ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 12 (2025) No. 2, pp. 185-202
DOI:10.33168/JLISS.2025.0212

Understanding Elderly Adoption of Smart Care Applications in China: An Extended UTAUT Model with Attitude as Mediator

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Abstract. China faces significant challenges in elderly care with its rapidly aging population and evolving family structures. Smart elderly care applications offer potential solutions, yet their adoption remains low. This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating attitude as a mediator and technology anxiety as a direct predictor of intention to use smart elderly care applications. Data collected from 375 Chinese adults aged 60 and above were analyzed using structural equation modeling. Results reveal that attitude strongly predicts intention to use (β =0.78, $p<0.01$), while technology anxiety shows no significant effect. Performance expectancy (β =0.246, $p<0.01$), social influence (β =0.225, $p<0.01$), and facilitating conditions (β =0.076, $p=0.01$) positively influence attitude, but effort expectancy has no significant impact. The model explains 61.1% of the variance in intention to use, demonstrating its robustness. These findings suggest that developers should focus on enhancing the practical benefits of smart elderly care applications and leveraging social influence to foster positive attitudes, rather than overly emphasizing ease of use or addressing technology anxiety. This study contributes to technology acceptance literature by validating an extended UTAUT model specifically for elderly users in China's unique cultural and social context.

Keywords: Smart elderly care, UTAUT, Intention to use, Attitude, Technological anxiety

1. Introduction

Over the next three decades, the global population aged 65 and above is projected to quadruple, reaching approximately 1.6 billion by 2050, at which point older adults will constitute over 16% of the world's population (Zhou et al., 2024). Concurrently, the advancement and widespread application of computational sciences and information technologies, such as the Internet, the Internet of Things (IoT), and smart terminals, have facilitated the emergence of a new model of elderly care, commonly referred to as "smart eldercare" (Liu et al., 2023).

In China, demographic trends have shown a steady rise in the elderly population, coupled with a declining birth rate. It is anticipated that by 2035, the number of individuals aged 60 and above will exceed 400 million, representing more than 30% of the total population (IRCRI, 2022). This demographic shift signals China's transition into a deeply aged society. As this trend accelerates, the growing size and rapid expansion of the older population have intensified demand for both daily living assistance and medical care services (Xin & Fang, 2021).

As the country with the world's largest elderly population, China's approach to eldercare has long been shaped by traditional Confucian values, particularly filial piety, and institutionalized through the “9073” eldercare policy—wherein 90% of older adults are cared for by family members, 7% receive community-based services, and only 3% are supported by institutional care (Zhu et al., 2023). However, this traditional family-based model is increasingly inadequate in meeting the complex needs of the elderly, particularly in terms of professional medical care, emotional support, and personalized services. This growing gap between care needs and available services has spurred the development of intelligent eldercare solutions (Zhang et al., 2020).

Smart elderly care applications have the potential to optimize the allocation of elderly care resources, enhance service efficiency and quality, and improve convenience and safety for older adults (Zhang et al., 2020). Despite these advantages, the adoption of smart eldercare applications in China remains limited. User habits have yet to be established, and the utilization rate of such applications is notably low, as the sector is still in its early stages of development (Zhu et al., 2023). Most smart elderly care applications in China are commercially driven and developed by private enterprises. Even among those with over 10,000 downloads, all operate under a paid service model, offering services such as meal delivery, medical examinations, home cleaning, and age-friendly home modifications. The most downloaded application has 4.41 million downloads, representing just 1.43% of China's population aged 60 and above. These figures reflect the limited reach and acceptance of such technologies, despite significant government investment and policy support.

Understanding the psychological and behavioral mechanisms that drive individuals to form strong attachments to specific technologies—and eventually integrate them into their daily lives—is essential for the successful adoption of emerging digital services (Liwei Wang, 2022). To address the identified research gaps, this study aims to extend the Unified Theory of Acceptance and Use of Technology (UTAUT) model by incorporating “attitude” as a mediating variable, while also accounting for the psychological construct of technology anxiety. The objective is to investigate the key factors and their interrelationships that influence older Chinese people's intention to adopt smart elderly care applications.

2. Literature Review

Given the inherent complexity of predicting human behavior, numerous theories and models have been developed to explain the adoption and use of new technologies. As technology increasingly permeates all aspects of daily life, research on technology acceptance has emerged as a well-established field over the past two decades (Alomary & Woollard, 2015). Several theoretical frameworks have been proposed, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Value-based Adoption Model (VAM), the Theory of Planned Behavior (TPB), and the extended Unified Theory of Acceptance and Use of Technology (UTAUT2), among others. Among these, UTAUT has been selected as the foundational model for this study, as it has demonstrated superior explanatory power and predictive accuracy in comparison to other models (Venkatesh et al., 2003).

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

Venkatesh et al. (2003) combined the elements of eight different theories and models of technology acceptance: TRA, TAM, the motivational model, TPB, combined TAM-TPB, the model of PC utilization, innovation diffusion theory, and social cognitive theory. This allowed them to develop a unification theory. Performance expectancy, effort expectancy, social influence, and facilitating conditions are the four primary factors of usage and intention that were employed in the UTAUT model. The UTAUT has been utilized extensively and have proven to be valid and consistent in understanding usage patterns across various participants, technological, and study contexts(Chen & Chan, 2014).

2.2. Conceptual Framework

In this study, an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT) was adopted as the theoretical framework, as it integrates multiple models and theories related to technology acceptance, offering a comprehensive approach to evaluating and predicting user adoption behaviors. The UTAUT model has demonstrated greater robustness and explanatory power compared to other acceptance models, making it particularly suitable for analyzing consumer-oriented scenarios, such as the adoption of smart eldercare technologies in China. The proposed model comprises six key constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Attitude, and Technology Anxiety (see Figure 1). This study contributes a novel perspective by incorporating “Attitude” and “Technology Anxiety” into the traditional UTAUT framework, thereby addressing the psychological and behavioral characteristics specific to older adults in the context of technology use.

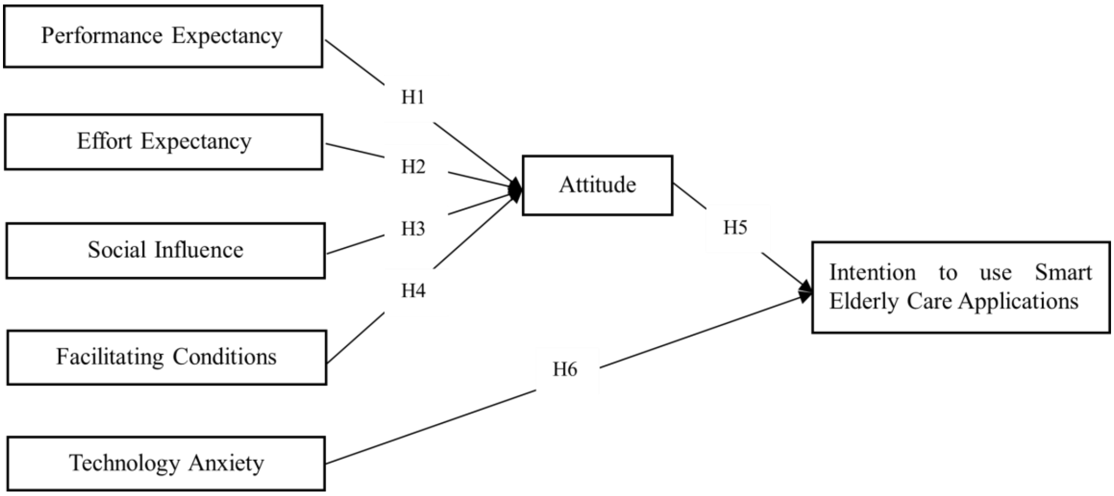

Fig.1: The Research Framework

2.3. Performance Expectancy (PE)

Performance Expectancy (PE) refers to the degree to which an individual believes that using a particular system will enhance their performance (Venkatesh et al., 2003). It is often identified as the strongest predictor of behavioral intention; the more individuals perceive a technology as useful in their daily lives, the more likely they are to develop a favorable attitude toward its adoption (Cai et al., 2021). A substantial body of research has demonstrated a positive relationship between PE and user attitude (Afrizal & Wallang, 2021; Allam et al., 2019; Cai et al., 2021; Kasilingam, 2020; Putri et al., 2021). In the context of this study, smart elderly care technologies are anticipated to offer tangible benefits to older adults, such as improved convenience, safety, and access to services. Accordingly, it is hypothesized that the perceived advantages of smart elderly care will positively influence older adults' attitudes toward these technologies. Thus, this study proposes the following hypothesis:

H1. Performance expectancy (PE) positively affects older people's attitudes towards the usage of smart elderly care applications.

2.4. Effort expectancy (EE)

Effort Expectancy (EE) is defined as the degree of ease associated with the use of a given system (Venkatesh et al., 2003). Prior research has consistently demonstrated a significant relationship between users' perceptions of the effort required to use a technology and their attitudes toward it (Afrizal & Wallang, 2021; Cai et al., 2021, 2021a; Jeng et al., 2022; Yang et al., 2015). This relationship is particularly salient among older adults, who often possess lower levels of technological literacy. For this demographic, ease of use is a critical determinant of their acceptance and evaluation of new technologies (Maswadi et al., 2020). Accordingly, this study posits that when smart elderly care applications are perceived as easy to use, older adults are more likely to form positive attitudes toward their adoption. Therefore, this study proposes the following hypothesis:

H2. Effort expectancy (EE) positively affects older people's attitudes towards the usage of smart elderly care applications.

2.5. Social influence (SI)

Social Influence (SI) refers to the degree to which an individual perceives that important others believe they should use a particular technology (Venkatesh et al., 2003). A considerable body of research has established that SI positively influences attitudes toward adopting new technologies (Cai et al., 2021; Jeng et al., 2022; Venkatesh et al., 2012). Older people often considered a vulnerable group within the context of the digital divide, tend to rely more heavily on external support and guidance when engaging with new technologies (Lang & Schütze, 2002). As such, their attitudes are significantly shaped by the opinions and behaviors of their family members, peers, and broader social networks. In this context, older adults are likely to adopt the perspectives of significant others, and their attitudes toward smart elderly care applications may be positively influenced by social encouragement and normative pressure. Therefore, this study proposes the following hypothesis:

H3. Social influence (SI) positively affects older people's attitudes towards the usage of smart elderly care applications.

2.6. Facilitating conditions (FC)

Facilitating Conditions (FC) refer to the extent to which an individual believes that the necessary organizational and technical infrastructure is available to support the use of a particular system (Venkatesh et al., 2003). Empirical studies have shown that individuals are more likely to adopt new technologies when they possess the requisite knowledge, resources, and external support conducive to effective use (Afrizal & Wallang, 2021; Cai et al., 2021b; Yoo, 2013). As a service model that tightly integrates digital technologies with caregiving functions, smart elderly care depends not only on technological readiness but also on organizational support from multiple stakeholders—including government agencies, communities, service providers, families, and broader societal structures—to ensure effective implementation and accessibility (Ransing Rasika & Rajput Manita, 2015).Therefore, this study proposes the following hypothesis:

H4. Facilitating conditions (FC) positively influence older people's attitudes toward the usage of smart elderly care applications.

2.7. Attitude (ATT)

Attitude (ATT) refers to user's overall perception and evaluation of smart elderly care technologies (Jeng et al., 2022). According to the Reasoned Action Approach, attitude plays a central role in shaping behavioral intentions, encompassing both the expected outcomes of a behavior and the valence assigned to those outcomes, whether they are perceived as positive or negative (Hong, 2015). A growing body of research has demonstrated that individuals' attitudes significantly influence their willingness to adopt Internet of Things (IoT)-based devices and services (Afrizal & Wallang, 2021; Inan et al., 2022; Kasilingam, 2020). In the context of smart elderly care, a positive attitude toward the technology is expected to increase the likelihood of adoption among older adults. Therefore, this study proposes the following hypothesis:

H5. Attitude (ATT) positively influences the intention to use smart elderly care applications.

2.8. Technology anxiety (TA)

Technology Anxiety (TA) refers to an individual's negative psychological state concerning their perceived ability and willingness to use technology (Dekkal et al., 2023). Research has shown that emotional responses, such as fear and anxiety, can significantly influence individuals' attitudes toward technological products, particularly when they are confronted with new or unfamiliar technology (Jeng et al., 2022). Older adults, in particular, experience higher levels of technology anxiety compared to younger generations, as they often face physical and cognitive challenges that hinder their technological competence (Fanbo Meng, 2020; Inan et al., 2022). This increased anxiety may serve as a barrier to the adoption and effective use of smart technologies, including smart elderly care systems. Therefore, this study proposes the following hypothesis:

H6. Technology anxiety (TA) negatively influences the intention to use smart elderly care applications.

3. Methods

The target population of this study is people over the age of 60 in China's first and second-tier cities who have not used smart elderly care applications. Two cities, Shanghai and Nantong, are selected as samples for this study. It is because Shanghai is a first-tier city with the highest degree of aging, and Nantong is a second-tier city with the highest degree of aging even in the country. Sampling involves selecting the appropriate respondents or sample for a study. This investigation employs non-probability sampling, specifically purposive sampling, to select participants based on relevant characteristics. This approach ensures alignment with research objectives and facilitates the collection of meaningful data. This study was conducted through an online survey from October 2024 to November 2024. Based on previously selected quotas, 477 responses were collected from Chinese older adults living in the cities of Shanghai and Nantong.

With the help of community workers and through social media channels, links to the Internet questionnaire were sent to an unlimited number of potential respondents and remained active until the necessary number of samples were collected. Request the community staff to forward the QR code or link of the electronic online questionnaire to the WeChat group of "grid management" of the retiree, and notify every member of the WeChat group. Make sure every retiree knows the questionnaire to the maximum extent. Due to the large number of people in China, the government implements "grid" management. The WeChat group is an important platform for "grid" management, and community staff will send notifications to all community members in the WeChat group. Chinese retirees and their families are required to join the corresponding WeChat groups to manage and publish information, such as pension confirmation, attending medical examinations, and receiving allowances. Therefore, with the help of community personnel, online questionnaires can be distributed to the target population most effectively and extensively.

Survey questions are listed in Table 1. The two Likert scale types are applied in this study to remedy procedural errors (Malhotra et al., 2017). After the questionnaire design, the research started to test the validity of the content, and 3 academic experts and 3 industry experts were invited to conduct the pre-test stage to provide validity. 9 respondents participated in the pre-test stage, and the questionnaire was modified according to the opinions of experts. This study employed IBM SPSS Statistics 27.0 software for data coding, data entry, and descriptive analysis. The model measurement and assessment analysis were done through the computation of the data in SmartPLS 4.1.0.3.

Table 1: Survey questions and measurement items

Constructs	Questionnaire Items	Source	Likert scale type
Performance Expectancy (PE)	**PE1:** I find the smart elderly care applications useful in my daily life.	(Venkatesh Viswanath et al., 2012)	Five-Point Likert Scale
	PE2: Using smart elderly care applications increases my chances of achieving things that are important to me.		
	PE3: Using smart elderly care applications helps me accomplish things more quickly.		
	PE4: Using the smart elderly care applications has increased my efficiency.		
Effort Expectancy (EE)	**EE1:** Learning how to use smart elderly care applications is easy for me.	(Venkatesh Viswanath et al., 2012)	Five-Point Likert Scale
	EE2: My interaction with the smart elderly care applications is clear and understandable (e.g., Button operation, service search, online payment, device connection, etc.).		
	EE3: I find smart elderly care applications easy to use.		
	EE4: It is easy for me to become skillful at using smart elderly care applications.		
Social Influence (SI)	**SI1:** People who are important to me would think that I should use smart elderly care applications.	(Venkatesh Viswanath et al., 2012),(Korkmaz et al., 2021)	Five-Point Likert Scale
	SI2: People who are familiar with me think that I should use smart elderly care applications.		
	SI3: People who influence my behavior think that I should use smart elderly care applications.		
	SI4: People whose opinions I value would like me to use the smart elderly care applications.		
Facilitating Conditions (FC)	**FC1:** I have the resources necessary to use smart elderly care applications (e.g., smartphones, Internet broadband, etc.).	(Venkatesh Viswanath et al., 2012)	Five-Point Likert Scale
	FC2: I have the knowledge necessary to use smart elderly care applications.		
	FC3: Smart elderly care applications are compatible with other technologies I use.		
	FC4: I can get help from others when I have difficulties using smart elderly care applications.		
Attitude (ATT)	**ATT1:** Using smart elderly care applications is a good idea.	(Kassim & Ramayah, 2015)	Seven-Point Likert Scale
	ATT2: I feel that using smart elderly care applications is pleasant.		
	ATT3: In my opinion, it is desirable to use smart elderly care applications.		

	ATT4: In my view, using smart elderly care applications is a wise idea.		
Technology anxiety (TA)	**TA1:** I feel apprehensive about using smart elderly care applications.	(Dekkal et al., 2023)	Seven-Point Likert Scale
	TA2: I have avoided the smart elderly care applications because they are unfamiliar to me.		
	TA3: I hesitate to use smart elderly care applications for fear of making mistakes I cannot correct.		
Intention to use (IU)	**IU1:** I intend to use smart elderly care applications in the future.	(Gansser & Reich, 2021; Hoque & Sorwar, 2017)	Seven-Point Likert Scale
	IU2: I will always try to use smart elderly care applications in my daily life.		
	IU3: I plan to use smart elderly care applications frequently.		
	IU4: I will recommend others to use smart elderly care applications.		

4. Analysis and Results

4.1. Demographic Profile

The initial screening contains blank responses screening, straight lining, checking missing values. SPSS version 27 was used in this study to determine the variance of the straight line questions. Four hundred and seventy-seven cases were evaluated, of which 102 were excluded from further analysis. 375 cases remained valid after being deleted by Straight Lining.

This study aimed to eliminate CMV by examining its impact on questionnaire design and model construction, using the PLS marker variable method to detect and control for common method variance. As a result, the addition of marker variables does not significantly alter either the Beta (β) value (differences between 0.000 and 0.071) or the R^2 changes (the difference between 0.000 and 0.026). As a result, it can be said that this study's CMV is not a significant problem.

This study collected a total of 375 available responses, and the respondent demographics are presented in Table 4.7, where the various categories of respondent demographics and their percentages can be viewed, along with the descriptive analysis of the instruments generated by SPSS version 27, including the gender, age, race, marital status, city, highest academic, occupation, income, working experience are the factors that will be examined.

Table 2: Profile of Demographic

Demographic Data	Items	Frequency	Percent (%)
Gender	Male	167	44.5
	Female	208	55.5
Age	60-65 years old	89	23.7
	66-70 years old	129	34.4
	71-80 years old	120	32.0
	81 years old and above	37	9.9
Education Qualification	Secondary school and below	245	65.3
	College	83	22.1
	Undergraduate	46	12.3
	Master’s degree	1	0.3
	PhD	0	0

Respondent's Income	Less than ¥1000	4	1.1
	¥1001 to ¥2000	9	2.4
	¥2001 to ¥3000	74	19.7
	¥3001 to ¥4000	122	32.5
	¥4001 to ¥5000	73	19.5
	Above ¥5001	93	24.8
Physical Condition	Never felt uncomfortable	71	18.9
	Occasional discomfort	277	73.9
	Frequent discomfort	27	7.2
How many children will support you in your old age	0	10	2.7
	1	298	79.5
	2	56	14.9
	3	9	2.4
	4	1	0.3
	Above 4	1	0.3

Note: n=375 (after deleted by Straight Lining)

4.2. Assessment of the measurement model

This research's measurement model was assessed in four steps: indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The assessment is followed by the guidelines of (Hair et al., 2017).

First, Indicator reliability explains the commonality of an item or indicator. If an indicator's outer loading value is more than 0.7, it is considered reliable since the structure explains at least 50% of the variance in the indicator (Hair et al., 2017). As shown in Table 4.8, the outer loadings of all measurement items range from 0.814 to 0.942, indicating good indicator reliability.

Next, Cronbach's α scores and composite reliability (CR) were used in the study to evaluate the constructs' internal consistency validity. The CR suggests that the acceptable value for reliability is above 0.7(Hair et al., 2021). This study's Cronbach's α scores range from 0.852 to 0.957, meeting the minimum threshold value of 0.7 (shown in Table 3).

The convergent validity was then examined using the average variance extracted (AVE). When a construct's AVE value is greater than 0.50, it is considered to have sufficient convergent validity because it can account for at least 50% of the variation of its items(Hair et al., 2017). Table 4.8 demonstrates all AVEs above 0.50, with a range of 0.753-0.886, showing that the convergent validity of all constructs is within an acceptable range.

Furthermore, discriminant validity assessment is the final stage of measurement model evaluation. This research used the Fornell-Larcker's criterion, Cross Loading, and Heterotrait-Monotrait (HTMT) criterion to determine discriminant validity. As the cross-loading table in Table 4.10 shows, in this study, all the constructs themselves are well loaded into their own constructs, and their loading values are greater than the loading values of the measured items with other constructs, so there is no cross-loading between the constructs in this study model, which also provides support for the discriminant validity of the model. The results of the Fornell and Lareker Criterion are shown in Table 4. According to the criteria established by Dijkstra & Henseler (2015) , the model has discriminant validity if the HTMT is smaller than 0.9. The HTMT values for all constructs were below 0.9, indicating that the model had discriminant validity

Table 3: Outcomes of Measurement Model

Constructs	Items	Indicator Reliability	Convergent Validity	Internal Consistency Reliability	
		Outer loadings	Average Variance Extracted (AVE)	Composite Reliability (CR)	Cronbach's Alpha
Attitude	ATT1	0.946	0.886	0.969	0.957
	ATT2	0.956			
	ATT3	0.921			
	ATT4	0.942			
Effort Expectancy	EE1	0.814	0.765	0.929	0.898
	EE2	0.902			
	EE3	0.913			
	EE4	0.866			
Facilitating Conditions	FC1	0.838	0.753	0.924	0.89
	FC2	0.888			
	FC3	0.861			
	FC4	0.882			
Intention to Use	IU1	0.89	0.846	0.956	0.939
	IU2	0.934			
	IU3	0.935			
	IU4	0.919			
Performance Expectancy	PE1	0.843	0.812	0.945	0.922
	PE2	0.938			
	PE3	0.931			
	PE4	0.891			
Social Influence	SI1	0.921	0.843	0.955	0.938
	SI2	0.931			
	SI3	0.9			
	SI4	0.919			
Technology Anxiety	TA1	0.819	0.766	0.907	0.852
	TA2	0.881			
	TA3	0.923			

Table 4: Fornell and Larcker

	ATT	EE	FC	IU	PE	SI	TA

ATT	**0.941**						
EE	0.539	**0.875**					
FC	0.648	0.763	**0.867**				
IU	0.782	0.515	0.59	**0.92**			
PE	0.61	0.622	0.644	0.501	**0.901**		
SI	0.671	0.675	0.793	0.594	0.673	**0.918**	
TA	-0.183	-0.196	-0.14	-0.151	-0.178	-0.155	**0.875**

Table 5: Discriminant Validity (HTMT)

	ATT	**EE**	**FC**	**IU**	**PE**	**SI**	**TA**
ATT							
EE	0.574						
FC	0.697	0.849					
IU	0.822	0.551	0.644				
PE	0.646	0.676	0.704	0.535			
SI	0.706	0.729	0.864	0.631	0.721		
TA	0.197	0.213	0.155	0.16	0.196	0.167	

4.3. Assessment of the structural model

After the measurement model has been assessed, the structural model should be evaluated using the following procedures: collinearity assessment, path coefficient, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), PLS prediction, and hypothesis testing.

The VIF value should not exceed 5 (Hair et al., 2017). As shown in Table 7, the VIF of all constructs in the internal model of this study is less than 5, and their VIF values range from 1.034 to 3.666. The results indicate that the degree of covariance in this model is within the acceptable range.

As a rule, R^2 values below 0.25 indicate very weak, whereas 0.75, 0.50, and 0.25 indicate substantial, moderate, and weak values, respectively (Hair et al., 2019). ATT, IU were the endogenous variables, and their respective R^2 values were 0.516 and 0.611. Suggested standards for estimating effect size are $f^2 \geqslant 0.02$, $f^2 \geqslant 0.15$, and $f^2 \geqslant 0.35$, which equate to small, medium, and large effect sizes of exogenous constructs, respectively (Cohen, 1992). The effect size f^2 was from 0 to 1.512.

Predictive Relevance (Q^2) is evaluated as the structural model's fourth assessment. The fact that the Q^2 values for this research's structural model were greater than zero means that the model's explanatory and predictive power was significant (Manley et al., 2021). The endogenous constructs of ATT and IU were 0.784 and 0.719, respectively.

Lastly, the PLS predicted assessed the predictive power of IU. Based on Table 6, each indicator's RMSE values are lower than the naive linear regression model (LM) benchmark. According to (Shmueli et al., 2019), the model has high predictive power.

To examine the significance level of the paths, the bootstrapping function of Smart PLS 4.0 was employed to obtain t-statistics for each path. The bootstrap procedure was configured with a significance level of 0.05, a one-tailed test, and 10000 bootstrap subsamples (Hair et al., 2017). The research results determined that the predictors could explain 51.6% of the variance in ATT and 61.1% of the variance in IU.

H1, H2, H3, and H4 are the hypotheses about the potential critical factors that affect attitude. The result shows that H1 (β = 0.246, t = 4.08, p (0) < 0.01), H3 (β = 0.225, t = 3.958, p (0) < 0.01), H4 (β = 0.076, t = 3.088, p (0.001) = 0.01) were supported, meanwhile, H2 (β = -0.024, t = 0.327, p (0.327) > 0.01) was not supported. H5 and H6 are the hypotheses about the factors influencing intention to use. The research shows that H5 is supported because of the results (β = 0.78, t = 26.741, p (0.000) < 0.01). Meanwhile, H6 (β = -0.009, t = 0.218, p (0.414) > 0.01) was not supported.

Table 6: PLS predict

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
ATT1	0.469	1.051	0.804	1.074	0.819
ATT2	0.498	1.025	0.799	1.054	0.817
ATT3	0.366	1.088	0.845	1.138	0.889
ATT4	0.433	1.067	0.836	1.108	0.863
IU1	0.347	1.143	0.928	1.186	0.947
IU2	0.31	1.219	0.97	1.256	0.985
IU3	0.286	1.255	0.99	1.294	1.016
IU4	0.327	1.266	1.024	1.302	1.029

Table 7: Hypothesis Testing

Hypothesis	Relationship	Std. Beta	Standard deviation (Std. Error)	T statistics	P values	f^2	Q^2	VIF	R^2	Supported
H1	PE -> ATT	0.246	0.06	4.08	0	0.061		2.043		Yes
H2	EE -> ATT	-0.024	0.074	0.327	0.372	0		2.597		No
H3	SI -> ATT	0.225	0.081	3.958	0	0.068		3.093		Yes
H4	FC -> ATT	0.076	0.082	3.088	0.001	0.036		3.666		Yes
H5	ATT -> IU	0.78	0.029	26.741	0	1.512	0.784	1.034	0.516	Yes
H6	TA -> IU	-0.009	0.04	0.218	0.414	0	0.719	1.034	0.611	No

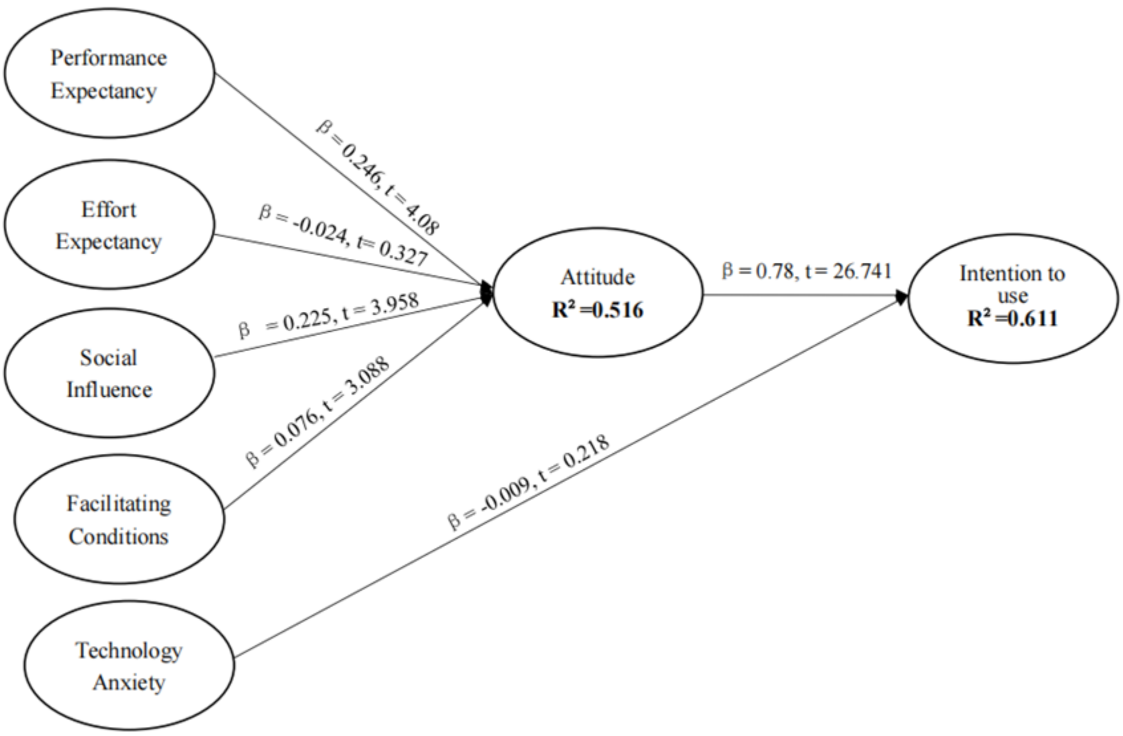

Fig.2: Hypothesis Testing Results

5. Discussion and Implications

5.1. Discussion

The findings of this study indicate that Performance Expectancy (PE) has a significant positive influence on attitude, supporting Hypothesis 1. This result aligns with the majority of previous research (Ben Arfi et al., 2021; Gansser & Reich, 2021; Korkmaz et al., 2021; Medeiros et al., 2022; Zaid Kilani et al., 2023). For instance, during the pandemic, consumers were more likely to embrace drone delivery services, recognizing the convenience of contactless transactions (Arar et al., 2021). Similarly, consumers tend to exhibit positive attitudes toward logistics technologies when the perceived benefits outweigh the effort required to use them (Cai et al., 2021). In the context of smart elderly care, the findings suggest that older people in China have high expectations for these technologies, particularly regarding their potential to enhance elderly care services and improve the quality of life and health outcomes. Thus, the greater the perceived performance expectancy of smart elderly care applications, the more favorable the attitudes toward their adoption.

The results also show that Effort Expectancy (EE) does not have a significant impact on attitude, leading to the rejection of Hypothesis 2. This finding is consistent with studies such as those by Alam et al. (2020), which found that Effort Expectancy did not affect the intentions of Bangladeshi university students to adopt mobile health technologies, and Chang et al. (2021), who reported similar results for Chinese hospital patients. A possible explanation for this finding is the high level of technological familiarity among older adults in urban China, who have become proficient in using mainstream digital platforms such as WeChat, despite these platforms not being designed with older users in mind (Zhu et al., 2023). Consequently, older users may expect smart elderly care applications to be straightforward, intuitive, and easy to use without requiring significant learning or adaptation. This familiarity with digital technology may diminish the perceived importance of effort expectancy in shaping their attitudes toward new technologies.

In contrast, the study found that Social Influence (SI) positively influences attitudes toward the use of smart elderly care applications, supporting Hypothesis 3. This result is consistent with a substantial body of research (Cai et al., 2021; Jeng et al., 2022; Venkatesh et al., 2012). Previous studies have shown that social influence from family, friends, and colleagues significantly shapes individuals' attitudes toward technology adoption (Zhu et al., 2023). For older adults, who typically have strong family ties and established social networks, feedback and support from these social connections are crucial in shaping their attitudes. As a result, if older individuals receive positive social support regarding smart elderly care technologies, they are more likely to develop a favorable attitude toward their adoption.

Facilitating Conditions (FC) were also found to positively influence attitudes toward the usage of smart elderly care applications, supporting Hypothesis 4. According to theoretical perspectives, individuals with access to the necessary resources and support are more likely to adopt a technology (Cai et al., 2021). This study suggests that when older people have access to appropriate environmental, technological, and knowledge-based resources, the barriers to using smart elderly care applications are reduced, fostering a greater willingness to engage with the technology.

Furthermore, the study confirmed that attitude (ATT) positively influences usage intention (IU), supporting Hypothesis 5. Numerous studies have highlighted the strong link between attitude and behavioral intention (Afrizal & Wallang, 2021; Perumal et al., 2022). The findings of this study reveal that attitude ($\beta = 0.78$, $t = 26.741$, $p < 0.01$) is the most significant predictor of usage intention, surpassing factors such as perceived trust and life satisfaction. Older individuals, due to their unique physical and psychological conditions, tend to be more resistant to change. Their attitudes toward new technology significantly influence their willingness to adopt it—positive attitudes correspond to higher adoption intentions, while negative attitudes inhibit adoption.

Lastly, the study did not support a negative relationship between Technology Anxiety (TA) and usage intention, leading to the rejection of Hypothesis 6. This finding contrasts with research conducted in Bangladesh, which found that technology anxiety negatively impacted middle-aged users' intentions to use m-health services (Moudud-Ul-Huq et al., 2021). One potential explanation for this discrepancy is that, in China, many older adults face significant challenges in accessing traditional elderly care services due to physical limitations and the shortcomings of offline care models. As a result, smart elderly care technologies offer a promising alternative, providing convenient, efficient, and user-friendly services. This strong motivation to overcome the barriers associated with traditional care options may help offset technology-related anxiety. Additionally, most older people in China live with their children, who provide substantial assistance in using smart applications. Furthermore, many older adults have already gained experience using digital technologies such as WeChat, TikTok, and online shopping platforms like AliExpress. As a result, technology anxiety is no longer a primary barrier to the adoption of smart elderly care applications.

5.2. Theoretical Contributions

This paper makes several valuable contributions to the literature on technology adoption among elderly users. It extends the UTAUT model by incorporating attitude and technology anxiety specifically for elderly users in China, providing insights into how these factors influence technology adoption in this demographic. It addresses a significant research gap by focusing on smart elderly care applications in China, which has the world's largest elderly population and faces enormous challenges in elderly care provision. The study provides empirical evidence that attitude is a critical determinant of intention to use (with a strong $\beta = 0.78$), while technology anxiety does not significantly impact adoption intentions among the Chinese elderly. It offers practical implications for application developers, policymakers, and service providers seeking to increase adoption rates of smart elderly care applications. Additionally, the research model demonstrates strong explanatory power ($R^2 = 0.611$ for intention to use), validating the approach for future studies in this context.

5.3. Practical Implications

The findings of this study shed light on the key factors influencing the intention to use smart elderly care applications, offering valuable theoretical insights and practical guidance for businesses, governments, institutions, and target audiences involved in the development and promotion of these technologies. These insights are crucial for driving the adoption of such applications, ultimately contributing to their widespread acceptance and use.

To increase the adoption rate of smart elderly care applications, the design of these technologies should prioritize user practicality. The results underscore the importance of performance expectancy, facilitating conditions (FC), and social influence (SI) in shaping users' attitudes. As such, the usefulness and ease of use of these applications are critical for fostering positive perceptions and enhancing user acceptance.

Moreover, the design of smart elderly care applications should emphasize compatibility with widely used smart devices. In first- and second-tier cities in China, smartphones have become ubiquitous among older people. To improve convenience, these applications should ensure high compatibility with smartphones and integrate seamlessly with frequently used apps, such as those for social media, online shopping, and payment services. Leveraging the traffic from these popular apps can significantly boost the download and usage rates of smart elderly care applications.

Additionally, it is essential for smart elderly care applications to align closely with the specific needs of older adults. By focusing on core functionalities such as daily care, service bookings, health monitoring, social interactions, and family communication, these applications can better cater to the comprehensive needs of older users. Meeting the expectations of older adults for integrated, user-friendly services will likely improve both the acceptance and usage rates of these applications.

The government also plays a pivotal role in encouraging the growth of the smart elderly care sector.

This includes fostering nationwide demonstrations of smart health and elderly care applications, promoting smart home and health products, and exploring the implementation of safety risk warning systems for home-based elderly care. To address the evolving demand for elderly care services, the government should also invest in enhancing a unified national aged care service information platform, thereby improving the coordination and efficiency of elderly care services across the country.

6. Conclusion, Limitations and Future Studies

This study advances our understanding of technology adoption among elderly users by extending the UTAUT model to investigate factors influencing the intention to use smart elderly care applications in China. Our findings reveal that attitude is the most powerful predictor of usage intention (β =0.78), serving as a critical mediating variable between UTAUT factors and behavioral intentions. Performance expectancy, social influence, and facilitating conditions significantly influence attitude formation, while effort expectancy does not play a significant role. Contrary to expectations, technology anxiety has no significant impact on usage intention, suggesting that Chinese elderly users' concerns about technology may be mitigated by other factors such as perceived benefits and social support.

These findings have important theoretical implications. First, they validate the value of incorporating attitude as a mediating variable in the UTAUT model when studying elderly users, enhancing the model's explanatory power. Second, they challenge assumptions about technology anxiety as a barrier to adoption among older adults, at least in the Chinese context. Third, they highlight the importance of considering cultural and contextual factors when applying technology acceptance models across different populations and settings.

For practitioners, our results suggest several strategies to enhance the adoption of smart elderly care applications. Developers should emphasize practical benefits, leverage social influence through family and community networks, and ensure adequate technical and knowledge support for users. Government agencies should continue supporting the smart elderly care industry through policy initiatives, infrastructure development, and public education.

Despite its contributions, this study has several limitations that provide valuable directions for future research. As a cross-sectional study focusing on usage intention rather than actual behavior, it offers only a snapshot of the adoption process. Consequently, the findings may not fully capture the dynamic nature of technology adoption. Moreover, the sample is limited to first- and second-tier cities in China, potentially overlooking important rural-urban disparities in the adoption of smart elderly care applications. This geographical limitation calls for further research that includes a more diverse range of settings, particularly in smaller cities and rural areas, where unique challenges and opportunities may exist.

Additionally, the data collection method used in this study was based on an online survey, which, while appropriate for capturing the usage context of smart elderly care applications, may exclude older individuals who are less familiar with the internet or smartphones. This exclusion could result in missing data for a segment of the population who may face challenges in accessing or using digital technologies. Future studies could incorporate face-to-face interviews or alternative data collection methods to ensure more comprehensive representation, particularly among less technologically savvy older adults.

Another limitation of this study is the absence of control variables such as gender, age, and health status. These demographic factors can significantly influence individuals' adoption behaviors and perceptions. Future research should incorporate these variables to examine how different characteristics might affect the intention to use smart elderly care applications. It is also important to analyze various subgroups separately to uncover more nuanced insights, as older people's needs and behaviors may differ according to these factors.

Finally, future studies could explore actual usage behaviors through longitudinal designs that track sustained usage over time. Such research would provide deeper insights into how users engage with smart elderly care applications in the long term, beyond initial intentions. In light of the evolving landscape of economic and social development in China, particularly in smaller cities and rural areas, extending research to these regions would offer a more comprehensive understanding of smart elderly care adoption across diverse segments of society. Additionally, examining the moderating roles of demographic factors such as age, gender, and health status in the intention to use smart elderly care applications would further enrich our understanding of the adoption process in different contexts.

Acknowledgements

I am sincerely grateful to Dr Normalini Binti Md Kassim for her guidance and support. Your guidance and encouragement are a beacon on my way to scientific research. It's my honor to work with you.

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