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Article

The impact of smart elderly care service acceptance on elderly service usage behavior in Xi'an: An analysis of mediating effects based on the UTAUT model and the moderating role of digital literacy

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Abstract: As the aging trend intensifies, the Chinese government prioritizes technological innovation in smart elderly care services to enhance quality and efficiency, catering to the diverse needs of the elderly. This study examines the acceptance and usage behavior of smart elderly care services among elderly individuals in Xi'an, using a modified Unified Theory of Acceptance and Use of Technology (UTAUT) model that includes digital literacy as a moderating variable. Data were collected via a survey of 299 elderly individuals aged 60 and above in Xi'an. The study aims to identify factors influencing the acceptance and usage behavior of smart elderly care services and to understand how digital literacy moderates the relationship between these factors and usage behavior. Regression analysis assessed the direct effects of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) on usage behavior. These dimensions were then integrated into a comprehensive index Service Acceptance to evaluate their overall impact on usage behavior, with behavioral intention examined as a potential mediating variable. Results indicate that EE and SI significantly impact the adoption of smart elderly care services, whereas PE and FC do not. Behavioral intention mediates the relationship between these variables and usage behavior. Additionally, gender, age, and digital literacy significantly moderate the impact of service acceptance on usage behavior. This study provides valuable theoretical and practical insights for designing and promoting smart elderly care services, emphasizing the importance of usability and social promotion to enhance the quality of life for the elderly.

Keywords: smart elderly care services; UTAUT model; digital literacy; elderly population; acceptance factors; usage behavior

1. Introduction

With the rapid growth of China's elderly population, higher demands are being placed on the provision of elderly care services in China. The swift progression of technologies such as big data, the Internet of Things (IoT), and artificial intelligence, coupled with their profound amalgamation with traditional elderly care practices, has catalyzed the emergence of innovative paradigms and business models. This includes smart elderly care services. These advancements are steering the evolution of elderly care towards a more intelligent, information-rich, and digital-oriented future (Lian and Zhang, 2018). In response, the Chinese government has issued a series of policies dedicated to optimizing service supply and developing smart elderly care systems to meet the diverse and multi-level service needs of the elderly, for reasons both of citizen satisfaction and equity issues.

Smart elderly care services leverage modern information technologies such as the internet, social networks, and cloud computing to provide personalized and convenient life support for senior citizens, ensuring their ability to enjoy a high-quality and dignified life in later years (Zuo, 2014). Peng and Sui (2016) further underscore the immense potential of the 'Internet + home-based elderly care' model in addressing issues like supply-demand mismatching and limited-service content commonly encountered in traditional home-based elderly care services.

However, the development of smart elderly care services also encounters a series of challenges. These include limited product availability, small-scale operations, low adoption rates, and a lack of enthusiasm for research and development. Consequently, the eldercare technology industry remains in a nascent stage of development (Meng, 2020). Elderly care technology remains an ambiguous concept for the majority of older individuals, primarily due to their limited knowledge and minimal utilization of technological products. However, the pivotal role of technology in enhancing the lives of elderly people has been inadequately acknowledged (Li et al., 2017). Comprehending the acceptance and usage patterns of smart elderly care services within this population has emerged as a crucial research inquiry.

This study focuses on investigating the usage behavior and influencing factors of elderly individuals towards smart elderly care services in Xi'an, a central city in northwest China. Recent statistics reveal that Xi'an has a population of 2,075,318 people aged 60 and above, accounting for 16.02% of the total population, while those aged 65 and above amount to 1,411,727 people or 10.9%. These figures not only indicate a significant aging trend but also reflect an increasing demand for complex elderly care services in Xi'an. Selecting Xi'an as a research case holds substantial academic and practical implications by providing empirical support and theoretical foundations to promote the development of smart elderly care services in this city. It can also serve as a reference for other cities facing challenges posed by aging populations. Moreover, analyzing acceptance levels and usage behaviors among specific groups towards smart elderly care services in this area will provide representative insights into related issues and facilitate the formulation of precise policies for rational allocation of eldercare resources in similar cities. Simultaneously, through an extensive analysis of user behaviors, existing service provision shortcomings can be identified while driving improvement opportunities alongside technological innovations that better meet the actual needs of the elderly.

Specifically, our study focuses on examining the influence of smart elderly care services acceptance on usage behavior among older adults using the UTAUT model, while considering digital literacy as a potential moderating variable. This extension enhances the applicability and explanatory power of the UTAUT model, aiming to gain a comprehensive understanding of older adults' acceptance and utilization processes regarding smart elderly care services.

2. Materials and methods

2.1. Smart elderly care services

Smart elderly care was initially proposed by British Life Trust under the name "completely smart senior care system" (Lou, 2023). It empowers older adults to lead a high-quality and fulfilling life in their own residences without being constrained by time or geography for their daily activities (Zhou, 2019). Smart elderly care service is built upon advanced technologies including medical care, IoT, cloud computing, big data, and mobile internet. Collecting, reorganizing, and analyzing dynamic data relevant to the needs of older adults provides intelligent, specialized, personalized, and diversified elderly care services encompassing aspects like daily living assistance, nursing support, recreational entertainment, and spiritual solace (Wang, 2018).

The smart elderly care system is structured around three primary components: smart nursing products, online service platforms, and offline service networks (Sun and Yu, 2017). At its core, this system leverages advanced technologies to provide comprehensive care for the elderly, encompassing daily life activities, medical health, rehabilitation, and the automatic monitoring and intelligent processing of elder-related information. By employing modern scientific technologies and intelligent devices, this service model significantly enhances the quality and efficiency of care services while simultaneously reducing labor and time costs. It aims to maximize the fulfillment of elderly care needs with minimal resource expenditure (Zuo, 2014).

2.2. Research model

Research on technology acceptance occupies a pivotal role in the fields of information systems and social psychology. The Technology Acceptance Model (TAM), introduced by Davis (1989), stands as a landmark in this area. Grounded in the Theory of Reasoned Action (TRA), TAM posits that perceived ease of use and perceived usefulness are the two crucial factors influencing user acceptance of technology. Over time, TAM has undergone numerous extensions and refinements. Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), as shown in **Figure 1**, which integrates four core constructs from eight previously established theoretical models: performance expectancy, effort expectancy, social influence, and facilitating conditions. According to the model, these constructs jointly influence an individual's intention to use technology and their actual usage behavior.

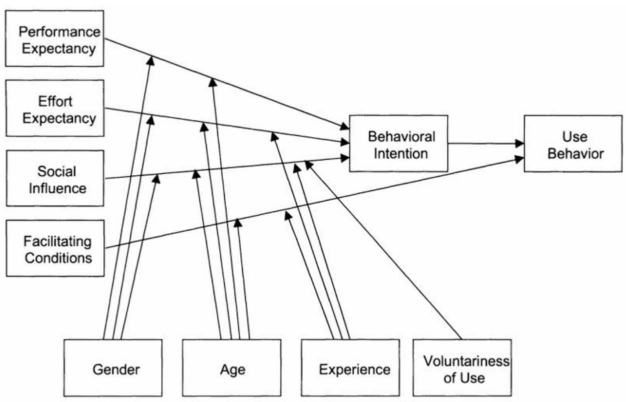

Figure 1. UTAUT model.

Performance expectancy refers to the degree to which an individual believes that using a specific technology will enhance their job performance. Effort expectancy pertains to the ease of use associated with the technology. Social influence involves the perceived pressure from significant others to use the technology, including colleagues, management, or societal norms. Facilitating conditions are the perceived organizational and technical support available, such as resource availability, technological compatibility, and user skills. The UTAUT model also includes gender, age, experience, and voluntariness as moderating variables, which can influence the relationships between core constructs and both behavioral intention and usage behavior (Venkatesh et al., 2003). UTAUT is considered to have greater explanatory power than TAM, explaining a substantial variance in user behavioral intention in nearly half of technology acceptance studies (Karsh and Holden, 2010).

Since its introduction, the UTAUT model has been extensively applied in empirical studies across various technological, cultural, and organizational contexts, demonstrating significant explanatory power in the field of smart elderly care services. Li and Mao (2015) conducted an empirical study on the "One-Click" smart senior care service in Wuhan using a modified UTAUT model. They found that social influence, facilitating conditions, effort expectancy, performance expectancy, perceived trust, and perceived security are key factors influencing the elderly's use of smart elderly care services, with facilitating conditions being the critical factor for the adoption of the "One-Click" service. Li et al. (2017) constructed an acceptance model for elderly care technology based on the UTAUT model. Through a survey of elderly residents in Beijing, Nanjing, and Xianyang, they analyzed the impact of individual characteristics, product factors, and children-related factors on the elderly's use of care technologies. Their findings indicate that product functionality and support from children significantly influence the elderly's acceptance of care technologies. Feng and Yang (2020) further indicated that effort expectancy, performance expectancy, and social influence have a significant positive impact on the elderly's willingness to use smart elderly care products, with effort expectancy having the greatest impact. Kang et al. (2022) integrated the UTAUT and Task-Technology Fit (TTF) models to analyze the acceptance behavior of users of smart home health services (SHHS) in South Korea. Their study revealed that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence SHHS acceptance, with performance expectancy and facilitating conditions having the most substantial impact on behavioral intention. Therefore, the following hypotheses are proposed:

H1: Performance expectancy (PE) positively influences the elderly's use behavior (UB) of smart senior care services.

H2: Effort expectancy (EE) positively influences the elderly's use behavior (UB) of smart senior care services.

H3: Social influence (SI) positively influences the elderly's use behavior (UB) of smart senior care services.

H4: Facilitating conditions (FC) positively influence the elderly's use behavior (UB) of smart senior care services.

Considering that the aforementioned four factors are core components of technology acceptance, the combined effect of these factors is further hypothesized as follows:

H5: The services acceptance (SA, a composite index of PE, EE, SI, and FC) positively influences the elderly's use behavior of such services.

Additionally, this study considers the mediating role of behavioral intention (BI) between the acceptance of smart elderly care services and actual usage behavior (Venkatesh, 2003; Venkatesh and Bala, 2008)

H6: BI mediates the relationship between SA and UB of smart senior care services.

The UTAUT model also posits that age and gender moderate the relationships between technology acceptance, usage intention, and behavior. Venkatesh et al. (2003) highlighted significant age differences in the technology acceptance process. Multiple studies confirm that older users exhibit more concerns when adopting new technologies compared to younger users (Igbaria et al., 1989; Laguna et al., 1997). Lian (2015) found that in the context of Taiwanese residents' adoption of e-government services, performance expectancy and social influence significantly impacted behavioral intention, with gender moderating the relationship between social influence and behavioral intention. Therefore, the following hypotheses are proposed:

H7: Age moderates the impact of SA on UB.

H8: Gender moderates the impact of SA on UB.

2.3. The role of digital literacy

Digital literacy is a multifaceted concept that encompasses "… the ability effectively to use information in a digital environment", according to Gilster (1997), who emphasized that digital literacy extends beyond technical skills to include understanding and evaluating information. Eshet-Alkalai (2004) further expanded this concept, proposing a comprehensive framework that includes multiple literacies such as photo-visual literacy, reproduction literacy, branching literacy, information literacy, and socio-emotional literacy. Buckingham (2003) linked digital literacy with media literacy, exploring learning and culture in digital media environments and emphasizing critical thinking and creative expression. In the healthcare domain, Norman and Skinner (2006) introduced the concept of eHealth literacy, which they define as "… the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem".

Digital literacy is essential for the elderly to effectively utilize smart elderly care services. Existing research has indicated that higher levels of digital literacy are associated with greater willingness and ability to use digital health technologies (Hargittai and Hunsaker, 2018). Enhancing the elderly's cyber security awareness and digital skills can help them adapt better to digital lifestyle and enjoy the conveniences of information technology (Xie and Yue, 2019). Therefore, the following hypothesis is proposed:

H9: Digital literacy moderates the impact of smart elderly care SA on the UB of these services among the elderly.

2.4. Measurement of digital literacy

Numerous methods have been proposed to measure digital literacy, with researchers offering various evaluation frameworks and tools. Ng (2012) explored how to cultivate and assess digital literacy in education, proposing a framework that includes technical operation, information evaluation, creativity, and critical thinking. Deursen and Dijk (2010) focused on measuring internet skills, proposing specific indicators for evaluating these skills, which are a crucial part of digital literacy. Ala-Mutka (2011) systematically reviewed various aspects of digital literacy and proposed a comprehensive conceptual model that acknowledges the convergence of information, digital, and media literacies as a result of evolving technologies. This model emphasizes that digital literacy is a multi-layered, multi-dimensional concept. It encompasses not only technical skills but also the ability to evaluate, process, and create information, as well as to communicate and collaborate effectively in a globalized and networked environment. Ferrari (2013) in his DigComp (Digital Competence) framework, detailed five areas of digital literacy: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving. In addition, he nominated relevant measurement standards, thereby providing a comprehensive tool for understanding and assessing digital literacy. Vuorikari et al. (2016) further expanded on the existing framework, updating and refining the dimensions without altering its fundamental five-competence structure.

In this study, the European Union’s DigComp2.1 framework offers a comprehensive and detailed tool for assessing digital literacy. Developed from Ferrari (2013) work, the DigComp2.1 framework further refines the five areas of digital literacy: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving (Carretero et al., 2017). These areas cover the search for, evaluation and management of digital resources; interaction and collaboration through digital technologies; creation and editing of digital content; management and protection of personal data and privacy; and the ability to identify and solve technical problems.

Using the DigComp2.1 framework to measure participants’ digital literacy is highly appropriate. First, it provides a systematic and comprehensive tool for measuring digital literacy, effectively assessing the various digital capabilities needed by the elderly when using smart elderly care services. Second, the standardization and wide recognition of the DigComp2.1 framework enhance the credibility and comparability of the research results.

2.5. Summary

Despite the extensive research conducted on the acceptance and usage behavior of smart elderly care services, there are still several research gaps that need to be addressed. Firstly, most studies have primarily focused on examining the impact of individual variables, lacking a comprehensive analysis of multiple factors. Secondly, limited attention has been given to investigating digital literacy as a moderating variable, and a systematic theoretical framework is yet to be established in this regard. Therefore, this study aims to bridge these research gaps by employing the UTAUT model along with digital literacy as a moderating variable for conducting a systematic analysis of the SA and UB of smart elderly care services. This endeavor can offer valuable insights into effective strategies for promoting the adoption of such services among older adults, facilitating their widespread development, and ultimately enhancing their quality of life. The findings hold significant theoretical and practical implications.

3. Research method

3.1. Research design

The original UTAUT model was refined in this study to align with the research objectives and the specific context of the research object. As depicted in **Figure 2**, the fundamental independent variables of the UTAUT model, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), were retained. These variables were then integrated into a comprehensive construct termed service acceptance (SA) to assess their collective impact on smart elderly care services' usage behavior. Moreover, acknowledging the potential mediating role of behavioral intention, digital literacy, gender, and age were introduced as moderating factors to assess their influences on the relationships within the conceptual framework.

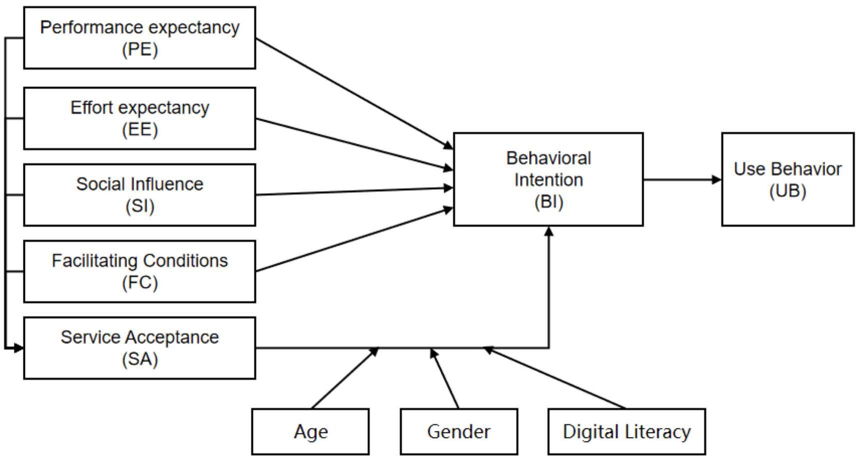

Figure 2. Research model of the present research.

In this study, Performance Expectancy (PE) refers to the anticipated benefits that older adults expect from smart elderly care services; Effort Expectancy (EE) measures the perceived ease of use of these services; Social Influence (SI) pertains to the impact of the social environment and the influence of others on the adoption of smart elderly care services; Facilitating Conditions (FC) encompass the support and resources deemed necessary for utilizing these services. Service Acceptance (SA) is a comprehensive indicator integrating PE, EE, SI, and FC, representing the extent to which older adults embrace smart elderly care services. Behavioral Intention (BI) signifies the subjective inclination towards using smart elderly care services, while Usage Behavior (UB) reflects the actual extent of their utilization by older adults.

From the original UTAUT model, the moderating variable "voluntariness" was removed, and "digital literacy" was introduced as a new moderating variable. Extensive literature indicates that the adoption of such services by elderly users is likely influenced more by health needs, ease of use of technology, and social support, rather than voluntary use alone (Li and Mao, 2015; Li, 2017). Additionally, the use of smart elderly care services is often viewed as a practical necessity rather than purely voluntary behavior.

The rationale for incorporating "digital literacy" as a moderating variable lies in its reflection of the elderly's understanding and ability to use modern information technology, which significantly impacts the acceptance and utilization of smart elderly care services (Lee, 2007; Xie and Xu, 2019). With ongoing technological advancements, it is essential for elderly individuals to possess basic digital literacy to leverage these services effectively. Consequently, digital literacy partly determines the successful adoption and use of smart elderly care services by older adults. Including this variable in the model enables a more precise assessment of its impact on elderly service usage behavior.

3.2. Measurement

The data collection method employed was a self-administered survey questionnaire. Designed to align with the research objectives and model, it integrated the UTAUT model and theories on digital literacy. Question formulation drew upon original scales from relevant theories and literature. Prior to its finalization, the questionnaire underwent a pilot test involving 30 participants from diverse backgrounds. This preliminary phase aimed to gauge question clarity, questionnaire usability, and the overall smoothness of data collection. Based on pilot feedback, necessary revisions were made, including rephrasing ambiguously worded questions and optimizing the questionnaire structure to enhance readability and efficiency. Moreover, the pilot test served to identify and mitigate potential issues affecting data quality, ensuring the efficacy of the final questionnaire and the seamless execution of the survey. The finalized questionnaire comprised three sections: demographic information, digital literacy, and inquiries pertaining to acceptance and usage behavior of smart elderly care services.

3.2.1. Demographic information

The demographic section included measurements for the moderating variables of gender and age. In this study, answers of the questionnaire were scored to allow for more precise statistical analysis. Gender was scored as a binary variable: male = 1, female = 2. Age was grouped into 5-year intervals, with each interval assigned a corresponding numerical value. The scoring scheme is as follows: age 60–64 = 1, age 65–69 = 2, age 70–74 = 3, age 75–79 = 4, and age ≥80 = 5.

3.2.2. Digital literacy assessment

This study drew upon the DigComp 2.1 framework to create a set of 5-point Likert scale-type survey questions designed to assess the digital literacy of elderly individuals. The objective was to evaluate their digital skills across five key areas:

information and data literacy, communication and collaboration, digital content creation, safety, and problem solving. Responses were synthesized into a composite digital literacy index using principal component analysis (PCA), where a higher score indicates a higher level of digital literacy.

Table 1 details the specific measurement items. Information and Data Literacy was assessed by evaluating the ability to browse, search, and find necessary information on the Internet. Communication and Collaboration focused on the ability to communicate with others via social media or email. Digital Content Creation examined the ability to create or edit digital content. Safety was measured by the ability to protect personal data, devices, and privacy. Problem Solving was assessed by the ability to identify and solve problems related to digital technology.

Table 1. Measurement of digital literacy based on DigComp 2.1 framework.

Competence area	Code	Items	References
Communication and collaboration	CC1	I communicate with others via social media software or email.	Carretero et al., 2017; Ferrari, 2013; Li et al., 2022; Vuorikari et al.
	CC2	I can post content and share information on social media platforms.	
	CC3	I can participate in discussions on messaging platforms.	
	CC4	I use polite language and a respectful attitude in online interactions.	
	CC5	I carefully consider the potential impact of social media content on my personal image and reputation before posting.	
Digital content creation	DC1	I can edit documents using word processing software.	Carretero et al., 2017; Ferrari, 2013; Li et al., 2022; Vuorikari et al.
	DC2	I can create or edit simple images or videos.	
	DC3	I understand and comply with copyright regulations for online content.	
Safety	SF1	I know how to set password protection for my phone or computer.	Carretero et al., 2017; Ferrari, 2013; Li et al., 2022; Vuorikari et al., 2016
	SF2	I know how to prevent online scams.	
	SF3	I know how to protect my phone from viruses.	
	SF4	I know how to protect my personal information while online.	
	SF5	I understand the potential health impacts of prolonged use of electronic devices.	
Problem solving	PS1	I can solve simple issues with phone usage.	(Carretero et al., 2017; Ferrari, 2013; Vuorikari et al., 2016
	PS2	I can select appropriate mobile apps or computer software as needed.	
	PS2	I can seek and use online tutorials to learn new skills.	

During the design of the survey questions, we thoroughly analyzed the specific needs and challenges elderly individuals face when using digital technology. This ensured that the questions comprehensively covered the key competency areas outlined in the DigComp 2.1 framework, with appropriate adjustments and additions based on the characteristics of the elderly. Furthermore, the survey design took into account the cognitive characteristics of the elderly, employing clear and straightforward language and instructions to ensure that participants could easily understand and complete the survey.

3.2.3. Acceptance and usage behavior towards smart elderly care services

A multi-item scale was designed to measure five variables, including performance expectations, effort expectations, social influence, facilitating conditions, and usage intentions. It is used to assess the acceptance of smart elderly care services among older adults, as shown in **Table 2**. The item design of the scale is based on established scales that have been empirically validated and align with the conceptual requirements of the research variables outlined in relevant literature. It has been appropriately tailored to suit the specific research context and incorporates insights obtained from interviews conducted with professionals within the smart elderly care industry. A 5-point scale is employed to measure the dimensions of the research variables. Participants are able to evaluate each item based on their individual circumstances, ranging from "1 = completely disagree" to "5 = completely agree".

Table 2. Acceptance of smart elderly care services scale.

Construct	Code	Items	References
Performance Expectancy (PE)	PE1	Using smart elderly care services can improve the quality of my life.	Davis, 1989; Venkatesh, 2003
	PE2	Using smart elderly care services can help me better manage my health.	
	PE3	Using smart elderly care services allows me to live more independently.	
	PE4	Using smart elderly care services can enhance the efficiency of my daily life and make it more convenient.	
Effort Expectancy (EE）	EE1	It is easy for me to learn how to use smart elderly care services (or devices).	Davis, 1989; Venkatesh, 2003; Liu, 2012; Zhang et al., 2023; Wang, 2023
	EE2	The process of using smart elderly care services (or devices) is clear and understandable for me.	
	EE3	I can easily utilize smart elderly care services or devices to meet my need.	
Social Influence (SI)	SI1	My family encourages me to use smart elderly care services.	Venkatesh and Davis, 2000; Venkatesh, 2003; Wang, 2023; Yao et al., 2021
	SI2	My friends have a supportive attitude toward using smart elderly care services.	
	SI3	My peers around me generally use smart elderly care services.	
	SI4	People around me recommend that I use smart elderly care services.	
	SI5	The promotion from hospitals and communities as well as encouragement from national policies motivate me to use intelligent healthcare and eldercare services.	
Facilitating Conditions (FC)	FC1	I am able to access the necessary equipment for using smart elderly care services.	Venkatesh, 2003; Venkatesh and Davis, 2000; Wang, 2023
	FC2	I have access to detailed guidance and training on the usage of smart elderly care services (or devices).	
	FC3	If I encounter difficulties or problems while using these services, I can receive necessary support and assistance.	
	FC4	I believe the technology and systems of smart elderly care services are reliable.	
	FC5	Smart elderly care services are compatible with my existing devices.	
Behavioral Intention (BI)	BI1	If given the opportunity, I would consider using smart elderly care services.	Venkatesh, 2003; Venkatesh and Davis, 2000; Yao et al., 2021
	BI2	I plan to frequently use smart elderly care services in the future.	
	BI3	I would recommend others around me to use smart elderly care services.	

To evaluate the combined impact of performance expectations, effort expectations, social influence, and facilitating conditions on usage behavior, Principal Component Analysis (PCA) was employed to integrate these four variables into a composite indicator termed "Service Acceptance (SA)". The application of PCA offers several methodological advantages. Primarily, PCA reduces the dimensionality of the dataset while retaining a significant portion of its information content (Cadima and Jolliffe, 2002). By consolidating multiple related variables into a single composite indicator, PCA simplifies the data structure and addresses multicollinearity issues, thereby enhancing the robustness and interpretability of subsequent statistical analyses (Abdi and Williams, 2010). Furthermore, PCA enhances the model's explanatory capacity, rendering the research findings more intuitive and comprehensible (Bishop and Tipping, 1999). Consequently, the strategic application of PCA in this research facilitates a more nuanced and effective evaluation of the aggregate impact of these factors on usage behavior.

The dependent variable in this study is the usage behavior (UB) of elderly individuals towards smart elderly care services. We not only assess their adoption of such services, but also evaluate the extent to which they embrace them. In the questionnaire, smart elderly care services are categorized into six types, and a simple scoring method is employed to quantify the usage behavior of the elderly towards these services. Each respondent receives 1 point for each selected category of service, and the total score reflects their level of adoption towards smart elderly care services. Additionally, those who select "none of the above services have been used" receive a score of 0. These categories are:

Health monitoring—real-time tracking of health indicators like heart rate, blood pressure, and blood sugar through wearable devices such as intelligent bracelets, with data transmitted to doctors or family members;

Telemedicine—virtual consultations with doctors via video calls or online inquiries to obtain medical advice and diagnosis;

Emergency rescue—wearing a smart emergency button that can send distress signals to family members or rescue centers by simply pressing it during emergencies;

Health management—utilizing smart applications that assist in developing personalized health plans and remind users about timely medication intake, daily exercise engagement, and regular check-ups;

Life assistance—employing smart home devices that automatically regulate indoor temperature, control lighting settings, and provide reminders regarding daily tasks to enhance quality of life;

Social interaction—utilizing internet connectivity and smart devices to offer social platforms and online communities that facilitate communication between individuals while alleviating feelings of loneliness and depression.

3.3. Data collection

A random sampling technique was employed to survey elderly individuals aged 60 and above in Xi'an city. The research utilized a self-administered questionnaire administered through an online survey platform called Wenjuanxing. Participant recruitment was conducted via the WeChat social media platform. A total sample size of 299 was achieved. **Table 3** presents the demographic characteristics of the participants.

Table 3. Participants' demographic characteristics.

Items	Categories	N	Percent (%)
Gender	Female	164	54.85
	Male	135	45.15
Age	60–64	126	42.14
	65–69	71	23.75
	70–74	53	17.73
	75–79	26	8.7
	80 and above	23	7.69
Total		299	100.0

Source: Based on the authors' calculations.

3.4. Data analysis

The data analysis was conducted using STATA software. Initially, a comprehensive assessment of the questionnaire's reliability and validity was performed, followed by regression analysis to examine hypotheses empirically.

3.4.1. Reliability and validity testing

This study employs Cronbach's α to assess the reliability of the questionnaire, with a value of 0.70 or above indicating high reliability, as commonly accepted in the literature (Nurmaly, 1970). As presented in **Table 4**, the values of Cronbach's α are 0.969, 0.945, 0.929, 0.8914, 0.938 and 0.914 for digital literacy, PE, EE, SI, FC and BI, indicating a high level of internal consistency in the obtained data results.

Table 4. Reliability statistics.

Variables	*N* of items	Cronbach's α
digital literacy	19	0.969
PE	4	0.945
EE	3	0.929
SI	5	0.914
FC	5	0.938
BI	3	0.914

Source: Based on the authors' calculations.

Table 5 displays the outcomes of the validity assessment for service acceptance scale, revealing a KMO value of 0.932 and $p < 0.05$, which suggests that the research data is highly suitable for information extraction and demonstrates robust validity from an alternative perspective.

Table 5. KMO and Bartlett's test.

KMO		**0.951**
Bartlett's test of sphericity	Chi-Square	6617.498
	df	190
	p	0.000

Source: Based on the authors' calculations.

3.4.2. Hypothesis testing

In order to test the research hypotheses, this study employs the regression analysis method. Firstly, it examines the direct impact of PE, EE, SI, FC on BI and usage behavior. The regression analysis method is an effective tool for analyzing causal relationships as it reveals both the direction and strength of independent variables' influence on dependent variables.

Secondly, this study incorporates mediation effect analysis to explore the mediating role of BI between the aforementioned four core dimensions and usage behavior. Mediation effect analysis helps identify indirect relationships between variables and provides a deeper understanding of interaction mechanisms among them.

Additionally, to understand comprehensively the combined effects of various independent variables, this study consolidates the four core constructs of the UTAUT model into a single composite indicator: SA. This composite score is then used in a regression analysis to evaluate its impact on usage behavior. Composite scores are commonly used in the social sciences as dependent and independent variables in statistical models, simplifying model structures and providing an aggregate indicator to assess overall effects (Rose et al., 2019). This method allows for a more accurate prediction of user behavior, as it considers the combined effects of multiple influencing factors, thereby reflecting a more realistic usage scenario (Fu and Yu, 2004; Rose et al., 2019).

Finally, this study investigates gender, age, and digital literacy as moderating variables that affect the model by employing interaction term analysis in multiple regression analysis method. Interaction term analysis uncovers how moderating variables influence the relationship between independent variables and dependent variables, thereby offering more insights into older adults' acceptance level towards smart elderly care services under different backgrounds.

3.5. Ethical considerations

Before commencing the online questionnaire, participants were directed to an informational page outlining the study's objectives and the measures taken to safeguard their privacy. Participants were clearly informed of the voluntary nature of their participation and their right to withdraw at any time without repercussions. To ensure participant confidentiality, all questionnaires were anonymized and did not collect any personally identifiable information. Collected data were securely downloaded and stored on encrypted hard drives, accessible exclusively to the research team, while records in the online survey system were promptly deleted.

4. Results

The study initially evaluated the influence of four fundamental dimensions in the UTAUT model—PE, EE, SI and FC on UB. The results, as presented in **Table 6**.

Table 6. Direct influence of UTAUT dimensions on UB.

	(1)
Variables	**UB**
PE	−0.071
	(0.067)
EE	0.161*
	(0.084)
SI	0.213**
	(0.105)
FC	0.139
	(0.118)
Constant	1.398***
	(0.090)
Observations	299
R-squared	0.119

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6 demonstrates that both EE ($\beta = 0.161$, $p < 0.1$) and SI ($\beta = 0.213$, $p < 0.05$) exert a significant positive impact on UB. This suggests that when older adults perceive lower levels of effort required for utilizing smart elderly care services and are influenced by their social environment, they tend to embrace a wider range of such services. However, PE and FC do not exhibit statistical significance, indicating that these two factors do not significantly affect the UB.

Next, an analysis was conducted to examine the impact of the four dimensions on UB, employing BI as a mediating variable. The results are shown in **Table 7**.

As presented in **Table 7**, PE ($\beta = 0.312$, $p < 0.01$), SI ($\beta = 0.286$, $p < 0.01$), and FC ($\beta = 0.267$, $p < 0.01$) all exhibited significant and positive effects on BI. When considering BI as a mediator, the direct influence of PE on UB becomes non-significant; however, the effects of EE ($\beta = 0.160$, $p < 0.1$) and SI ($\beta = 0.216$, $p < 0.1$) remain significant, indicating their indirect impact through BI. This suggests that BI plays a partial mediating role between these independent variables and UB.

Table 7. Mediation analysis with behavioral intention.

	(1)	**(2)**	**(3)**
Variables	**UB**	**BI**	**UB**
BI			−0.011
			(0.114)
PE	−0.071	0.312***	−0.068
	(0.067)	(0.034)	(0.076)
EE	0.161*	−0.067	0.160*

Table 7. (*Continued*).

	(1)	**(2)**	**(3)**
Variables	**UB**	**BI**	**UB**
	(0.084)	(0.043)	(0.084)
SI	0.213**	0.286***	0.216*
	(0.105)	(0.054)	(0.110)
FC	0.139	0.267***	0.142
	(0.118)	(0.060)	(0.122)
Constant	1.398***	0.000	1.398***
	(0.090)	(0.046)	(0.090)
Observations	299	299	299
R-squared	0.119	0.650	0.119

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To understand comprehensively the combined impact of these factors, the four dimensions were synthesized into a composite index SA. The results are shown in **Table 8**.

Table 8. Impact of SA on UB.

	(1)	**(2)**	**(3)**
Variables	**UB**	**BI**	**UB**
BI			−0.071
			(0.107)
SA	0.306***	0.597***	0.348***
	(0.052)	(0.029)	(0.083)
Constant	1.398***	−0.000	1.398***
	(0.090)	(0.049)	(0.090)
Observations	299	299	299
R-squared	0.103	0.596	0.104

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results presented in **Table 8** indicate that SA exhibits a significant positive influence on both BI ($\beta = 0.597$, $p < 0.01$) and UB ($\beta = 0.306$, $p < 0.01$). Even after controlling for BI, the impact of SA ($\beta = 0.348$, $p < 0.01$) on UB remains statistically significant. However, the direct relationship between BI itself and UB is not found to be significant ($\beta = -0.071$, $p > 0.1$). The change in the impact coefficient of SA on service usage behavior from 0.306 to 0.348 when controlling for BI indicates that BI serves as a partial mediator in this relationship. This suggests that SA not only directly impacts UB but also indirectly influences it by strengthening BI.

The moderating effects of gender, age, and digital literacy on the model were also explored. As demonstrated in **Table 9**, the interaction term between gender and self-efficacy (SA) is statistically significant ($\beta = -0.211$, $p < 0.05$), indicating that gender moderates the relationship between SA and usage behavior (UB). Specifically, the effect of SA on UB is more pronounced among males.

Table 9. Moderating effects of gender.

	(1)
Variables	**UB**
SA	0.399***
	(0.069)
1. gender	0.104
	(0.181)
0b. gender#co. SA	0.000
	(0.000)
1. gender#c. SA	−0.211**
	(0.106)
Constant	1.335***
	(0.121)
Observations	299
R-squared	0.116

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0$, it can be seen that the interaction term between gender and SA is significant ($\beta = -0.211$, $p < 0.05$), indicating that gender moderates the relationship between SA and UB, with the effect being stronger for males.

Table 10. Moderating effects of age.

	(1)
Variables	**UB**
SA	0.512***
	(0.100)
age	−0.019
	(0.071)
c. SA#c. age	−0.086**
	(0.035)
Constant	1.414***
	(0.178)
Observations	299
R-squared	0.120

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10 indicates that the interaction term between SA and age is significant ($\beta = -0.086$, $p < 0.05$), suggesting that the positive effect of SA on service usage behavior decreases with age.

Table 11. Moderating effects of digital literacy.

	(1)
Variables	**UB**
SA	0.214***
	(0.062)
digital_literacy_new	0.191***

Table 11. (*Continued*).

	(1)
Variables	**UB**
	(0.058)
c. SA#c.digital_literacy_new	0.052**
	(0.022)
Constant	1.309***
	(0.095)
Observations	299
R-squared	0.158

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11 shows that digital literacy significantly moderates the relationship between SA and service usage behavior ($\beta = 0.052$, $p < 0.05$), implying that higher digital literacy enhances the positive impact of SA on service usage behavior.

5. Discussion

This study uncovers several critical insights into factors influencing elderly individuals' use of smart elderly care services. EE and SI significantly impact UB, consistent with Davis and Venkatesh (2000) research results and Venkatesh et al. (2003) UTAUT model, which underscores the importance of external social pressures and ease of use. Braun (2013) support this by noting that ease of use positively affects individual responses, and Zhang et al. (2023) confirms that perceived ease of use has a greater effect on usage intention than perceived usefulness or safety.

The findings suggest that the adoption of smart elderly care services is influenced not only by seniors' knowledge but also by their social environment. SI's significant direct and indirect effects on UB emphasize the role of SI in shaping both the intention and actual usage of smart elderly care services. This finding underscores the importance of social endorsement and peer influence in promoting the adoption of smart elderly services among the elderly. Similarly, Yao et al. (2021) have highlighted the pivotal role that family members, friends, and neighbors occupy in shaping the decision-making processes of the elderly. At the same time, due to limited awareness of smart elderly care policies, support from personnel of community elderly care service institutions and government officials can significantly enhance seniors' confidence and commitment to using these services, thereby increasing their willingness to adopt, thereby fostering an enhanced usage behavior.

In contrast, PE and FC do not show a significant effect on usage behavior. Although existing research suggests that performance expectancy (PE) generally influences technology use, in certain cases, its explanatory power regarding behavior may be diminished by other factors that have not been fully considered. For instance, users' contexts or task demands may weaken its influence (Sun and Zhang, 2006). Bagozzi (2007) also proposed that factors such as emotions, social norms, group cultural factors, and self-regulation processes may influence technology acceptance and usage. These factors may moderate the impact of PE on usage behavior (UB) in different contexts. The study by Im et al. (2011) found that in certain cultural contexts, social norms and ease of use may have a greater impact on technology adoption than performance expectancy. Furthermore, the studies by Hoque and Sorwat (2017) and Wang et al. (2023) also found that FC does not significantly influence elderly individuals' UB regarding smart elderly care services. This implies that, for the elderly, anticipated technological benefits and external support conditions are not decisive in using these services. This may be related to seniors' familiarity with technology, their acceptance of new innovations, and their confidence in resolving technological issues (Braun, 2013; Lian and Zhang, 2018). Additionally, it suggests that seniors may base their adoption decisions more on others' experiences and recommendations rather than solely on the technology's ease of use. Therefore, when designing and promoting smart elderly care services, it is crucial to focus on service usability and social outreach rather than just technological performance or external support improvements.

The mediation analysis of BI reveals how PE, EE, SI, and FC indirectly affect usage behavior through BI. The analysis shows that PE, SI, and FC positively influence BI, yet BI does not directly impact usage behavior significantly. This aligns with the TAM proposed by Davis (1989), which highlights that while BI is a key variable, actual usage behavior is also influenced by other external factors. This indicates that although elderly individuals may express a high intention to use smart elderly care services, this intention does not always translate into actual usage. As noted by Peek et al. (2014), despite a positive attitude towards smart elderly care products, actual usage and acceptance rates remain low. Thus, seniors may face various barriers despite expressing a positive intention to use these services.

By integrating PE, EE, SI and FC into a single composite measure SA, this study more comprehensively reflects the acceptance of smart elderly care services. This approach not only simplifies the analytical model but also provides a holistic perspective on understanding service acceptance. The results support this integration method, indicating that SA significantly impacts both BI and UB. However, when SA is included in the model as an independent variable, the effect of BI on UB is not significant. This finding suggests that although BI is influenced by acceptance levels, it does not play a significant mediating role in translating acceptance into actual usage behavior. Consequently, efforts to directly enhance the SA more effectively increase their UB than merely increasing BI. Furthermore, the results indicate that while forming BI is important, intentions alone are insufficient to guarantee actual usage. This implies that other factors, such as technological complexity, perceived usefulness, social influence, consumer attitudes and capacity, and trust in technology, may play a crucial role in converting intentions into actual usage behavior (Bai et al., 2024; Chen and Shao, 2021; Heart and Kalderon, 2013; Peek et al., 2014; Venkatesh et al., 2012).

The moderation analysis of gender, age, and digital literacy reveals significant differences in the use of smart elderly care services among elderly individuals from different backgrounds. Notably, males exhibit a stronger response to SA compared to females. Morris and Venkatesh (2000) found that men tend to prioritize the usefulness of technology in its application, while women, in addition to considering the usefulness, may also place greater emphasis on the ease of use and social influences, such as the opinions of peers or superiors. This suggests that, given the same level of technology acceptance, men may be more inclined to actively use the technology, particularly when they perceive its potential utility. As age increases, the positive impact of SA on usage behavior diminishes, potentially reflecting lower acceptance of new technology among older seniors or greater challenges in usage. Consistent with the findings of Levine et al. (2016) and Hargittai and Hunsaker (2018), elderly individuals with higher digital literacy are more likely to accept and use smart elderly care services, as enhanced digital literacy improves their capability and confidence, thereby strengthening the impact of SA on usage behavior. These findings suggest targeted policy recommendations, such as developing gender-specific engagement strategies and providing tailored training programs to enhance digital literacy, particularly for the oldest age groups, to foster better acceptance and utilization of smart elderly care services.

6. Conclusion

This study unveils the significant roles of effort expectancy and social influence in driving the adoption of smart elderly care services among older adults, while highlighting the intricate mechanism of behavioral intention as a partial mediator. Furthermore, this research identifies that gender, age, and digital literacy significantly moderate the impact of these factors on usage behavior. These findings provide valuable theoretical foundations and practical guidance for designing and promoting smart elderly care services.

While the study provides a robust examination of the factors influencing the adoption of smart elderly care services, it also has limitations that should be acknowledged. The cross-sectional nature of the data limits the ability to infer causality and observe changes over time, which is essential for understanding the evolution of technology acceptance among the elderly. Additionally, the study’s focus on a specific demographic in Xi’an may restrict the generalizability of the findings to other populations with different cultural and socioeconomic backgrounds. The reliance on self-reported surveys could introduce subjective biases, potentially affecting the accuracy of the results. Future research, as suggested, could address these limitations by employing longitudinal designs to capture the dynamics of acceptance over time and by incorporating a more diverse sample that reflects varied cultural, socioeconomic, and health conditions.

Future research can explore other potential mediators and moderators such as cultural background, socioeconomic status, and health conditions. Additionally, incorporating longitudinal study designs and employing mixed methods research combined with qualitative interview data will contribute to a more comprehensive understanding of older adults’ acceptance and usage behavior towards smart elderly care services. Through thorough analysis and continuous exploration, we can effectively promote the application of smart elderly care services among the elderly population to enhance their quality of life.

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