0.878 | 0.591 |
| | PE2 | 0.927 | 0.056 | 16.544 | *** | 0.760 | | |
| | PE3 | 0.903 | 0.058 | 15.628 | *** | 0.726 | | |
| | PE4 | 0.858 | 0.051 | 16.824 | *** | 0.770 | | |
| | PE5 | 0.836 | 0.050 | 16.760 | *** | 0.768 | | |
| EE | EE1 | 1.000 | | | | 0.773 | 0.839 | 0.566 |
| | EE2 | 0.994 | 0.069 | 14.449 | *** | 0.747 | | |
| | EE3 | 1.033 | 0.070 | 14.670 | *** | 0.759 | | |
| | EE4 | 0.986 | 0.070 | 14.149 | *** | 0.731 | | |
| SI | SI1 | 1.000 | | | | 0.786 | 0.857 | 0.601 |
| | SI2 | 0.854 | 0.058 | 14.725 | *** | 0.726 | | |
| | SI3 | 0.942 | 0.061 | 15.419 | *** | 0.758 | | |
| | SI4 | 1.070 | 0.064 | 16.800 | *** | 0.827 | | |
| BI | BI1 | 1.000 | | | | 0.812 | 0.862 | 0.610 |
| | BI2 | 0.993 | 0.060 | 16.677 | *** | 0.787 | | |
| | BI3 | 0.903 | 0.055 | 16.414 | *** | 0.776 | | |
| | BI4 | 0.826 | 0.052 | 15.780 | *** | 0.749 | | |
| UB | UB1 | 1.000 | | | | 0.863 | 0.896 | 0.684 |
| | UB2 | 0.985 | 0.051 | 19.347 | *** | 0.800 | | |
| | UB3 | 0.921 | 0.046 | 19.893 | *** | 0.815 | | |
| | UB4 | 0.924 | 0.045 | 20.361 | *** | 0.828 | | |

Table 7. Discriminant validity

| | PAIT | PAIE | FC | PE | EE | SI | BI | UB |
|---|---|---|---|---|---|---|---|---|
| PAIT | **0.719** | | | | | | | |
| PAIE | 0.256** | **0.758** | | | | | | |
| FC | 0.266** | 0.398** | **0.805** | | | | | |
| PE | 0.303** | 0.303** | 0.300** | **0.769** | | | | |
| EE | 0.300** | 0.314** | 0.301** | 0.313** | **0.752** | | | |
| SI | 0.379** | 0.295** | 0.300** | 0.328** | 0.267** | **0.775** | | |
| BI | 0.350** | 0.322** | 0.344** | 0.340** | 0.330** | 0.279** | **0.781** | |
| UB | 0.293** | 0.378** | 0.324** | 0.291** | 0.328** | 0.286** | 0.322** | **0.827** |

Note that bold numbers on the diagonal represent the square root of the AVE value

## 4.6 Structural Equation Modeling Analysis

### 4.6.1 Model Fit Indices

This study employed comprehensive indices recommended by multiple scholars [43,44,45] to assess model adequacy. Results indicate (as shown in Table 8) that all key indices met ideal discrimination criteria, demonstrating good fit between the theoretical model and sample data.

### 4.6.2 Path Analysis

Based on the path analysis results in Table 9, the key hypothesis tests in this study are as follows: PAIE significantly and positively influences PE ($\beta = 0.393$, $p < 0.05$) and EE ($\beta = 0.412$, $p < 0.05$) SI significantly promotes PAIT ($\beta = 0.454$, $p < 0.05$), while PAIE exerts a strong positive influence on FC ($\beta = 0.499$, $p < 0.05$). In the formation mechanism of behavioral intention, both PE ($\beta = 0.229$, $p < 0.05$) and EE ($\beta = 0.245$, $p < 0.05$) significantly enhanced BI, whereas SI's direct effect on BI did not reach statistical significance ($\beta = 0.098$, $p > 0.05$). Furthermore, PAIT significantly enhanced BI ($\beta = 0.232$, $p < 0.05$). Finally, BI ($\beta = 0.281$, $p < 0.05$) and FC ($\beta = 0.270$, $p < 0.05$) jointly exerted a significant positive driving effect on UB.

Table 8. Model Fitting Metrics

| Common indicators | Judgment criteria | statistical value | Fitting Situation |
|---|---|---|---|
| CMIN | - | 776.194 | - |
| DF | - | 549 | - |
| CMIN/DF | <3 | 1.414 | Good |
| RMSEA | <0.08 | 0.032 | Good |
| GFI | >0.90 | 0.903 | Good |
| IFI | >0.90 | 0.969 | Good |
| CFI | >0.90 | 0.968 | Good |
| RFI | >0.90 | 0.902 | Good |
| NFI | >0.90 | 0.900 | Good |
| PNFI | >0.50 | 0.831 | Good |

### 4.6.3 Mediating Effect Analysis Results

This study employed the Bootstrap method to test mediating effects, conducting 5,000 repeated samples to calculate confidence intervals for indirect effects. Table 10 presents the indirect effects for each path and their significance test results. The bias-corrected Bootstrap method tested the direct effect of SI→BI. Results indicate a direct effect of 0.042 with a 95% confidence interval of [-0.031, 0.118], which includes zero, suggesting the direct effect is insignificant. Therefore, SI's influence on BI is fully mediated by PAIT, constituting a complete mediation effect.

Table 9. Path Coefficients

| Path | Estimate | S.E. | C.R. | P | STD | Suppose |
|---|---|---|---|---|---|---|
| PAIE → PE | 0.556 | 0.082 | 6.785 | *** | 0.393 | Established |
| PAIE → EE | 0.434 | 0.063 | 6.836 | *** | 0.412 | Established |
| PE → BI | 0.194 | 0.045 | 4.261 | *** | 0.229 | Established |
| EE → BI | 0.278 | 0.063 | 4.404 | *** | 0.245 | Established |
| SI → BI | 0.096 | 0.061 | 1.589 | 0.112 | 0.098 | Not established |
| BI → UB | 0.306 | 0.059 | 5.165 | *** | 0.281 | Established |
| FC → UB | 0.325 | 0.065 | 5.035 | *** | 0.27 | Established |

Note: *** $p < 0.001$.

### 4.6.4 Hypothesis Interpretation

Figure 3 illustrates the hypotheses tested in this study. Hypotheses H1a, H1b, H2, H3, H5, H6, and H7 were supported, while H4 was rejected. Concurrently, higher coefficients indicate a more pronounced influence of the independent variables on the dependent variables.

Table 10. Mediation Path

| Mediation Path | Indirect effects | Standard error | 95% confidence interval | Significance |
|---|---|---|---|---|
| PAIE→PE→BI | 0.127*** | 0.032 | [0.072, 0.194] | Significant |
| PAIE→EE→BI | 0.098** | 0.028 | [0.051, 0.159] | Significant |
| SI→PAIT→BI | 0.156*** | 0.041 | [0.089, 0.247] | Significant |

## 5. Discussion

Based on the quantitative analysis of the collected sample data using structural equation modeling, this study elucidates the complex mechanisms influencing older adults' adoption of AI-HVAs. The following sections discuss the key findings, their theoretical implications, and practical insights.

## 5.1 Validation of the Internally Driven Experience Pathway and Analysis of Mediation Mechanisms

The study confirmed that PAIE serves as a key antecedent variable shaping older adults' PE and EE (H1a, $\beta= 0.393$, $p < 0.05$; H1b, $\beta= 0.412$, $p < 0.05$). This suggests that older users' judgments regarding a technology's usefulness and ease of use stem largely from their sensory and emotional feedback during interactions with AI systems. According to Cohen's (1988)[46] criteria, the$\beta$values of 0.393 and 0.412 represent medium effect sizes, indicating that PAIE has substantial explanatory power over PE and EE. This finding extends technology acceptance research beyond the tool-rational framework of UTAUT, incorporating an experiential-rational paradigm that integrates interaction fluency, comprehensibility, and affective responses.

Mediation analysis further clarified the internal experience pathway. The indirect effect of PAIE on BI through PE was 0.127 (95% CI [0.072, 0.194], $p < 0.05$), while the indirect effect through EE was 0.098 (95% CI [0.051, 0.159], $p < 0.05$), supporting the mediating roles of PE and EE in the path "PAIE→PE/EE→BI." This indicates that high-quality AI interaction experiences can reduce cognitive load, build usage confidence, and ultimately enhance adoption intention among elderly users.

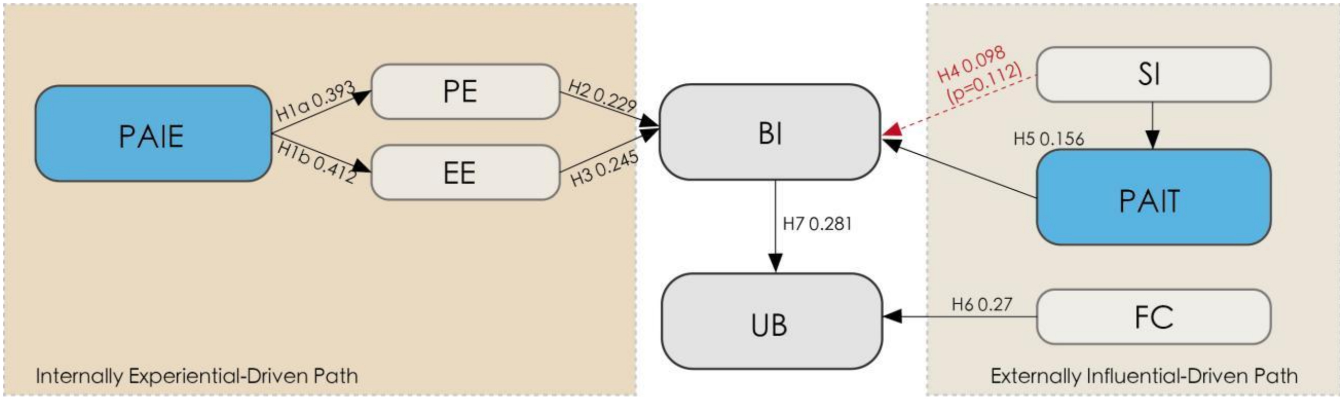


**Figure 3.** Research Model

Furthermore, high-quality AI experiences can be viewed as an effective mechanism for mitigating technology anxiety. Positive interaction quality directly reduces anxiety among older adults, with each successful interaction helping to dispel the stereotype that "technology is complex and difficult to use." Immediate positive experiences characterized by low cognitive load and high feedback quality can lower emotional resistance, foster initial trust, and enhance perceived control. This supports the theoretical view that "successful usage experiences are the most effective way to reduce anxiety."

Both PE and EE exerted significant positive effects on BI (H2, $\beta = 0.229$, $p < 0.05$; H3, $\beta = 0.245$, $p < 0.05$), with small-to-medium effect sizes, supporting the applicability of these classical UTAUT constructs in the AI context for older users. The identified pathway—from interaction experience to functional belief to behavioral intention—addresses the UTAUT model's limitation in capturing early experiential interactions with highly interactive technologies.

## 5.2 Validation of the External Influence Pathway and Full Mediation Effect

For external influence pathways, the direct effect of Social Influence (SI) on BI was not significant (H4, $\beta$= 0.098, $p > 0.05$). However, SI exerted a significant indirect effect on BI through PAIT . A full mediation test confirmed that the direct effect was nonsignificant, while the indirect effect was 0.156 (95% CI [0.089, 0.247], $p < 0.05$), indicating that PAIT fully mediates the relationship between SI and BI. This underscores the complexity of social influence mechanisms within technology acceptance models.

This result suggests that for AI technologies involving personal health data and potential risks, older users do not adopt them based solely on social pressure. Instead, they treat external recommendations as risk signals, requiring independent assessment of the technology's reliability and safety before forming usage intention. Trust thus emerges as a core psychological mechanism for resolving uncertainty. Theoretically, social influence acts as an institutional signal, implying that significant others have conducted "compensatory risk evaluations," thereby reducing uncertainty among potential users. Older adults internalize SI as trust—a process grounded in social assurance. The pathway "SI → PAIT → BI" underscores the central role of trust in the adoption of high-risk technologies, offering an important refinement to the SI mechanism in UTAUT.

## 5.3 FC and Direct Drivers of UB

FC had a significant positive effect on UB (H5, $\beta$= 0.27, $p < 0.05$), and the path from BI to UB was also supported (H7, $\beta$= 0.281, $p < 0.05$), with effect sizes in the small-to-medium range. This indicates that even when older users are psychologically willing to use AI-HVAs, the translation of intention into sustained usage behavior still depends heavily on external support—such as stable internet access, device compatibility, timely assistance, and age-friendly interfaces. For older adults who may face a digital divide, improving the FC ecosystem is critical for bridging the gap between "BI" and "UB".

# 6. Conclusions

## 6.1 Theoretical Contributions

The theoretical contributions of this study are reflected in the following three aspects:

First, from a theoretical perspective, this research extends the UTAUT model by introducing two key constructs—PAIE and PAIT—to develop a dual-pathway model of "internal experience and external influence." It shifts the focus of elderly users' adoption decisions from purely functional assessment to the more complex psychological processes of interaction experience and trust formation. Specifically, the study proposes and validates "experiential rationality" as an important antecedent to both PE and EE, revealing the foundational role of high-quality human–AI interaction in shaping older adults' perceptions of usefulness and ease of use. This perspective not only aligns with the particular demands of high-risk health management contexts but also offers a more nuanced theoretical framework for understanding technology adoption among the elderly.

Second, in terms of underlying mechanisms, empirical analyses show that the influence of SI on BI is fully mediated by PAIT, rather than being direct. This finding provides a context-sensitive refinement to the classic UTAUT assumption regarding the direct effect of social influence, highlighting a core theoretical proposition: in high-risk, high-uncertainty AI health technology adoption scenarios, social influence must be converted into behavioral intention through a trust mechanism. This underscores the pivotal bridging role of "relational rationality" in the decision-making processes of older users.

Finally, this study systematically examines the applicability of the extended model using a sample of older adults in China eastern. It not only confirms the robustness of the dual-path hypothesis but also provides tailored measurement tools and a structured data analysis framework. These contributions establish an empirical basis for understanding aging-related technology adoption within specific cultural and social settings.

## 6.2 Practical Implications

Based on the aforementioned research findings, this study offers the following practical insights for the age-friendly design, promotion, and ecosystem development of AI-HVAs.

First, for product designers and developers, prioritizing the optimization of interactive experiences is essential, with a focus on resolving age-related usage barriers—cognitive, physiological, cultural, and beyond. The following features, embodying "experiential rationality," should be developed:

- To support memory decline, design systems with progressive learning and contextual memory capabilities. AI-HVAs should retain past conversations and user preferences, offering proactive and concise prompts in subsequent interactions. For example, when a user asks, "What should I do about that discomfort I mentioned yesterday?" the system should contextually retrieve relevant records to provide coherent recommendations, significantly reducing cognitive load.
- To compensate for hearing impairments, integrate multimodal interaction and audio enhancement technologies. Beyond optimizing noise-reduction algorithms for speech recognition, provide features like speech speed adjustment, adaptive volume enhancement, and real-time text transcription. When the system detects repeated requests or high background noise, it should automatically trigger a text display mode to ensure barrier-free communication.
- To adapt to dialects and accents, strengthen dialectal speech databases and semantic error tolerance mechanisms. Given the diverse linguistic backgrounds of older adults in China, it is crucial to build speech recognition models that incorporate major dialects and enhance accuracy in understanding accented Mandarin.

Secondly, for marketers and policymakers, strategies should transcend mere information dissemination and focus on building social trust networks. SI indirectly promotes BI through perceived anthropomorphism and PAIT, initiatives such as "intergenerational digital mentoring" programs can be highly effective. These programs can encourage younger family members to act as "trust translators," conveying their own technological confidence to older adults. Simultaneously, fostering a "peer demonstration effect" within senior communities—where older volunteers who have adopted the technology share authentic experiences—can effectively lower psychological barriers and perceived risks for their peers.

Finally, governments and community organizations should collaborate to enhance FC. Even when elderly users possess the BI to use AI-HVAs, converting this intention into actual UB remains highly dependent on external support. This includes ensuring stable and affordable internet access, providing compatible devices, conducting targeted digital literacy training, and establishing clear user support channels. Building a comprehensive FC support ecosystem is key to bridging the "intention-behavior" gap and providing the systematic backing seniors need to overcome the digital divide.

## 7. Research Limitations

This study has several limitations that should be considered when interpreting the findings. First, the geographical distribution of the sample was relatively concentrated, primarily drawn from eastern China. Future research could expand the sampling scope to include less developed central and western regions, as well as more socioeconomically and culturally diverse elderly populations, to improve the generalizability of the findings .

Second, the study employed a cross-sectional questionnaire design, with all data collected at a single point in time. While this approach allowed for the examination of correlations among variables, it limits the ability to draw causal inferences. Future studies could adopt longitudinal or experimental designs to track the evolving trajectories of technology adoption among older adults and better uncover the underlying causal mechanisms.

Finally, the sample size, though adequate for the initial model testing, constrained the application of more complex statistical analyses. Subsequent research could recruit larger and more diverse samples to facilitate subgroup analyses, validate the model's robustness, and enable a deeper exploration of complex mediating or moderating pathways.

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## Institutional Review Board Statement

To collect data, the necessary permission/approval was obtained from the Ethics Committee of the School of Art and Design at the Nanjing Institute of Technology (Approval No.: NJIT-SADE-20250224-12 ).

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