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Exploring Key Considerations for Artificial Intelligence Robots in Home Healthcare Using the Unified Theory of Acceptance and Use of Technology and the Fuzzy Analytical Hierarchy Process Method

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Abstract: Most countries face declining birth rates and an aging population, which makes the persistent healthcare labor shortage a pressing challenge. Introducing artificial intelligence (AI) robots into home healthcare could help address these issues. Exploring the primary considerations for integrating AI robots in home healthcare has become an urgent topic. However, previous studies have not systematically examined the factors influencing elderly individuals' adoption of home healthcare AI robots, hindering an understanding of their acceptance and adoption. Furthermore, traditional methods overlook the relative importance of each consideration and cannot manage the ambiguity inherent in subjective human cognition, potentially leading to biased decision-making. To address these limitations, this study employs the unified theory of acceptance and use of technology (UTAUT) as a theoretical framework, integrating the modified Delphi method (MDM) and the fuzzy analytical hierarchy process (FAHP) to identify the key considerations. The research determined the order of importance of four evaluation criteria and fourteen evaluation sub-criteria, revealing that customization, accompany, and subjective norms are key factors that influence elderly individuals' adoption of home healthcare AI robots.

Keywords: artificial intelligence robots; home healthcare; unified theory of acceptance and use of technology; modified Delphi method; fuzzy analytical hierarchy process

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1. Introduction

With the continuous progression of medical technology, the average human lifespan is gradually increasing. In most countries, demographic trends have shifted toward an aging population and declining birth rates, intensifying the demand for healthcare resources [1,2]. The healthcare workforce has long been insufficient, raising concerns about its capacity to meet substantial healthcare demands [3,4]. Therefore, identifying complementary or alternative solutions to address these challenges has become imperative. To address the shortage of healthcare resources, home healthcare services provide a promising solution [5–8]. Artificial intelligence (AI) technology is already being integrated into home healthcare [9,10]. The combination of machine learning and big data has facilitated the development of robots suitable for home healthcare. Integrating AI robots into healthcare equipment is valuable for clinical data analysis, disease diagnosis, and rapid patient assessment, thereby alleviating stress on healthcare professionals and mitigating the challenges related to workforce shortages [11–13]. Consequently, the popularization of home healthcare AI robots represents an inevitable trend for the future [14–16]. The introduction of AI

robots in healthcare is an emerging technological issue involving numerous considerations, making it a complex multi-criteria decision-making (MCDM) issue. However, past research has not systematically examined the factors influencing the elderly's adoption of home healthcare AI robots, resulting in a limited understanding of their behavioral intentions and adoption patterns. In addition, traditional methods overlook the relative weight of each factor and cannot manage the ambiguity inherent in subjective human cognition, which may lead to key considerations being overlooked or misjudged in the context of elderly individuals' adoption of home healthcare AI robots.

In recent years, numerous studies have explored the application of artificial intelligence (AI) robots in home healthcare, offering valuable insights. For example, Yang et al. [8] proposed a new vision and features for homecare robotic systems (HRSs) based on cyber–physical systems (CPSs). Sarker et al. [11] examined the role of AI robots in combating the COVID-19 pandemic. Cantone et al. [17] investigated the use of robots in elderly home care by introducing a comprehensive and functional architecture within the framework of the Internet of Robotic Things (IoRT). Chen et al. [18] analyzed the impact of social robot interventions on depression, loneliness, and quality of life among older adults in long-term care (LTC). Tan and Taeihagh [19] explored the adoption of innovative technologies, such as robotics and autonomous systems, in LTC settings. Lastly, Holland et al. [20] reviewed various robotic technologies and their applications in the healthcare sector. However, past research has not systematically examined the factors influencing the elderly's adoption of home healthcare AI robots, resulting in a limited understanding of their behavioral intentions and adoption patterns. In addition, traditional methods overlook the relative weight of each factor and cannot manage the ambiguity inherent in subjective human cognition, which may lead to key considerations being overlooked or misjudged in the context of elderly individuals' adoption of home healthcare AI robots. Thus, the following research questions have been generated: (1) What are the evaluation criteria and sub-criteria for home healthcare AI robots? (2) How should each evaluation criterion and sub-criterion be prioritized? (3) What are the key considerations influencing the adoption of home healthcare AI robots? (4) How can the inherent uncertainty and ambiguity in human cognition be addressed to ensure decision-making outcomes align with realistic needs?

To effectively explore elderly individuals' perspectives on the integration of AI robots into home healthcare, the unified theory of acceptance and use of technology (UTAUT) is suitable for explaining and forecasting individual behaviors regarding the acceptance and use of emerging technologies. The UTAUT encompasses several factors, including performance expectancy, effort expectancy, social influence, and facilitating conditions, aiming to comprehensively elucidate individuals' acceptance and adoption of technology. This framework is commonly applied in academic investigations and practical contexts related to technology adoption, user experience design, market research, and policy formulation [21–23]. The adoption of home healthcare AI robots among the elderly is considered a future trend, necessitating a comprehensive understanding of their perceived value, user experience, and potential impact on social interactions.

Additionally, the modified Delphi method (MDM) is well suited for addressing emerging and complex MCDM problems by using expert groups to evaluate specific issues and determine the final set of evaluation criteria. The MDM is a structured decision-support technique designed to derive relatively objective conclusions and insights through multiple rounds of expert opinion solicitation and subjective judgment. This method aggregates closely related feedback from a panel of experts via iterative questionnaires to formulate strategies and plans. Its primary characteristic is its suitability for exploratory issues that lack precise analytical techniques and involve uncertainty, synthesizing and consolidating experts' thoughts and perspectives on a specific topic. Experts participating in the study

reflect independently and provide their insights, which are then collectively integrated to form conclusions until their opinions converge and reach an optimal consensus. The MDM is widely used in research areas such as healthcare, nursing, and technology innovation. For example, Basinska et al. [24] used the MDM to enhance care in nursing homes for nurses in expanded roles. Niederberger and Spranger [25] conducted systematic reviews of Delphi techniques across various health sciences sectors. Toillier et al. [26] employed the Delphi method to explore approaches for assessing agricultural innovation systems from a transformation perspective.

To understand the relative importance of each factor influencing the elderly's adoption of home healthcare AI robots and to address inherent cognitive imprecision and fuzziness in their evaluations, Saaty [27] introduced the analytic hierarchy process (AHP) to solve complex MCDM problems featuring hierarchical structures. AHP not only deconstructs complex problems into multiple criteria and sub-criteria but also prioritizes these sub-criteria, reveals subjective preferences, and identifies key factors influencing the final decision-making process. Additionally, Zadeh [28] introduced fuzzy sets to address cognitive imprecision and fuzziness in decision-making problems. The fuzzy analytic hierarchy process (FAHP) combines the strengths of AHP and fuzzy sets to manage uncertainty and fuzzy information in subjective human judgments, producing results that better align with human cognition. The FAHP offers distinct advantages over traditional AHP. Traditional AHP typically relies on experts' subjective judgments for comparisons between elements; however, these judgments are often influenced by experts' perceptions and experiences, which may introduce biases. In contrast, many real-world decision-making problems involve ambiguity and uncertainty. To address these complexities, the FAHP incorporates the concepts of fuzzy sets, offering a more robust approach to managing the uncertainties inherent in decision-making. This method enables the integration of expert knowledge and subjective judgment into the analytical process, resulting in outcomes that are better aligned with real-world conditions and have greater persuasiveness and credibility. FAHP has been applied to various research areas concerning the elderly, including healthcare decision-making, nursing service optimization, and technology adoption. For instance, Chen [29] applied the fuzzy geometric mean (FGM) and FAHP method to evaluate critical factors in applying smart technology for mobile medical care. Wang et al. [30] integrated FAHP with the technique for order preference by similarity to the ideal solution (TOPSIS) to assess the operation efficiency of the daycare center. Zhou et al. [31] used FAHP to develop an integrated conceptual path model for a smart elderly care information system.

The specific contributions of this study are as follows. (1) The acceptance and adoption situation of home healthcare AI robots among the elderly can be systematically assessed using the UTAUT. This approach identifies specific considerations shaping elderly individuals' acceptance of AI robots in home healthcare, enhancing the development and implementation of these technologies to effectively meet their needs. (2) Based on UTAUT, this study utilizes MDM and FAHP to identify evaluation criteria, sub-criteria, and key considerations for home healthcare AI robots. (3) From the perspective of theoretical contribution, this study provides actionable insights for developers, policy-makers, and healthcare providers, offering opportunities to facilitate the adoption of home healthcare AI robots among elderly users.

The remainder of this study is organized as follows. Section 2 provides a concise overview of the UTAUT, fundamental definitions, and computational rules of MDM and FAHP. It also introduces the evaluation criteria and sub-criteria for home healthcare AI robots. Section 3 outlines the research model and implementation steps. Section 4 presents the results of two rounds of MDM analysis conducted by the expert panel, along with the

FAHP analysis results from participant assessments. Finally, Section 5 concludes the study and offers practical suggestions.

2. Literature Review

2.1. Unified Theory of Acceptance and Use of Technology

Venkatesh et al. [32] proposed UTAUT as a comprehensive theoretical framework to explain users' acceptance and adoption behavior toward new technologies. UTAUT examines the influence of four primary factors on technology acceptance: performance expectation (PE), effort expectation (EE), social influence (SI), and facilitating conditions (FC). These factors impact individuals' behavioral intention and adoption behavior in the decision-making process of technology adoption [33], as shown in Figure 1.

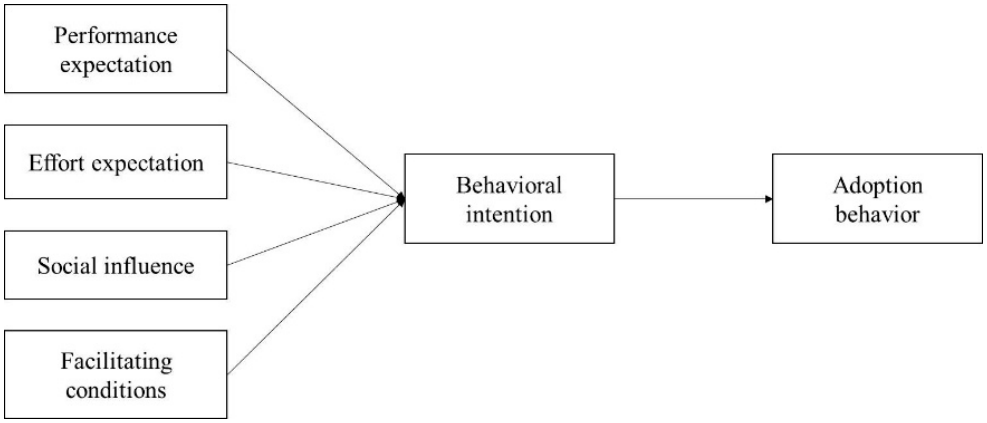


Figure 1. UTAUT theoretical framework.

The definitions of the four factors are as follows. (1) PE represents an individual's belief in the potential advantages and utility of a specific information system or technological product or service. It measures the extent to which users expect the technology to enhance their overall task performance, explaining users' motivations to adopt these systems or services for achieving task outcomes. For example, users may believe that a particular technology is effective, reliable, and meets their functional expectations [34]. In other words, when users believe that a technology can significantly improve work efficiency or achieve goals, their likelihood of accepting and adopting it increases. (2) EE pertains to a user's perception of the ease of acquiring and using a specific technological system. It assesses whether the technology's operation is perceived as simple or complex and the time, money, and effort users believe are necessary when engaging with a technological product or informational service [35]. Therefore, providers should align product or service design with user expectations by offering intuitive interfaces, reasonable pricing, and efficient functionality [36]. (3) SI refers to the impact of external factors, including the opinions and expectations of influential individuals or groups, such as peers, superiors, or colleagues, on an individual's decision to accept and adopt a particular technology. When individuals perceive positive expectations from their social groups or believe that technology usage is a social norm, this social pressure can strengthen their behavioral intention and adoption [37]. This factor encompasses social environment influences, such as regulations, prominent figures, and public perception; individuals' acceptance and adoption may fluctuate depending on the sway of these social factors. (4) FC refers to the extent to which an individual's perception of sufficient external resources and support is necessary for using a technological system. When individuals perceive adequate support from their environment, their intention to adopt the technology is likely to increase. Support may include customizable services, infrastructure availability, system reliability,

and additional functionalities, all of which contribute to perceptions of organizational and technological support [38].

2.2. Modified Delphi Method

Dalkey and Helmer [39] proposed the Delphi method, a well-established technique suitable for novel and specialized research topics. The process centers on synthesizing the professional knowledge, experience, and opinions of expert groups to achieve consensus. The MDM is an improved version of the original Delphi method, which addresses previous limitations while maintaining its foundational approach. This adoption shortens the questionnaire timeline and enables experts and scholars to concentrate on the research topics rather than engaging in speculation. The MDM relies on independent expert judgments and iterative group feedback from multiple questionnaire rounds. Each analysis result and subsequent questionnaire updates are shared with participating experts to establish consensus and resolve complex, uncertain issues [40,41]. The MDM establishes relevant verification indicators to assess the importance, concentration, and dispersion of each item to ensure consistency and stability of opinions. These indicators include the mean (M), mode (MO), $|MO - M|$, quartile deviation (QD), and standard deviation (SD). If each item meets these indicators, consensus and consistency are achieved, indicating convergence and item retention; otherwise, non-compliant items are removed. This iterative process lays the groundwork for the FAHP questionnaire. The definitions are as follows.

Definition 1 ([42]). *Let M indicate the concentration trend of experts' degree of agreement, with values > 3.5 as the screening threshold.*

$$M = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{1}$$

where X_i represents the rating from the i-th expert, and n denotes the total number of experts.

Definition 2 ([41]). *Let MO represent the most frequently chosen value by experts, reflecting the most common opinion among the experts.*

Definition 3 ([41]). *Let $|MO - M|$ measure the difference between the mode and the mean, which measures the concentration of expert opinions. Values ≤ 1 indicate a high degree of agreement among the experts, while values > 1 suggest disagreement.*

Definition 4 ([43]). *Let QD represent the degree of data distribution dispersion. A QD value < 0.6 denotes high consensus, a QD between 0.6 and 1 indicates moderate consensus, and a QD value > 1 indicates a lack of consensus.*

$$D = \frac{Q3 - Q1}{2} \tag{2}$$

where Q3 represents the third quartile, and Q1 represents the first quartile.

Definition 5 ([44]). *Let SD indicate the degree of data distribution dispersion, reflecting expert rating variability. An $SD < 1$ shows low dispersion in agreement; values nearer to 0 signify greater opinion concentration.*

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - M)^2} \tag{3}$$

where X_i represents the rating provided by the i-th expert, M denotes the mean, and n is the total number of experts.

2.3. Fuzzy Analytic Hierarchy Process Method

Saaty [27] introduced the AHP method to streamline and structure complex and uncertain problems using pairwise comparative evaluation to support MCDM. This study employed a three-layer hierarchy as an example: the first layer represents the ultimate goal, the second layer consists of evaluation criteria, and each evaluation criterion is further divided into several measurable evaluation sub-criteria (third layer). This hierarchical approach simplifies decision-making analysis by ensuring that each layer contains no more than seven factors, as shown in Figure 2.

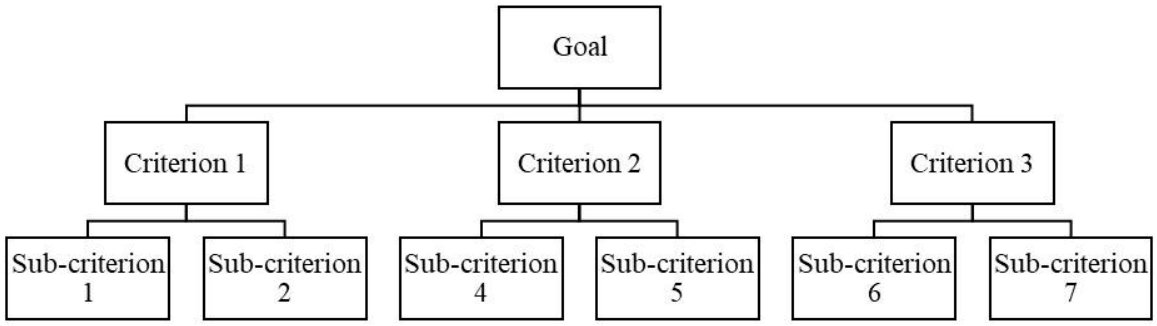


Figure 2. Three-layer hierarchy.

From the perspective of fuzzy theory, human judgments and preferences in decision-making cannot be accurately represented by precise numbers due to cognitive uncertainties. Ignoring the ambiguity inherent in human behavior during decision-making may lead to incorrect conclusions [45]. The FAHP method captures the relative fuzzy weight between two factors using triangular fuzzy numbers (TFNs). The triangular fuzzy function represents the cognition of relative weights among assessment criteria, helping to determine the fuzzy weight of each decision factor and thereby improving accuracy [46]. The calculation rules for TFNs are as follows.

Definition 6 ([47]). *Considering that two TFNs are* $A_1 = (l_1, m_1, u_1)$ *and* $B_1 = (l_2, m_2, u_2)$, *the operation rules are defined as follows:*

$$A_1 \oplus B_1 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (4)$$

$$A_1 \ominus B_1 = (l_1, m_1, u_1) \ominus (l_2, m_2, u_2) = (l_1 - u_2, m_1 - m_2, u_1 - l_1) \quad (5)$$

$$A_1{}^{-1} = (l_1, m_1, u_1)^{-1} = (1/u_1,\ 1/m_1, 1/l_1) \quad (6)$$

where l_1 *and* l_2 *represent the lower bounds of the TFNs,* m_1 *and* m_2 *represent the middle values, and* u_1 *and* u_2 *represent the upper bounds.*

The execution steps of the FAHP method are as follows [48].

Step 1: Construct a hierarchy of assessment criteria. Develop a hierarchy derived from the assessment questions and identify the corresponding criteria.

Step 2: Construct a pairwise comparison matrix. Determine the relative importance of evaluation criteria through pairwise comparisons. Table 1 presents a pairwise comparison of the relative importance of the evaluation criteria [49]. Based on this table, the respondents established a pairwise comparison matrix of evaluation criteria grounded in their past experiences.

Table 1. The relative importance of the assessment criteria.

Linguistic Variable	Assessment Scale	TFNs	Reciprocal of Assessment Scale	Reciprocal of TFNs
Equally important	1	(1, 1, 1)	1	(1, 1, 1)
Equally to moderately important	2	(1, 2, 3)	1/2	(1/3, 1/2, 1)
Moderately important	3	(2, 3, 4)	1/3	(1/4, 1/3, 1/2)
Weakly important	4	(3, 4, 5)	1/4	(1/5, 1/4, 1/3)
Important	5	(4, 5, 6)	1/5	(1/6, 1/5, 1/4)
Strongly important	6	(5, 6, 7)	1/6	(1/7, 1/6, 1/5)
Very important	7	(6, 7, 8)	1/7	(1/8, 1/7, 1/6)
Very strongly important	8	(7, 8, 9)	1/8	(1/9, 1/8, 1/7)
Absolutely important	9	(8, 9, 9)	1/9	(1/9, 1/9, 1/8)

Step 3: Defuzzify the TFN values. Let $A_1 = (l_1, m_1, u_1)$ be a TFN and defuzzify (DF) the A_1 value as follows [47]:

$$DF(A_1) = \frac{1}{3}(l_1 + m_1 + u_1) \tag{7}$$

Step 4: Implement a consistency test of respondents' opinions. The FAHP method employs the consistency ratio (CR) to evaluate the consistency of respondents' views. This ratio is mainly used to detect any inconsistencies, incompatibilities, or contradictions in the evaluation process to avoid misjudgment. When $CR \leq 0.1$, it indicates that the consistency of the matrix is reliable, and the relative weights and priorities are both qualified and valid. The CR value is calculated using the maximum eigenvalue (λ_{max}) of the pairwise comparison matrix (M), the consistency index (CI) value, and the random index (RI) value. n represents the number of square matrices, and w represents the relative weight of the assessment criteria. Based on the different sizes of the matrix, the corresponding RI is shown in Table 2 [27].

$$Mw = \lambda_{max} w \tag{8}$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{9}$$

$$CR = \frac{CI}{RI} \tag{10}$$

Table 2. Random index.

Size of Matrix	1	2	3	4	5	6	7
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32

2.4. The Assessment Criteria and Assessment Sub-Criteria of Home Healthcare AI Robots

This study systematically reviewed the literature on home healthcare AI robots through the lens of the UTAUT framework, generalizing 16 assessment sub-criteria according to the definitions of four assessment criteria: PE, EE, SI, and FC. Each assessment sub-criteria is described below, as delineated in Table 3.

The PE criterion includes the following assessment sub-criteria: effectiveness, reliability, functionality, and accompany. (1) Effectiveness: AI robots enhance the quality of elderly care, medical efficiency, and precision in diagnosis and treatment plans [50]. (2) Reliability: AI robots ensure streamlined operations, maintain high-quality standards, establish trustworthiness, and provide a sense of security [51,52]. (3) Functionality: this criterion reflects AI robotics' diverse healthcare features, including monitoring vital signs,

blood pressure, and oxygen levels, as well as detecting anomalies such as arrhythmias and strokes, catering to the varied needs of the elderly [17]. (4) Accompany: AI robots tailor the level of care provided to the elderly based on their specific requirements, offering flexible, round-the-clock, and one-on-one care to deliver the most appropriate and individualized assistance [18–53].

The EE criterion includes the following assessment sub-criteria: convenience, affordability, practicality, and cost savings. (1) Convenience: AI robots enhance accessibility through an intuitive interface [54,55]. (2) Affordability: pricing strategies that fit consumers' budgets increase demand and widespread adoption of AI robots in the healthcare industry [56]. (3) Practicality: these technologies empower elderly individuals to autonomously address their healthcare needs, thereby reducing their reliance on external assistance and enhancing their autonomy [19–57]. (4) Cost savings: potential cost savings are associated with reduced costs of hiring healthcare professionals [58].

The SI criterion includes the following assessment sub-criteria: commercial engagement, subjective norms, social perceptions, and regulations. (1) Commercial engagement: the appeal of commercial endeavors undertaken by AI robots, such as free trial product offerings and product seminars, plays a vital role in shaping purchase decisions, as it is deeply closely linked to the influence exerted by external factors [59,60]. (2) Subjective norms: individual purchasing intentions are significantly influenced by the experiences and feedback of relatives and friends who have previously engaged with AI robots, representing a crucial aspect of social influence [61]. (3) Social perceptions: public satisfaction with the use of AI robots directly impacts consumers' purchasing intentions, highlighting the importance of collective sentiment in the decision-making process [62,63]. (4) Regulations: national regulations and policies significantly impact consumers' purchasing intentions [64].

The FC criterion includes the following assessment sub-criteria: customization, technical assistance, system compatibility, and value-added features. (1) Customization pertains to the ability to adapt healthcare services to meet individual needs, ensuring personalized functions [20]. (2) Technical assistance involves providing support through a telephone customer service line that responds promptly to technical inquiries related to AI robots' interface operations, software and hardware maintenance, updates, and related issues [65,66]. (3) System compatibility ensures the seamless integration of the AI robot system, including mobile phone connectivity, Bluetooth, the Internet of Things, and other functionalities, while facilitating real-time monitoring of the robot's operational status [67,68]. (4) Value-added features are incorporated to offer supplementary functionalities to elderly users, such as professional rehabilitation training and in-home mobility support, along with further enhancements [69].

Table 3. The assessment criteria, assessment sub-criteria, and definition of home healthcare AI robots.

Assessment Criteria	Assessment Sub-Criteria	Definition	Literature Source
PE	Effectiveness	Enhancing the quality of elderly care, medical efficiency, and diagnostic accuracy	Carpenter et al. [50]
	Reliability	Maintaining high quality, establishing trust, and offering security	Xu and Saleh [51]; Ahmed and Ishtiaq [52]

Table 3. *Cont.*

Assessment Criteria	Assessment Sub-Criteria	Definition	Literature Source
PE	Functionality	Offering diverse healthcare features, including vital signs monitoring and anomaly detection	Cantone et al. [17]
	Accompany	Tailoring care to the specific needs of the elderly through one-on-one support	Chen et al. [18]; Bressan et al. [53]
EE	Convenience	Enhancing user-friendliness through an intuitive AI robotics interface	Klaus and Zaichkowsky [54]; Chen [55]
	Affordability	Competitive pricing strategies that encourage the widespread adoption of AI robotic technologies in healthcare	Liu et al. [56]
	Practicality	Empowering the elderly to address their healthcare needs independently through technology	Tan and Taeihagh [19]; Shareef et al. [57]
	Cost savings	Reducing expenses associated with hiring healthcare professionals	Wirtz [58]
SI	Commercial engagement	The appeal of AI robots in commercial initiatives influencing purchase decisions	Dwivedi et al. [59]; Prentice et al. [60]
	Subjective norms	The impact of experiences and feedback from friends and family on purchasing intentions	Gursoy et al. [61]
	Social perceptions	Public satisfaction with AI robot adoption influencing consumer purchasing decisions	Seo and Lee [62]; Pizzi et al. [63]
	Regulations	The influence of national regulations and policies on consumer purchasing intentions	Östlund et al. [64]
FC	Customization	Ensuring a personalized approach to healthcare services for the elderly	Holland et al. [20]
	Technical assistance	Providing telephone customer service for prompt technical assistance related to AI robots	Yang et al. [65]; Pantano and Pizzi [66]
	System compatibility	Seamless integration of the AI robot system with various platforms and functionalities	Huang et al. [67]; Choi et al. [68]
	Value-added features	Incorporating features like professional rehabilitation training and in-home mobility support for elderly users	Martinho et al. [69]

3. Research Method

3.1. Research Framework

The aging population is an undeniable reality, leading to a growing need for alternative healthcare solutions, especially in the context of limited healthcare workforce availability. Home healthcare services, enhanced by AI technology, are poised to become an essential component of future care strategies by integrating AI robots. However, current understanding of the elderly's behavioral intentions and adoption patterns regarding home healthcare AI robots remains insufficient. Specifically, the factors that influence their adoption, the prioritization of these factors, and the most critical considerations are not yet well defined. To address this gap, this study employed the UTAUT as its theoretical foundation, integrating the MDM and FAHP to construct the UTAUT-FAHP research framework. The first layer of this framework aims to identify key considerations for adopting AI robots in home healthcare. The second layer categorizes these considerations into four assessment criteria: PE, EE, SI, and FC. The third layer explains the relative assessment sub-criteria classified according to their characteristics. The research model is illustrated in Figure 3.

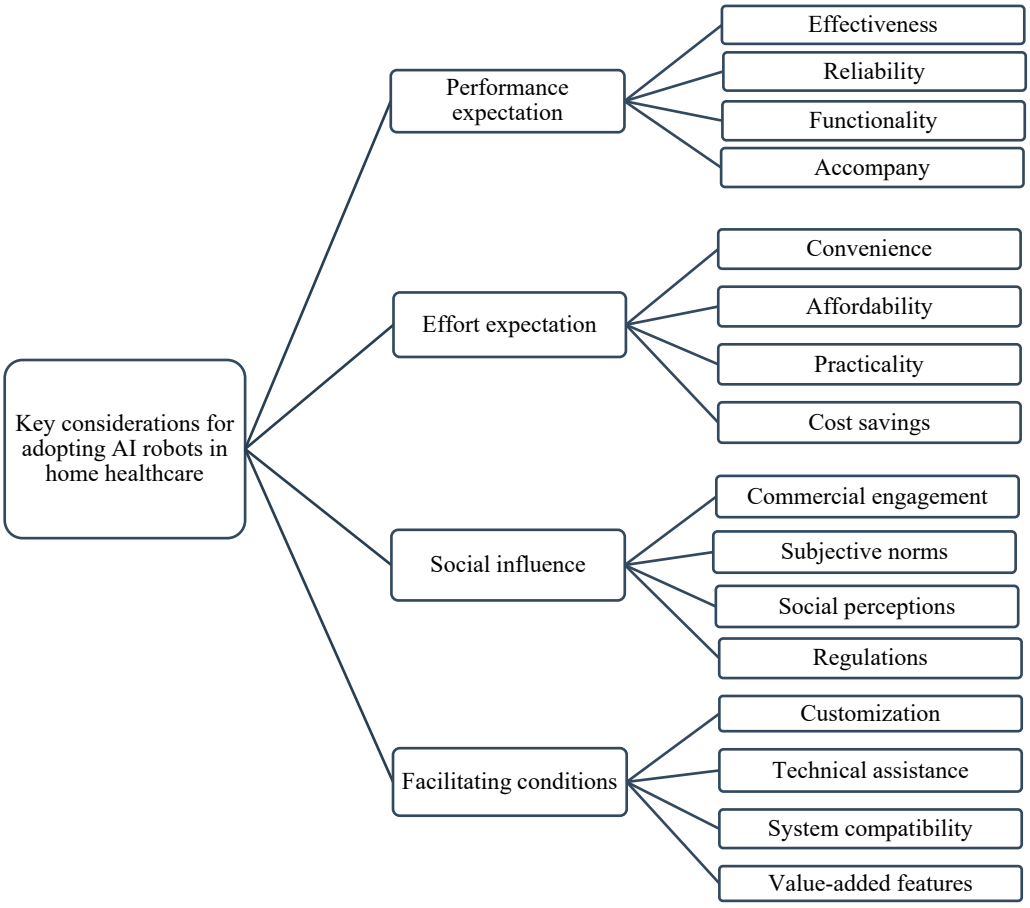


Figure 3. UTAUT-FAHP framework.

3.2. Research Design

The study is divided into two distinct phases, with the implementation phases and steps of the research design illustrated in Figure 4.

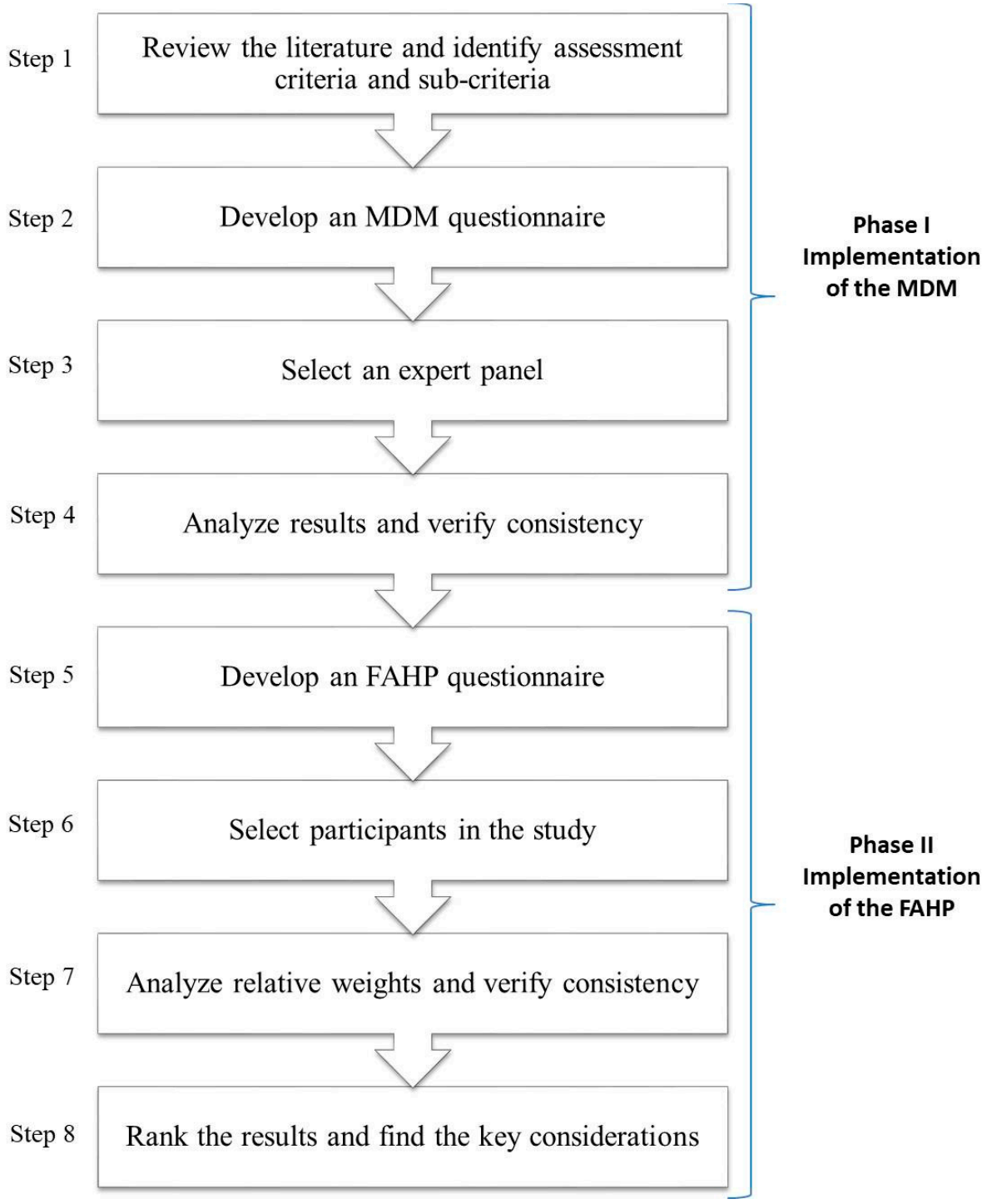


Figure 4. The implementation phases and steps of the research design.

Phase I. Implementation of the MDM

Step 1. Review the literature and identify assessment criteria and sub-criteria.

Informed by the UTAUT theory, the key factors influencing the adoption of AI robots in home healthcare were preliminarily identified, and a hierarchical framework of assessment criteria and sub-criteria was constructed.

Step 2. Develop an MDM questionnaire.

The MDM questionnaire was designed with a semi-open structure. It employed a five-point Likert scale, ranging from 1 to 5 points, where each point corresponded to the

following responses: 1—strongly disagree, 2—disagree, 4—have no opinion, 4—agree, and 5—strongly agree. Examples of the MDM questionnaire are provided in Table 4.

Table 4. The MDM questionnaire example.

Degree of Cognition	Sub-Criteria Definition	1	2	3	4	5	Suitable	Suitable After Modification	Not Suitable
		Strongly Disagree	**Disagree**	**No Opinion**	**Agree**	**Strongly Agree**			
Effectiveness	Enhancing the quality of elderly care, medical efficiency, and diagnostic accuracy	☐	☐	☐	☐	☐	☐	☐	☐
Suggestions for correction									

Step 3. Select an expert panel.

The MDM was employed to gather insights from experts with significant knowledge and interest in the topic. This panel included several nurses selected from various medical settings, such as medical centers, hospitals, clinics, and long-term care institutions. The objective was to ensure a comprehensive review of the questionnaire content by experts affiliated with diverse medical institutions, thereby enhancing the quality of the study.

Step 4. Analyze results and verify consistency.

SPSS version 20.0 was utilized to analyze each expert's assessment values for the evaluation sub-criteria and verify whether the values of M, $|MO - M|$, QD, and SD for each sub-criterion met the required thresholds. Sub-criteria that met the thresholds were retained for the second round, while those that did not were eliminated.

Phase II. Implementation of the FAHP

Step 5. Develop an FAHP questionnaire.

Based on the assessment criteria and sub-criteria determined by the MDM, the FAHP questionnaire was constructed. The FAHP questionnaire involved pairwise comparisons of the assessment criteria and sub-criteria influencing the adoption of AI robots in home healthcare to determine the relative weight of each factor. The evaluation scale ranged from 1 to 9, with 2, 4, 6, and 8 representing intermediate values. A sample of the questionnaire is presented in Table 5.

Step 6. Select participants in the study.

The FAHP was used to administer a questionnaire survey targeting elderly individuals to elucidate the primary factors influencing the integration of AI robots into home healthcare. To enhance understanding of the AHP questionnaire process among elderly respondents and eliminate potential confusion regarding the questionnaire format or evaluation method, this study employed face-to-face visits and illustrative examples. Additionally, clear and comprehensible operational definitions were provided for each evaluation sub-criteria to more accurately capture the participants' genuine perceptions.

Table 5. The FAHP questionnaire example.

What Is the Relative Importance of Assessment Criteria for Home Healthcare AI Robots?																		
Left Criteria	**Absolutely Important**		**Very Important**		**Important**		**Moderately Important**		**Equal Importance**		**Moderately Important**		**Important**		**Very Important**		**Absolutely Important**	**Right Criteria**
	9	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
Performance expectancy	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	Effort expectancy
Performance expectancy	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	Social influence
Performance expectancy	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	Facilitating conditions

Step 7. Analyze relative weights and verify consistency.

For data analysis, this study employed Power Choice version 4.1 to analyze the response data from each participant and verify whether the *CR* value for each criterion met the consistency requirements. Fuzzy set theory was integrated into the elderly questionnaire, and the FAHP was utilized to compare relative weights. This choice was made because the participants were elderly individuals who may possess rich experiences or knowledge. However, due to factors such as language proficiency, memory constraints, or other cognitive limitations, semantic ambiguity might arise when evaluating different choices, impeding the accurate expression of their opinions. Therefore, the FAHP method was used to provide a better understanding of their viewpoints and preferences, thereby enhancing the validity of the questionnaire.

Step 8. Rank the results and find the key considerations.

Based on the results of the FAHP analysis, the weighted relative importance of each assessment sub-criteria was ranked, leading to the identification of the critical considerations.

4. Results

4.1. Overview

Understanding the behavioral intention and adoption patterns of the elderly population regarding home healthcare AI robots is an important issue; it involves many factors and constitutes a complex MCDM problem. An effective evaluation method can provide insights into the acceptance and adoption of home healthcare AI robots among the elderly. To gain a more accurate understanding of the elderly's real perceptions regarding the adoption of home healthcare AI robots and the key considerations, the research sample included 30 elderly individuals associated with a specific community health promotion association in Taiwan. This organization is committed to improving the physical and mental health and quality of life of the elderly through various services, including health education and promotion, regular health screenings, exercise rehabilitation programs, psychological counseling, social activities organization, community care, and resource provision. These services not only enhance the elderly's health but also promote their interaction and participation in society, thereby improving their overall quality of life. Among the 30 participants in this association, 19 were living alone, while 11 were cohabiting with others. In terms of health status, 5 participants were classified as healthy, 17 as having fair health, and 8 as having poor health. The participants' ages ranged from 65 to 81 years. The majority exhibited fair health, with a higher proportion living alone, particularly among female participants. Furthermore, this case study recruited ten nurses from various healthcare institutions in Taiwan, including clinics, hospitals, long-term care facilities, and medical centers. These ten nurses comprised the expert panel for the implementation of MDM in this study, tasked with identifying and validating the criteria and sub-criteria influencing the integration of AI robots into home healthcare. They expressed strong interest in this research topic and were willing to provide valuable opinions. Through face-to-face questionnaires and interviews, the researchers aimed to accurately understand the experts' genuine perceptions of home healthcare AI robots.

This study comprised a cohort of ten nurses recruited from various healthcare institutions, including clinics, hospitals, long-term care facilities, and medical centers. These professionals possess extensive expertise across diverse specialties, such as oncology nursing, hemodialysis, clinical care, general medical care, and long-term care. Their years of experience range from 11 to 22 years. The cohort included individuals serving as head nurses, case managers, and physician assistants. Their specialized knowledge and substantial experience contribute significantly to their respective healthcare settings and patient care practices. A detailed list of the experts is provided in Table 6.

Table 6. Expert panel profiles.

No.	Organization	Position	Professional Field	Seniority
1	Clinic	Head nurse	Cancer care	22
2	Clinic	Head nurse	Hemodialysis, clinical care	20
3	Clinic	Nurse	Medical care	19
4	Hospital	Nurse	Hemodialysis, clinical care	16
5	Hospital	Outpatient nurse	Medical care	16
6	Long-term care institution	Head nurse	Kidney medical	21
7	Long-term care institution	Home nurse	Medical care	20
8	Medical center	Case manager	Cancer care	16
9	Medical center	Nurse	Long-term care	15
10	Medical center	Physician assistant	Long-term care	11

4.2. Modified Delphi Method Analysis

This study conducted a two-round Delphi method questionnaire survey involving ten experts. The results were as follows. (1) In the context of PE, effectiveness scored a slightly lower mean with a notable standard deviation in Round 1, indicating diverse expert opinions; consequently, the item was eliminated. Furthermore, reliability showed improvement in Round 2 with a reduced standard deviation and a convergence in $|MO - M|$, reflecting increased consensus. Functionality and accompany consistently received high ratings across both rounds, with low variability, indicating strong agreement on their importance. (2) In the context of EE, affordability gained slightly more emphasis in Round 2, with reduced variability suggesting stronger consensus among experts. Additionally, practicality and cost savings were consistently regarded as important, with reduced variability in Round 2 highlighting greater agreement. (3) In the context of SI, commercial engagement maintained high consensus. Subjective norms and social perceptions demonstrated improved expert agreement between rounds, as evidenced by reduced standard deviation (*SD*) and quartile deviation (*QD*). Conversely, regulations retained lower scores with substantial variability, leading to the elimination of the item. (4) In the context of FC, customization, technical assistance, and value-added features remained priorities across both rounds, exhibiting stable scores and reduced *SD* and *QD*, reflecting enhanced agreement on their significance. Furthermore, system compatibility achieved the highest mean score, underscoring the importance of seamless system integration. The results of the two-round Delphi method are detailed in Table 7.

Table 7. The two-round Delphi method results.

Assessment Criteria and Sub-Criteria		*M*	*MO*	$\lvert MO-M \rvert$	*SD*	*QD*
PE	Effectiveness	3.90/-	4/-	0.10/-	1.00 */-	0.50/-
	Reliability	3.70/4.00	¾	0.70/0.00	0.82/0.67	0.50/0.13
	Functionality	4.50/4.60	5/5	0.50/0.40	0.53/0.52	0.50/0.50
	Accompany	4.10/4.20	4/4	0.10/0.20	0.74/0.63	0.29/0.20
EE	Convenience	4.50/4.40	5/5	0.50/0.60	0.71/0.84	0.50/0.63
	Affordability	4.50/4.60	5/5	0.50/0.40	0.71/0.52	0.50/0.50
	Practicality	4.40/4.40	5/5	0.60/0.60	0.84/0.70	0.63/0.50
	Cost savings	4.40/4.40	5/4	0.60/0.40	0.70/0.52	0.50/0.25
SI	Commercial engagement	4.60/4.20	5/4	0.40/0.20	0.52/0.63	0.50/0.20
	Subjective norms	3.56/4.20	4/4	0.44/0.20	0.93/0.42	0.75/0.20
	Social perceptions	3.50/4.20	3/5	0.30/0.80	0.82/0.79	0.24/0.02
	Regulations	3.18 */-	3/-	0.20/-	1.25 */-	0.5/-
FC	Customization	4.30/4.30	4/4	0.30/0.30	0.67/0.48	0.50/0.24
	Technical assistance	4.20/4.20	5/4	0.80/0.20	0.79/0.63	0.63/0.20
	System compatibility	4.67/4.60	5/5	0.33/0.40	0.50/0.52	0.50/0.50
	Value-added features	4.30/4.50	5/5	0.70/0.50	0.82/0.53	0.63/0.50
Average value		4.13/4.34	-	0.44/0.37	0.77/0.60	0.51/0.36

Note: 1. First round/second round analysis results. 2. * indicates that it did not meet the testing standards and was deleted. It was not considered in the second round (presented in a gray background).

The mean value of the overall questionnaire agreement mean (M) in the second round was 4.34, an improvement from 4.13 in the first round, suggesting a consensus among experts regarding the appropriateness of the questionnaire content. The average value of $|MO - M|$ in the second round decreased to 0.37, slightly lower than the 0.44 recorded in the first round, indicating enhanced consistency in expert opinions. In the second round, the average SD reduced to 0.6, reflecting a higher concentration of opinions within the expert group compared to the 0.77 recorded in the first round. Furthermore, the average QD in the second round was 0.36, lower than the 0.51 observed in the first round, indicating that the revised standards achieved a high consensus level ($QD < 0.6$). Based on the analysis results, the test criteria were met, forming the basis for constructing the FAHP questionnaire. The results are detailed in Figure 5.

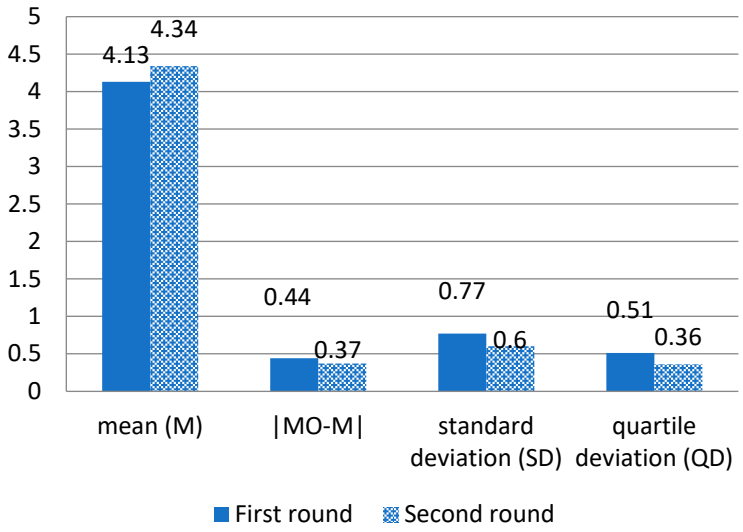


Figure 5. Comparison of assessment sub-criteria of the two-round Delphi method.

4.3. Fuzzy Analytic Hierarchy Process Analysis

To prevent participants from feeling confused by the items in the FAHP questionnaire, face-to-face interviews were conducted, explaining each item's definition and content in detail to accurately capture their true perceptions. Additionally, fuzzy logic was applied to mitigate the inherent imprecision and vagueness in the elderly participants' responses, thereby enhancing the validity of the questionnaire. Data analysis revealed that FC (weight value 0.334) was the most important assessment criterion. The assessment sub-criteria were ranked as follows: customization (weight value 0.164), followed by accompany (weight value 0.125) and subjective norms (weight value 0.092). From the perspective of various assessment criteria, accompany was the more important sub-criterion within the PE category, while functionality was less important. The more important sub-criterion in the EE category was affordability, while cost savings were less important. In the SI category, the more important sub-criterion was subjective norms, while social perceptions were less important. The most important sub-criterion in the FC category was customization, while value-added features were less important. The relative weights of assessment criteria and sub-criteria are shown in Table 8 and Figure 6.

Table 8. The relative weight of assessment criteria and sub-criteria.

Assessment Criteria and Sub-Criteria			Sub-Criteria Weight	Ranking	Total Weight	Total Weight Ranking
PE 0.294	B01	Reliability	0.301	2	0.089	4
	B02	Functionality	0.274	3	0.081	5
	B03	Accompany	0.425	1	0.125	2
EE 0.195	B04	Convenience	0.307	2	0.060	8
	B05	Affordability	0.333	1	0.065	6
	B06	Practicality	0.242	3	0.047	12
	B07	Cost savings	0.118	4	0.023	14
SI 0.176	B08	Commercial engagement	0.286	2	0.050	11
	B09	Subjective norms	0.519	1	0.092	3
	B10	Social perceptions	0.195	3	0.034	13
FC 0.334	B11	Customization	0.491	1	0.164	1
	B12	Technical assistance	0.187	2	0.063	7
	B13	System compatibility	0.166	3	0.055	9
	B14	Value-added features	0.156	4	0.052	10

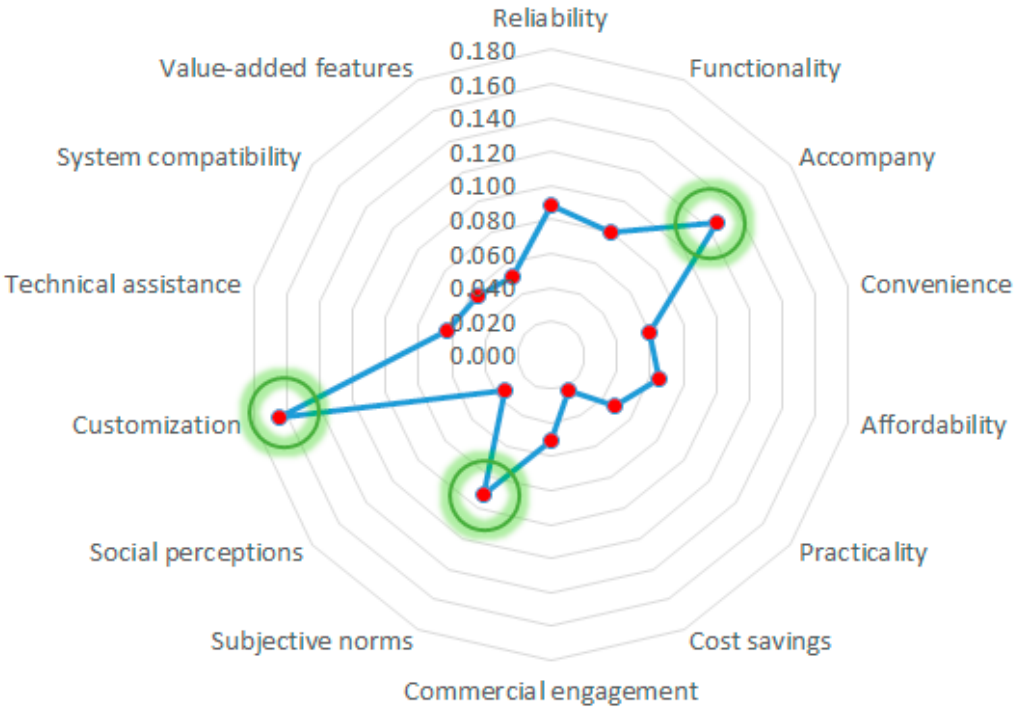


Figure 6. The relative weight distribution of assessment sub-criteria.

5. Conclusions and Suggestions

5.1. Conclusions

The burden on healthcare labor caused by population aging is becoming increasingly severe, and home healthcare services have emerged as an alternative solution to address the shortage of medical resources. Leveraging the integration of AI robots in home healthcare can help mitigate current challenges. The widespread adoption of home healthcare AI robots is a future trend. Therefore, it is essential to understand elderly behavioral intentions and adoption patterns regarding home healthcare AI robots and identify the key considerations influencing their decision-making. Based on the UTAUT-FAHP model, this study employed qualitative and quantitative analysis methods to provide valuable insights and construct a research framework that evaluates the integration of AI robots into home healthcare. The research identified four assessment criteria and fourteen assessment

sub-criteria, analyzing their importance level ranking. Consequently, it revealed the key considerations influencing the adoption of home healthcare AI robots.

In the context of PE, the elderly consider accompany to be the paramount consideration. They perceive companionship as a continuous process in which AI robots simulate accompanying individuals through life's difficulties, enabling seniors to navigate adversity. Given the prevalence of the elderly living alone, it can be inferred that they highly value the sense of one-on-one companionship. This finding aligns with the perspective of Chen et al. [18]. Conversely, functionality emerges as a less significant consideration. Empirical survey results indicate that the elderly prioritize emotional companionship while being less concerned about whether AI robots possess diverse features. Regarding EE, the elderly deem affordability to be the key consideration. They believe that a reasonable price enables them to afford AI robots according to their household financial capabilities. Conversely, cost savings rank as a less important consideration, as saving healthcare resources does not directly influence the welfare of the elderly. In terms of SI, the elderly regard the subjective norms as the foremost consideration. Due to limited information sources, predominantly relying on neighbors and acquaintances, the usage experiences and feedback of peers significantly influence the purchase intention of the elderly, similar to the findings of Ameen et al. [70]. Social perceptions emerge as a less significant consideration because the usage level, comments, or satisfaction of acquaintances have a more direct impact on the elderly's perception of adopting AI robots than the general public's views. Concerning FC, the elderly prioritize customization as the most key consideration. Tailoring specialized services according to the individual needs of the elderly is deemed important, as each individual's healthcare requirements vary. This aligns with the perspective of Holland et al. [64]. Conversely, value-added features rank as a less important consideration because customization already meets the needs of the elderly, obviating the necessity for additional services, thereby potentially increasing costs by adding unnecessary features.

5.2. Management Implications

When designing AI robots for integration into home healthcare, priority should be given to "customization", "companionship", "affordability", and "subjective norms". Given that the elderly place greater importance on these factors, aligning home healthcare services with their specific needs is imperative. These considerations can significantly influence their willingness to use these services, thereby meeting their expectations and purchasing intentions and addressing the issue of insufficient medical human resources.

In other words, the design of AI robots should prioritize personalized services tailored to the elderly's individual needs, health conditions, and lifestyle preferences while also addressing issues such as social isolation and lack of emotional support. Furthermore, a reasonable pricing strategy should ensure that elderly individuals with limited financial resources are not burdened. Regarding marketing strategies, emphasis should be placed on shaping perspectives and attitudes within the elderly's social network, as word-of-mouth communication plays a significant role.

5.3. Research Limitations and Future Directions

This study examined the elderly's cognitive levels regarding factors associated with the acceptance of home healthcare AI robots. However, the diverse backgrounds of the experts involved in this research, along with the rapidly evolving technological landscape, may have led to the omission of certain criteria or sub-criteria. Future research should include experts from broader fields (e.g., informal carers, physicians, and academics) to provide more comprehensive insights and reduce potential biases. Additionally, the sample size of elderly participants was relatively small, potentially limiting the representativeness

and generalizability of the findings. Future studies should expand the scope of research, consider additional demographic variables, and employ more diverse methodologies, such as a probabilistic hesitant fuzzy integrated cloud approach [71] and a cloud model within a multi-granularity linguistic environment [72], to address issues of uncertainty. This approach could better reflect the elderly's needs regarding the integration of AI robots into home healthcare, enabling the findings to be more broadly applicable within the related research domains.

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