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The factors affecting the community resident of purchasing Smart Elderly Care Products- A case study in Chaozhou

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Master's in Management of Services and Technology

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Iscte-Iul

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BUSINESS
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Abstract

With the development of the aging population, the demand for the elderly market is increasing, and elderly products play a vital role in it. However, elderly products not only need to effectively improve the physical literacy of users, but also need to consider ease of use, especially in the face of people of different ages, they need to stimulate their purchase demand. Therefore, this study aims to explore the factors influencing community residents' purchase of smart elderly care products, so as to better understand and predict the purchase demand of community residents for smart elderly care products.

This study uses quantitative research methods to conduct an in-depth study of the purchasing needs of community residents. First, sample data collection was carried out by using questionnaires in the community. Then, the results were analysed by the structural equation method through the Smart PLS software tool, and the different variables of the UTAUT model were focused on to explore the impact of different factors on the purchase of smart elderly care products by community residents. The results show that performance expectancy, effort expectancy, social influence and convenience conditions are very important to the purchase needs of community residents to purchase smart elderly care products. This study provides a new perspective for the academic research of intelligent elderly care, and provides useful enlightenment for improving the health security of the elderly and the quality of elderly care products.

Keywords: Elderly Market; Healthcare; Demand for Smart Products; China; M10

Resumo

O aumento da população idosa faz com que este segmento de mercado tenha vindo a ganhar cada vez mais importância e os produtos para cuidados aos idosos têm um papel importante neste segmento de mercado. Contudo os produtos produtos para os cuidados aos idosos não só precisam de explicar melhor a sua utilização como também necessitam de ter em consideração a facilidade do seu uso.

Este estudo tem como principal objetivo explicar os fatores que influenciam os residentes , de todas as idades, de uma determinada comunidade na China a comprar produtos inteligentes para idosos, assim como compreender melhor as razões da procura dos residentes da comunidade de produtos inteligentes para cuidados com idosos. Pensamos que uma melhor compreensão ajuda a prever a procura.

Palavras -Chave: Mercado de Idosos; Saúde; Procura de Produtos Inteligentes; China; M10

Contents

Chapter 1 Introduction

1.1 Background

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As of 2021, China's population reached 1.41 billion, and the number of people aged 60 and above has been growing rapidly since 2014. It is predicted that by 2035, China's elderly population will exceed 400 million (Office of the Leading Group for the Seventh National Population Census of the State Council, 2021a). This social demographic change has brought challenges to China, such as labor supply shortages and increased social security expenditures. As China's population ages, the demand for elderly care products and services such as health care, medical services and pension funds is expected to increase. The aging population drives the growth of medical and health expenses, and drives economic growth by improving health services, promoting consumption, and promoting the development of the medical and health service industry (Chen et al., 2022).

At the same time, the trend of social population aging has created opportunities for the development of the silver economy. The aging population has led to a shift in consumption patterns, promoted technological innovation, and driven the demand for elderly care services and products. Smart elderly care products include advanced technology solutions and smart elderly care products designed to help the elderly cope with the challenges of aging, as well as smart service platforms and smart service terminals tailored to meet the diverse needs of the elderly population. Data shows that the scale of China's smart elderly care market in 2022 is about 8.2 trillion CNY, a year-on-year increase of 34.43%. Analysts at the China Business Industry Research Institute predict that the scale of China's smart elderly care market will reach 11.4 trillion CNY in 2024, with broad room for future development (Office of the Leading Group for the Seventh National Population Census of the State Council, 2021).

These services utilize technologies such as the Internet of things, big data, cloud computing, and mobile Internet to provide elderly individuals with smart care and a safe, independent living environment. The Chinese government has implemented policies to promote the development of smart home care services, including the Action Plan for the Construction of a Smart and Healthy Elderly Care Industry.

However, there are still many barriers to the adoption of smart home care services, including socioeconomic issues, low acceptance of new technologies by some people, and low digital literacy among the elderly. To overcome these barriers, many efforts have been made to improve the digital literacy of the elderly, including the development of user-friendly smart products and smart systems that are easy to set up (Hung, 2022).

1.2 Research questions

Based on the discussion above, there are two research questions which will be explored in this research.

-Research question 1-What are primary factors influencing community residents' intention to purchase smart elderly care products?

-Research question 2- To what extent does facilitating condition (e.g., recommendations from family and friends) impact the decision of community residents to purchase smart elderly care products?

1.3 Research objectives

The promotion, popularization and adoption of smart elderly care products in China are not only related to the development of technology and services, but also closely related to the understanding and acceptance of these smart products by various age groups. Since foreign research on smart elderly care products is relatively mature and mainly focuses on product system development and smart home research, there are relatively few studies on the demand for smart elderly care products (Hoque, 2017). Most domestic research focuses on the willingness to use smart elderly care products (Wang et al., 2023), but less on the willingness to purchase. To better understand and predict the purchasing behavior of community residents on smart elderly care products, it is of great significance to explore its influencing factors.

This study combines the unified theory of technology acceptance and use to construct a research model and analyze the influencing factors that affect community residents' purchase of smart elderly care products, which will fill the gap in domestic research on this issue. Not

only beneficial to the future development of the smart elderly care industry, but also provide market feedback for product developers, provide theoretical guidance for government departments on elderly care needs, and provide suggestions to ensure that these products are purchased by community residents.

1.4 Research significance

This study is different from most previous studies in that it expands the age range of the research subjects from the elderly to individuals of all ages in the community and shifts from studying the factors that influence the use of smart elderly care products to conducting an in-depth discussion of the behaviors that influence the purchase of smart elderly care products.

The exploration and discovery of this study will lead to further exploration and discovery of smart elderly care in the academic field and can contribute to the research of future generations. In addition, it can also increase the attention of the industry and society to the elderly care market and make more contributions to the future development of the elderly care industry. For example, in a highly aging society, it can help people of all ages understand smart elderly care products, and through the learning and use of smart products by digitally literate people in families and communities, it can help more elderly people understand and use elderly care products independently and increase their health protection.

1.5 Structure

In this dissertation, there will be 5 chapters to show the research process. The research background of the first chapter is used as the starting point for the research introduction of this dissertation. The literature review section of Chapter 2 discusses the various parts of the research topic in detail, citing previous research and results to enrich the definition, research significance and unfinished research gaps of this study. Chapter 3 introduces and describes the methodology used in this study. Chapter 4 analyzes and summarizes the collected data, and

then presents the results. The last chapter, Chapter 5, will give an overall summary of the entire study.

Chapter 2 Literature Review

2.1 Introduction

As of 2021, China's population reached 1.41 billion, and the number of people aged 60 and above has been growing rapidly since 2014. It is predicted that by 2035, China's elderly population will exceed 400 million. (Office of the Leading Group for the Seventh National Population Census of the State Council, 2021b). With this demographic change in Chinese society, the demand for elderly care services is growing significantly every day and is driving innovation in the smart elderly care market. Smart elderly care products include technologies such as wearable health monitoring devices, smart home systems, and telemedicine platforms, with the aim of improving the quality of life for the elderly while reducing the burden on caregivers and the social healthcare system (Chen et al, 2023).However, there are barriers to the mass adoption of smart home care services, including the lack of digital literacy among the elderly population, financial concerns, and resistance to accepting new technologies. To overcome these barriers, efforts are being made to enhance digital literacy among the elderly, develop user-friendly smart devices (Hung, 2022).

Past research has focused on elderly users as the main adopters of smart elderly care products. This study examines the factors influencing the use of these technologies by older users, as well as the Unified Theory of Technology Acceptance and Use (UTAUT) model (Venkatesh et al., 2003), which is commonly used to understand the role of performance expectations, effort expectancy, social impacts, and enabling conditions. However, referring to the factors influencing the purchase of smart elderly care products by community residents of all ages (not just the elderly), the literature shows that there is a significant gap (Huang et al., 2022). Community residents may be young people who buy products that are currently popular in the senior care market for their older relatives, but they are often overlooked in mainstream research.

In order to understand and address this research gap, this dissertation will examine the factors that influence community residents to purchase smart elderly care products, with a focus on the UTAUT model. This dissertation will provide a chronological overview of the

literature, analyze its patterns, and discuss in depth the latest advances in the adoption of smart elderly care products.

2.2 Main body:

2.2.1 Smart Elderly Care Product

2.2.1.1 Definition

Wang et al. (2023) defined smart elderly care products as a product that integrate advanced modern technology, new smart hardware products and smart elderly care service information platforms and divided into two categories: smart elderly care service platform systems and smart elderly care service terminals. Among them, the smart elderly care service platform system refers to the perception, transmission, release, integration and service of the needs of the elderly based on information technology, while promoting communication among multiple subjects such as the medical security system, medical service institutions, families and even individuals, and further meeting the diverse needs of the elderly for smart products. In addition, smart elderly care terminals are smart devices that integrate advanced technologies such as robot doctors, smart nursing robots, and companion robots. They also help the elderly to actively face aging products and meet the broad market demand for smart elderly care in the future.

2.2.1.2 Type of the smart elderly care products

Wearable Devices

Wearable devices are widely used to monitor various health indicators, such as heart rate, blood sugar, blood pressure and sleep patterns. Common examples include smart watches, wearable sensors and smart bracelets. These AI-integrated elderly care products provide real-time data and alerts to caregivers, healthcare professionals and family members, providing personalized health reminders, allowing the elderly to better control and pay attention to their own health (Stavropoulos et al., 2020; Liu et al., 2023).

Smart Home System

Smart home systems are designed to create safer living environments for seniors. They integrate features such as automated lighting, temperature control, and emergency alerts. Products such as smart home hubs (e.g., Amazon Alexa, Google Home) connect to a variety of sensors that can identify and mitigate risks in the home environment and are used to monitor motion, detect falls, and send emergency alert notifications, thereby enhancing the ability of seniors to live independently (Rybenská et al., 2024).

Assistive and Rehabilitation Devices

These categories of devices include smart wheelchairs, smart glasses, and hearing aids, designed to assist older people with limited mobility, vision, or hearing, effectively providing feedback and improving usability, thereby significantly improving the quality of life for users with physical disabilities (Kang, S. Y, and Kang, S. A. 2018).

Companion Robots

Companion robots, such as "Elliq" and "Pepper," are developed to provide medication reminders, social interaction, and emotional support to older adults living alone. These robots aim to improve mental health in older adults and provide cognitive rehabilitation, improve overall well-being, and reduce loneliness (Rybenská et al., 2024).

Telehealth and Remote Monitoring Devices

Devices such as TytoPro and BioBeat help monitor users' health remotely and consult with healthcare professionals, making it unnecessary for seniors to visit hospitals as often. These products reduce the need for face-to-face care and make it easier for seniors to manage their own health (Rybenská et al., 2024).

The different types of smart elderly care products mentioned above all aim to improve the quality of life of the elderly by promoting independent living, reducing risks, and

strengthening health monitoring and management. This study takes into account the income of different age groups, so the scope of smart elderly care products is defined as wearable devices and assistive and rehabilitation devices.

2.2.1.3 Adoption

The earliest studies on smart elderly care technologies focused on the elderly as the primary users. Early studies, such as those by Venkatesh et al. (2003), used the UTAUT model to explore how factors such as performance expectancy (perceived usefulness of technology) and effort expectancy (ease of use) influence technology adoption. Performance expectation has been considered one of the major factors determining technology adoption among the older adults since smart elderly care products are believed to enable them to increase independence in daily life and, therefore, provide effective improvement of health outcomes for the older adults (Peek et al., 2014).

Starting from the 2010s, this focus started to shift toward what caregivers and family members need, reflecting an overall broader approach to studying the use of smart elderly care products (Pal et al., 2018). Meanwhile, this shift also made social influence a very important factor. It has also been noted in studies that the support from family members, caregivers, and social health care providers may motivate an older adult to accept smart technologies (Huang et al., 2022). The UTAUT model was expanded during this period to include these other social influences since older adults often rely on their families in making decisions when adopting new technologies.

However, there are still gaps in the research. Most studies still consider the elderly as the main users of these technologies, thereby ignoring community residents—especially the middle-aged group—who often make purchasing decisions for their elderly relatives (Zhou et al., 2024). As community elderly care services become more popular, this neglect of the purchasing needs of other age groups becomes more obvious, and people will shift more of the focus to community residents in the future, believing that they are the key decision makers in purchasing smart elderly care products.

2.2.2 Purchase Behavior

2.2.2.1 Definition

Purchase behavior refers to the decision-making process and actions undertaken by consumers when they acquire goods or services (Kotler, 2016). Purchase behavior involves non-phases, including identifying needs, searching for information, evaluating alternatives, purchasing decisions, and post-purchase behavior (Solomon, 2018). Consumer purchasing behavior is influenced by internal factors such as personal preferences and psychological motivations, as well as external factors such as economic, social and cultural habits (Schiffman & Kanuk, 2014). In addition to this, other than all these sociocultural factors, the purchasing behavior of a consumer is motivated by rational judgements of the product characteristics and emotional and psychological influences such as brand loyalty and perceived value (Belk et al., 2013). Buying behavior is researched by marketing researchers to gain an insight into how consumers reach a buying decision and influence decisions through effective marketing strategies (Kotler & Keller, 2015).

2.2.2.2 Key factors influencing purchasing behavior

According to Venkatesh et al., (2003), generally, customers consider the product attributes like functionality, appearance, and compatibility with the existing technologies. Dodds et al., (1991) emphasized that the consumer purchasing decisions are driven by perceived benefits and costs whereby perceived value has an important role to play. As highlighted by Brown and Reingen (1987), recommendations by family and friends around them and the social influence of certain online reviews can gainfully reflect on the consumers' decision-making. According to Gefen (2000) consumers' trust in a brand or business influences purchase intention, highlighting the importance of trustworthiness in marketing. Monroe (1973) showed, in a highly competitive market, where price is a key factor influencing purchasing decisions, the identification of price sensitivity is particularly important. Hart (1995) found that preferences for different services and personalized products can drive purchase behavior and meet consumers' personalization and customization needs. Donthu and Garcia (1999) advanced factors such as convenience in purchasing, home delivery, and after-sales service

contribute to consumer satisfaction and propensity to make repeat purchases. Stern (1962) mentioned emotional reactions, such as excitement or anger, can affect impulse buying.

2.2.3 UTAUT Model

2.2.3.1 Definition

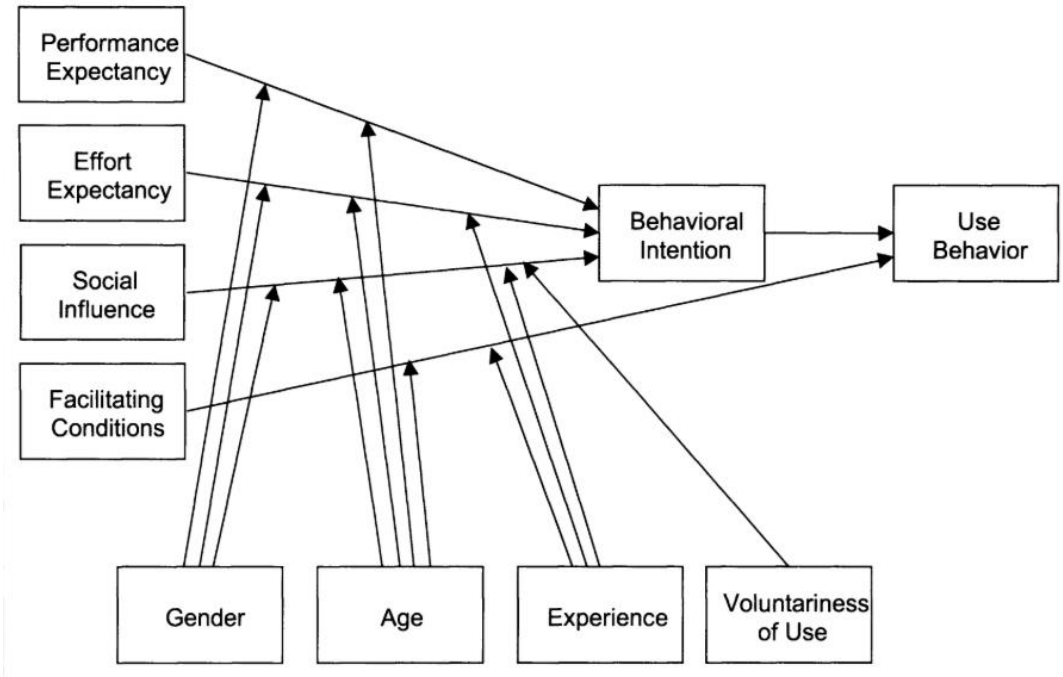

Figure 2.1 UTAUT Model

Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) as a comprehensive and integrated framework to understand technology acceptance by integrating several influential theoretical elements. For example, the Technology Acceptance Model (TAM) emphasizes the importance of user perception in shaping acceptance behavior. The Theory of Reasoned Action (TRA) emphasizes the social dimension of technology acceptance. The Theory of Planned Behavior (TPB) emphasizes the importance of self-performance in technology use. The Diffusion of Innovations Theory (IDT) provides insights into the social dynamics of technology acceptance. Social Cognitive Theory (SCT) helps understand the impact of social interaction on technology acceptance. The model leverages the strengths of different theoretical frameworks and their unique features to

improve the accuracy of predicting real-world technology acceptance and technology acceptance and usage behavior.

UTAUT model synthesizes four main variables as key constructs in the theory: performance expectancy, effort expectancy, social impacts, and facilitation conditions. In addition to this, the model identifies four moderating variables: sex, age, experience, and voluntary use (Venkatesh et al., 2003). Recent studies have found that the impact of core variables on users' willingness to adopt technology varies depending on the industry and environment (Balakrishnan et al., 2022).

In addition, the UTAUT model has also shown a wide range of applicability in the field of intelligent elderly care. Different studies have explored the relevance of this model in this area and illustrated how it can provide strategies to more effectively increase the acceptance of technology among older adults (Hoque & Sorwar, 2017; Cimperman et al., 2016; Tian & Wu, 2022; Boontarig et al., 2012; Mao & Li, 2015). These applications highlight the versatility of the model and promote the potential to improve technology integration in aged care settings.

2.2.3.2 Research model design:

As shown in Figure 2.2, this study combines the technology acceptance model based on previous research to create a research model. Given that the main focus of this study is purchase intention, this study deliberately excludes four moderating variables: user experience, gender, age, and voluntariness. In addition, in order to enhance the relevance of the model to smart elderly care products in a specific context, this study will also focus on the direct impact of four main variables on usage behavior. This addition allows us to have a more comprehensive understanding of the unique attributes and considerations that influence consumer behavior in this field. The model better reflects the complexity of the adoption of smart elderly care solutions. Because smart elderly care products are a relatively new category in the Chinese market, this comprehensive model provides a valuable framework for studying the key factors that influence community residents to purchase these products.

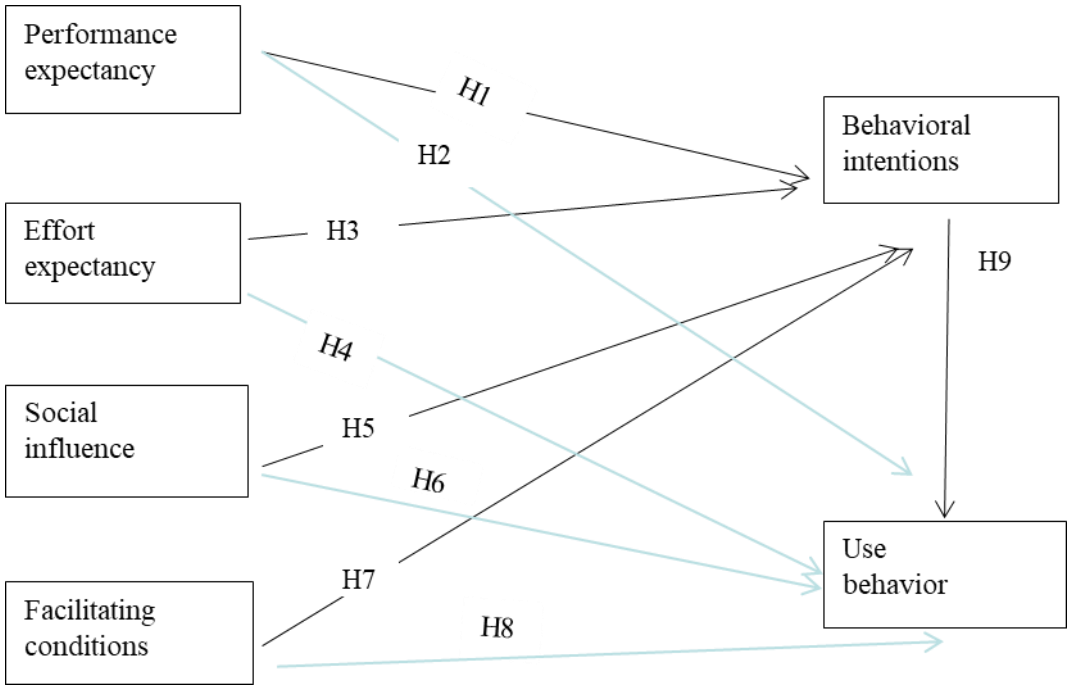

Figure 2.2 Research design model

2.2.3.3 Adoption

The various studies that have been applied using the UTAUT model have demonstrated that performance expectancy and behavioral intentions are the strongest factors to affect actual usage predictive power mainly when applied in different contexts like e-learning, health care systems, and e-banking in general (Dwivedi et al., 2019). Other external factors that have also been mentioned to bear an important impingement towards improving model predictive capabilities include trust and self-performance (Rana et al., 2015). Other external factors that have also been mentioned to bear an important impingement to despite its wide application in various industries, most of the research studies are limited by the size of the samples, cross-sectional data, or certain groups of users in which it was conducted, and therefore limits generalizability of the findings (Williams et al., 2015).

To overcome the limitations of these studies, encouragement of longitudinal research methods in future studies should be carried out, broadening of the study user base is also required (Dwivedi et al., 2017). Empirical evidence is available to prove the application of the UTAUT model in the environment of smart elderly care products. Evidence across regions and populations has established performance expectancy, effort expectancy, social influences,

and facilitation conditions to correlate in shaping adoption behavior (Chen et al., 2023; Wang et al., 2023). For example, a systematic review carried out by Peek et al. (2014) found support for these structures in the majority of studies on technology adoption in older adults. Besides this, quantitative studies those by Alaiad et al. (2023) and Wang et al. (2023) have shown statistical evidence to support that these various variables exert strong predictive power for explaining adoption intent.

2.2.4 Different themes in UTAUT model

2.2.4.1 . Performance Expectancy and Effort Expectancy

Venkatesh et al. (2003) showed that performance expectancy is defined in the UTAUT model as the degree to which an individual believes that using technology will provide benefits in job performance or personal effectiveness. In the context of smart elderly care products, perceived value plays a critical role in determining purchase decision. This is supported by research findings that show a tendency to purchase smart products with practical health benefits among the elderly, such as devices that monitor vital signs or send an alert to healthcare providers in case something goes wrong (Li, 2024). Smart home technology either with safety features or with health monitoring features is helpful in case something unfortunate happens. For example, in the case of living alone, immediate care by an alarm or notification was considered helpful (Cicirelli et al., 2016).

Venkatesh et al., (2003) has demonstrated that effort expectancy is about the degree of ease associated with an individual's belief of using technology. The findings indicate that in telehealth, clinicians and patients try to make use of technology when driven to learn a certain technological gadget and when the expectation to receive a reward for such effort is high, since adoption increases (Kohnke et al., 2014). When older adults made use of home telecare, when a lack of technical knowledge could lead to insufficient use and may require specific strategies to manage the problem (Karlsen et al., 2017). Research has shown that within the context of the adoption of smart technology, an intuitive and concise design interface reduces the mental burden placed on users and, thus, directly affects how easy the perception of use will be, making them more likely to continue using and recommend the technology (Li, 2019).

Therefore, developers of smart geriatric products must minimize the learning curve for older users to drive higher product adoption.

The consistent pattern in the literature is to emphasize how performance expectancy and effort expectancy are the leading drivers of users in the adoption of smart elderly care products. It has also been illustrated through various studies that community residents, just like the elderly users, would appreciate a product perceived to support improved health and independence for older people (Venkatesh et al., 2003; Wu et al., 2022). Ease of use is also considered an equally important factor as most of the time family members prefer products that don't require them to have extensive training or learning technology support to operate (Huang et al., 2022). Whether purchasing for themselves or older relatives, these two factors are crucial and thus need to be considered by researchers in understanding the decision of community residents.

2.2.4.2 Social Influence

According to the UTAUT, social influence is defined as the degree to which ones believes that important others think they should use new technology, and thus should have a significant impact on the adoption of smart elderly care products (Venkatesh et al., 2003). Some studies have shown that family composition and cultural expectancy of aged care could be some of the influential social factors in older adults' demand for smart elderly care products (Fu & Chui, 2020). Research also shows that intergenerational influence on technology use occurs given that family functions as an important daily life aide, with the ability to introduce and teach parents about various technologies, especially from adult children. This support was believed to increase the confidence of older adults and thus make them more willing to adopt new technologies, such as smartphones, digital devices, or online services, an important factor in shaping older adults' attitudes toward technology adoption (Kulczycki et al., 2020).

Social support, therefore, is a significant facilitator in bringing about an increase in the adoption of smart elderly care products for those older adults who may not be familiar with technology. Research shows that community residents are influenced by health professionals' recommendations on products based on knowledge about elder care and that social influence

will still prevail in the recommendation process where family members and caregivers are involved in recommending smart elderly care products (Pal et al., 2018).

2.2.4.3 Facilitating Conditions

Facilitating conditions refer to the extent to or degree at which persons believe that the organizational and technological infrastructural setup exists to support the use of new technologies (Venkatesh et al., 2003). For smart elderly care products, besides cost factors, easy access and technical support are very important factors that affect buying motives (Meng et al., 2020). High costs, especially, have shut the door on the possibilities for low-income elderly people to use most smart elderly care products, whose prices have gone beyond their financial capability (Fournier et al., 2020). Affordability has been one of the main issues identified, while fiscal incentives through government subsidies, among other means, may provide relief to reduce the burden and increase user adoption (Zhang et al., 2020).

In addition, the literature provides evidence that lack of assistance regarding the setting up, use, and troubleshooting of these smart devices has led to many elderly people developing issues, which in turn usually results in frustration of users and less utilization of technology. It would, therefore, be advisable to consider personalized digital skill training. Also, whether technical support and training are available or not drastically affects the ability of older adults to navigate their ways through and use the benefits of smart technology (Finkelstein et al., 2023).

Sufficient infrastructure and support will minimize barriers to adoption, hence increasing investment in smart elderly care products. For example, the availability of technical support and installation services also positively influence purchasing decisions. Knowing that help will be available in installing and maintaining the technology could increase possibilities among community members in buying smart elderly care products (Alaiad et al., 2019).

2.2.4.4 Total theme:

In fact, the literature on the UTAUT model identifies performance expectancy, effort expectancy, and facilitating conditions as the core themes that influence smart technology

adoption. Such themes are well supported by empirical evidence. For example, perceived benefits, such as improved health and independence, because of smart technologies' adoption are a primary motivating factor among the elderly repeatedly documented in the literature about the subject (Zhou et al., 2024). Similarly, the importance of user-friendly design is well documented; many studies emphasize that device interfaces must be simple and easy to use to improve usability for older adults (Alaiad et al., 2019). While social influence does not dominate the literature, it remains an important factor in adoption, especially when family members or caregivers are involved. Qualitative research often illuminates this topic through personal narratives, highlighting how social dynamics influence technology acceptance (Garcia Reyes & Reaiche, 2022). However, quantitative research suggests that the impact of social influences decreases over time as users gain confidence in using technology (Bagozzi & Dholakia, 2002).

Overall, a large body of evidence highlights the role of performance expectancy, effort expectancy, and convenience in the adoption of smart elderly care products. In contrast, the evidence on social influence is more mixed. Although social influence appears to have less impact on community residents than on elderly users, it is still important, especially when healthcare providers are involved (Attuquayefio & Addo, 2014).

2.2.5 Development of hypotheses - Hypothesis related to smart elderly care products characteristic factors

2.2.5.1 Relationship between Performance Expectancy and Behavioral Intention and Use Behavior

Performance Expectancy (PE) pertains to the anticipated performance improvements and transformative changes that users expect from a technology or product. This variable serves as a metric for assessing the degree to which a given technology or product is perceived as beneficial to the user.

Wang et al. (2023) affirmed that performance expectancy positively influences the willingness of older adults to adopt smart elderly care products. In this respect, the elderly are motivated by confidence in the fact that such products will generate substantial advantages

(Wang et al., 2023). Moreover, another research study showed that performance expectation also has a positive impact on students' behavioral intention to use the e-learning system, which again fully develops the results predicted by the UTAUT model (Abbad, 2021). Besides, Hazen et al. (2014) showed that performance expectation was one of the important predictors of the use of EA, hence applicable in a range of domains.

Oyewole (2018) also found that performance expectation was a significant determinant in the use of smartphones for mobile learning by graduate students at the University of Ibadan, Nigeria. Further, a study by Shatta and Shayo (2021) indicated that in developing countries like Tanzania, performance expectancy directly influences the patterns of adoption of e-procurement.

Collectively, these findings fill the gap in the literature on the facilitatory role of performance expectancy in driving technology adoption behaviors across diverse contextual and demographic contexts of users. Based on this, Hypotheses 1 and 2 have been proposed.

Hypothesis 1, Performance expectation is positively related to their behavioral intention.

Hypothesis 2, Performance expectancy directly influences use behavior.

2.2.5.2 Relationship between Effort Expectancy and Behavioral Intention and Use Behavior

Effort Expectancy (EE) refers to a user's anticipated ease of adoption of a technology or product. This variable is an indication of a person's level of effort required to adopt a specific technology or product. Physiological conditions include physical fitness, hearing, and memory, all of which appear to deteriorate with advancing age.

Boontarig et al. (2012) found that the effort expectancy was positively related to the behavioral intention of older adults in Thailand in using e-health service through smartphones. In the same vein, McDowd and Birren (1990) have also revealed that older adults usually display a reduced capacity to perform activities involving information processing, suggesting that their physical and cognitive functions are essentially instrumental to their interaction with technology. That relates a lot to smart elderly products, which have various functionalities, but the design must be user-friendly. The intuitive understanding and ease of using such

products can ease the burden brought about by use and reduces the associated complexity in those products.

Moreover, Oyewole (2018) depicted that effort expectancy was in a significant relation to graduate students using smartphones for mobile learning, reinforcing the importance of this variable in technology adoption (Bozan et al., 2015).

It is in this regard that Hypotheses 3 and 4 have been forwarded.

Hypothesis 3, Effort expectancy is positively related to their behavioral intention.

Hypothesis 4, Effort expectancy directly influences use behavior.

2.2.5.3 Relationship between Social Influence and Behavioral Intention and Use Behavior

Social Influence (SI) refers to the effect that the adoption of a particular technology or product has on individuals whom the user perceives as possessing high social status or as being significant within their social context. This variable serves as a measure of the degree to which users are affected by the attitudes and behaviors of their social groups.

Research by Attuquayefio and Addo (2014) found that social influence was not significantly associated with the behavioral intentions of MUCG students to utilize Information and Communication Technologies (ICTs) for learning and research purposes. In contrast, empirical evidence from Yu (2012) indicates that social influence is the most potent factor affecting individuals' willingness to adopt mobile banking, a finding that aligns with the conclusions drawn by Sripalawat et al. (2011). These contrasting results suggest that the influence of social factors may vary significantly across different contexts and technologies.

Additionally, Bozan, Davey, and Parker (2015) show that social factors in the forms of coercion and mimicry play the most significant roles in influencing the use of patient portals among older adults. This points to the importance of social dynamics in shaping technology adoption behaviors, especially in healthcare and elder care technologies.

Thus, the following hypotheses were formulated.

Hypothesis 5, Social influence is positively related to their behavioral intention.

Hypothesis 6, Social influence has a significant impact on user behavior.

2.2.5.4 Relationship between Facilitating Conditions and Behavioral Intention and Use Behavior

Facilitating Conditions (FC) refers to the extent to which a user may feel that by and large most technologies or products will get adequate support from social groups and further technological developments will become available. In other words, this variable captures how perceived the ease of availability and access to the support mechanisms are that allow users to use technology or the product effectively.

For instance, research by Oye, Iahad, and Ab. Rahim (2014) demonstrated that facilitating conditions positively influence the acceptance and use of Information and Communication Technologies (ICT) among academic staff at ADSU. Similarly, Boontarig et al. (2012) found a positive correlation between the facilitating conditions for smartphone access to e-health services and the behavioral intention to use such services among older adults in Thailand. Furthermore, Attuquayefio and Addo (2014) illustrated that accessibility directly impacts the behavioral intentions of MUCG students regarding their use of ICT for learning and research purposes.

In addition, Venkatesh, Brown, and Bala (2013) revealed that facilitating conditions exert a positive effect on usage behavior, particularly among older workers who possess increased experience. This suggests that the perceived availability of supportive resources significantly contributes to the effective adoption and sustained use of technology across different user demographics.

Therefore, Hypotheses 7 and 8 were proposed.

Hypothesis 7, Facilitating conditions are positively related to their behavioral intention.

Hypothesis 8, Facilitating conditions directly influence the use behavior.

2.2.5.5 Relationship between Behavioral Intention and Use Behavior

Behavioral Intention (BI) refers to an individual's predisposition to engage in a specific behavior. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), behavioral intention is posited to have a positive influence on actual user behavior.

Wang et al. (2023) investigated the behavioral intentions of older adults regarding the adoption of smart elderly care products, revealing that these intentions exert the most significant positive effect on actual usage behavior. Similarly, Prasetyo et al. (2021) confirmed that behavioral intentions are positively correlated with the utilization of e-learning platforms.

Therefore, Hypothesis 9 is proposed.

Hypothesis 9, Behavioral intention is positively related to use behavior

2.2.6 Different research methodologies:

Various research methodologies yield different insights when examining the factors influencing community residents' purchase of smart elderly care products. For instance, quantitative methods have been greatly relied on in analyzing how social factors influence the adoption behavior through the use of questionnaires. One of the most identifiable advantages of quantitative research is that the results can be generalized on larger groups. However, it could also be a limitation of these methods of research since it might conceal the complex social interactions that the qualitative approach can avail (Creswell, 2014). By contrast, qualitative methods such as interviews and focus groups would provide far deeper insights into the views of residents and their experiences with smart elderly care products. Qualitative methods would considerably be better attuned to capture subtler dynamics of social influence compared to quantitative methods-such things as peer recommendations and family discussions (Bai et al., 2020). However, qualitative studies often have limitations in generalizability since the sample size is generally smaller, as Denzin & Lincoln, 2011 have observed (Denzin & Lincoln, 2011). To such strengths in both methodologies, there has emerged a mixed methods research strategy. For example, one could commence with the collection of data on a quantitative basis and then undertake qualitative interviews with the view of investigating unexpected findings in more detail (Bryman, 2006a). This combined approach will be particularly helpful in understanding how different demographic groups, including younger residents, influence the adoption of smart elderly care products. Besides, Community-Based Participatory Research (CBPR) has been conducted in this area. The

CBPR approach looks upon researchers and community members as collaborators, which provides the nuances needed to understand the local contexts and social relationships. (Wallerstein & Duran, 2010). Indeed, this can be one valid avenue for earning valuable insights on the proper marketing of smart elderly care products across different age groups. However, this method is bound to require very extensive engagement and time-consuming investigations within the locality. Hence, this is perhaps not that appropriate to time-sensitive research such as the current study.

Different studies have indeed shown various insights on smart technology adoption by older adults; however, certain limitations still exist. Pal et al. (2018) adopted a mixed-method approach to collect data through survey and interview to explore old user experience in using the medial smart home technologies. While the current study had a limited sample size and narrowed down to one region only, it still gave essential feedback from the real world, especially concerning privacy and usability problems. Similarly, Huang et al. (2022) conducted a cross-sectional study through chi-square surveys and logistic regression analysis to investigate the factors that have been influencing smart elderly care choices of older adults. However, the model had limited generalization, since the focus was on a small sample in Xuzhou, China. Purvanto and Loiza (2020) applied the structural equation modeling upon survey data on usage associated with mobile banking in Indonesia. As in much previous research, their findings were based on a small sample size and a focus on urban users, further limiting wider applicability. More recently, Zhou et al. (2024) conducted a quantitative survey to assess the willingness of older adults to adopt smart home technologies. However, this study again has limitations for generalization since its user base comprises only older consumers in China. Taken together, these contributions provide strong evidence of the need for further, more diverse research studies that can enhance our understanding of smart technology adoption among older adults worldwide.

In summary, existing literature on this field comprises a rich framework in understanding the social factors likely to influence the adoption of smart elderly care products. The future research will, therefore, be able to address the identified gaps through an integration of quantitative, qualitative, and mixed methods that help develop more inclusive and effective adoption strategies.

2.2.7 Conclusions

From the literature review of this study, important factors were highlighted that influenced community residents in making a decision to adopt smart elderly care products. The Unified Theory of Acceptance and Use of Technology (UTAUT) model continues to provide an integrated framework where such decisions are put into consideration. Thus, the model does emphasize the performance expectancy (users expect improvements in care and convenience) and the effort expectancy (ease of use influences adoption), both being key in driving fundamental purchasing behavior. In addition, facilitating conditions (such as technological infrastructure and support services) further play a key role in encouraging adoption by providing the necessary environment for the successful use of these technologies.

While social influence is still seen as an important factor, its impact seems to vary by cultural context. In family-centric cultures, such as China, where the family structure is inseparable, and family members are interdependent, social influence can be very strong. However, the results show that social influence is less dominant among community residents, who are not necessarily as dependent on family member recommendations as older users. This highlights a unique difference, that is, the purchasing behavior of community residents may be more influenced by personal motivations, especially among relatively younger groups.

Even with these findings, there are still apparent gaps in research within the present study. One prominent area that warrants further exploration would be the is the need for research that aims at younger family members and their impact on purchase decisions. Up to now, much research has centered on the elderly themselves, with little insight into the potential for driving the purchase of such technologies on behalf of older relatives by younger generations.

Lastly, the expansion in research scope to cover all age groups among community residents will go a long way in providing a comprehensive insight into the factors that affect the adoption of smart elderly care products. The future research could, for instance, move from its current narrow focus on the elderly to the larger community ecology in which these products are used. Including younger and more technology-savvy participants in the analysis may perhaps underline cross-generational effects and inform strategies that have to be taken

to help improve the rate of adoption across demographic groups. These gaps addressed, future research can deepen and add nuance to the understanding of the smart elderly care product market and support more inclusive and effective adoption strategies.

Chapter 3 Method

3.1 Research method

The quantitative approach was used in this study. Quantitative methods are about structured examinations, utilizing numerical data and statistical techniques to explore phenomena in a variety of studies (Creswell, 2017). Quantitative methods focus on objectivity, reproducibility, and the ability to generalize research findings through careful quantification in measurement with the aim of achieving research objectives (Bryman, 2016b). The main goal of such research study usually is to uncover trends, patterns, and associations in the populations or samples being studied, and that could be achieved through systematic surveys, experiments, or analysis of existing data (Bougie & Sekaran, 2019). Simultaneously, this approach is characterized by high and extensive reliance on statistical means for extrapolation and substantiation of drawn conclusions hence allowing one to make evidence supporting their claims (Boslaugh, 2007).

The justification of the quantitative approach in this research design as it helps in systematic collection and analysis of digital data, which are critical in showing how patterns and relationships between various factors of purchase intent are affected (Creswell, 2017). This approach can also be used to assess structures like performance expectancy, effort expectancy, social impacts, and facilitation conditions, which are defined under the UTAUT model; hence, this gives a method through which the impact of these different factors on the decision-making process of the community members may be measured (Venkatesh et al., 2003). The questionnaire survey in this study has been done with the purpose of ensuring data from a large sample are collected in order to make findings more generalizable. This would be particularly helpful during the analysis of differences in opinions and perceptions across communities with diverse demographic characteristics, and thus their results can be generalized to be representative of a broader population (Bryman, 2016b)**.**

3.2 Questionnaire Survey

The primary data collection tool in this study is a questionnaire. A questionnaire has been considered a research tool or survey tool, usually consisting of a set of questions or prompts that are designed to gather information from an individual or group.

As a standardized data collection tool, questionnaires collect data by asking many people a series of questions related to a specific topic or research objective. Questions can be closed-ended or open-ended, and answers can be qualitative or quantitative. Questionnaires are widely used in many different fields, such as healthcare, research, and the social sciences, to collect data and insights from a target population.

The questionnaire for this study consists of 28 questions divided into two distinct sections. The first part is the demographic characteristics of different groups in the community, including gender, age, education level and monthly income, and a total of 4 questions deal with this information. The purpose of the second part is to assess the willingness of people of different ages in the community to purchase smart elderly care products, with a total of 24 questions, each corresponding to a specific dimension of concern.

3.3 Definition and Measurement of Variables in scale

This study started with the development of a comprehensive research model and the formulation of its corresponding hypotheses. Four key determinants were first identified that have a significant impact on behavioral intention and use behavior, including performance expectancy, effort expectancy, social influence and facilitating conditions. These different factors form the theoretical framework for the investigation.

An extensive and rigorous review of relevant domestic and international literature was conducted to ensure the reliability, stability, and validity of these variables. A thorough review of previous studies was conducted to ensure that the theoretical foundation of this study has a solid backing, which can be used to ensure that each variable will be clearly defined and supported by existing academic discourse. Based on the different insights gained from the multi-dimensional understanding of the literature review, this study designed a structured and methodologically sound questionnaire containing 24 different items, and each item was

carefully designed to be used to directly correspond to the dimensions identified in the research model (as shown in Table 3.1).

Table 3.1 Definitions of variable's operability. (Wang et al. 2023)

Category	Research variable	Definition of operability	Code	Measurement item
UTAUT model	Performance Expectancy	The community residents believe that the use of smart elderly care products can help them acquire better services in the future	PE1	The use of smart elderly care products can help me enjoy elderly care services better
			PE2	I think using smart elderly care products can save time and make daily life more convenient and faster
			PE3	I think using innovative smart elderly care products and technologies can promote healthy elderly care effects
			PE4	I think using smart elderly care products can improve the convenience of elderly care services
	Effort Expectancy	The ease of use of smart elderly care products considered by community residents	EE1	I can easily learn to use smart elderly care products without spending too much time
			EE2	For me, the operation process of smart elderly care products is simple and

				easy to understand and use
			EE3	I fully understand and know how to use smart elderly care products
			EE4	For me, the innovative application of smart elderly care products is not a challenge
			SI1	People around me influence my decision to use smart aged care products
			SI2	People who use smart elderly care products appear to be more capable than those who do not use them
	Social Influence	The extent to which the community residents are aware of whether others think they should use smart elderly care products	SI3	I want to keep up with the times, so I will use smart elderly care products because using smart elderly care products is a future trend
			SI4	The use of smart aged care products can improve one's social image
	Facilitating Conditions	The extent to which the community residents believe that the existing supporting resources can	FC1	I have the resources to use smart elderly care products
			FC2	I believe that smart elderly care products are

	support the use of smart elderly care products		comparable to other technology
		FC3	I have the skills to use smart elderly care products
		FC4	I can ask friends for help when I encounter difficulties in using smart elderly care products
		BI1	I think it is a good idea to use smart elderly care products
Behavioral Intentions	The behavioral tendency of the community residents uses smart aged-smart products	BI2	I think using smart elderly care products can improve my personal health
		BI3	I think smart elderly care products are very valuable
		BI4	I will use smart elderly care products in the future
		UB1	I am very willing to use smart elderly care products to manage my health
Use Behavior	The community residents use smart elderly care products	UB2	I am very willing to learn how to use smart elderly care products
		UB3	I prefer smart elderly care products to other health care products
		UB4	I will continue to use smart elderly care products

3.4 Sample & Data Collection

The data collection was conducted from September 1 to September 10, 2024, targeting two specific communities in Xiangqiao District, Chaozhou City, namely Nanmen Community and Kaiyuan Community. Respondents will answer using a 7-point Likert scale, so that their attitudes and opinions can be understood in detail. After eliminating 74 invalid questionnaires, this survey finally obtained 526 valid questionnaires, with a questionnaire efficiency of 87.6%. This robust sample size provides a strong basis for analyzing the factors that affect the adoption of smart elderly care products by the elderly.

As detailed in Table 3.2, the proportion of female respondents who indicated a willingness to purchase smart-aged products is 46.58%, while the proportion of male respondents is marginally higher, at 53.42%. This relatively even distribution suggests that the intention to purchase smart-aged products does not significantly differ between genders, indicating minimal variance in purchase behavior across this demographic factor. Such consistency underscores the conclusion that gender, in this instance, is not a key determinant of purchasing intention within the context of smart-aged products.

Regarding the age distribution of respondents, participants were classified into four distinct age groups: 18-30 years (12.74%), 31-43 years (21.29%), 44-56 years (48.86%), and those aged 57 years and above (17.11%). It is particularly noteworthy that the largest proportion of respondents falls within the 44-56 age bracket, comprising nearly half of the total sample. The distribution among the other age groups is relatively balanced, though the significant representation of the 44-56 demographic may suggest that middle-aged individuals are more inclined or positioned to engage with smart-aged products, potentially due to their closer proximity to the target market or greater familiarity with technology.

In terms of educational attainment, respondents are distributed across four categories: high school and below (44.11%), junior college (35.74%), bachelor’s degree (18.25%), and master’s degree or above (1.9%). The substantial proportion of respondents with a high school education or lower (44.11%) reflects the broader educational landscape in China and presents a limitation in assessing the impact of higher educational attainment on the intention to purchase smart-aged products. The comparatively smaller representation of respondents with

a bachelor's degree or higher (20.15%) suggests that educational level may not be a significant factor influencing purchase decisions in this study.

Finally, with respect to monthly income, respondents were categorized into four income brackets: less than 3,500 CNY (23.38%), between 3,501 and 5,000 CNY (44.49%), between 5,001 and 8,000 CNY (22.24%), and above 8,001 CNY (9.89%). This income distribution reveals that most respondents fall within the middle-income bracket of 3,501 to 5,000 CNY, accounting for nearly half of the sample.

Table 3.2 Basic information of respondents.

Item	Option	Frequency	Percentage (%)
Gender	Male	281	53.42
	Female	245	46.58
Age	18-30 years old	67	12.74
	31-43 years old	112	21.29
	44-56 years old	257	48.86
	Over 57 years old	90	17.11
Education background	Senior high school and under	232	44.11
	Junior college	188	35.74
	Undergraduate college	96	18.25
	Master's and above	10	1.9
Disposable monthly income	Below CNY 3500	123	23.38
	CNY 2501-5000	234	44.49

	CNY 5001-8000	117	22.24
	Over CNY 8001	52	9.89
Total		526	100

Chapter 4 Results

SmartPLS is a software tool for structural equation modeling (SEM), which stands for "Smart Partial Least Squares". Its principle is to allow researchers to evaluate and verify theoretical models by analyzing measurement models (reflective and formative structures) and structural models (relationships between structures). SmartPLS software use has the following benefits: it has an intuitive graphical interface; it is suitable for exploring complex models in the early stages of research; it supports users to evaluate model performance; it provides a variety of indicators and criteria to evaluate model fit.

This study used SmartPLS version 4.0 for data analysis.

4.1 Measurement model evaluation

4.1.1 Reliability and validity

Cronbach's alpha and composite reliability (CR) were used to evaluate the reliability and validity of the constructs. Composite reliability evaluates the overall reliability of the latent variables in the model, while Cronbach's alpha is used to evaluate the internal consistency. Reliability is acceptable when the value is greater than 0.7.

The result data of this study are shown in

Table 4.1. The Cronbach's alpha of BI is 0.795, which is slightly higher than the acceptable threshold, and the composite reliability is 0.867, showing strong reliability. The Cronbach's alpha and composite reliability of EE are 0.819 and 0.880, respectively, indicating good internal consistency and reliability. FC has high internal consistency, with a Cronbach's alpha coefficient of 0.852 and a composite reliability of 0.900. The Cronbach's alpha of PE is 0.826 and the composite reliability is 0.885, which are also within the acceptable range. The Cronbach's alpha of SI is 0.849 and the composite reliability is 0.898, showing high reliability. The Cronbach's alpha of UB is 0.839, and the composite reliability is 0.892, both of which show high internal consistency.

Specifically, the Cronbach's alpha and composite reliability of all constructs in this study reached a satisfactory level, which also confirmed their internal consistency and reliability.

Table 4.1 Reliability and validity.

Construct	Cronbach's alpha	Composite reliability
BI	0.795	0.867
EE	0.819	0.880
FC	0.852	0.900
PE	0.826	0.885
SI	0.849	0.898
UB	0.839	0.892

4.1.2 Outer loading

This study comprehensively displays the external loading value of each item in the measurement model in Table 4.2. To understand the intensity of the relationship between the observed indicators and their respective latent constructs, this study comprehensively displays the external loading values of each item in the measurement model in Table 4.2. The external load value of each item. The widely accepted threshold for the project is 0.5, which is necessary to demonstrate the reliability of the indicator. The external loadings of all items in this study ranged from 0.754 to 0.869, a result that confirmed that each item was significantly correlated with its associated construct, thereby enhancing the robustness of the model.

BI: The four items (BI1 to BI4) associated with BI had outer loading values starting 0.754 to 0.831, indicating moderate to high correlations. Specifically:BI1 had a loading of 0.831, BI2 was 0.803, BI3 was 0.760, BI4 had the lowest loading of 0.754.

EE: All four items (EE1 to EE4) for this construct demonstrated strong loadings between 0.769 and 0.834, signifying robust relationships with the latent construct. Notably:EE1 had the highest loading of 0.834, EE2 had a value of 0.804, EE3 was 0.811, EE4 had a value of 0.769.

FC: The four indicators (FC1 to FC4) for FC had loadings ranging from 0.783 to 0.874, representing reliable correlations. Specifically:FC1 was 0.874, FC2 was the value of 0.830, FC3 had a slightly lower loading of 0.783, FC4 had a value of 0.839.

PE: The four items (PE1 to PE4) had loadings between 0.788 and 0.838, indicating solid correlations with the latent variable. Specifically:PE1 had a loading of 0.788, PE2 had the highest value of 0.838, PE3 was 0.824, PE4 was the value of 0.792.

SI: The four SI items (SI1 to SI4) showed loadings between 0.765 and 0.869. These values indicate good reliability across items. Specifically:SI1 had a loading of 0.828, SI2 of 0.855, SI3 had a slightly lower value of 0.765, SI4 was 0.869.

UB: All four items (UB1 to UB4) showed outer loadings between 0.773 and 0.862, signifying strong relationships with the construct. Specifically: UB1 had a loading of 0.860, UB2 had the highest value of 0.862, UB3 had a loading of 0.773, UB4 had a value of 0.786.

Table 4.2 Outer loading

Item	Outer loading	Item	Outer loading
BI1 <- BI	0.831	PE1 <- PE	0.788
BI2 <- BI	0.803	PE2 <- PE	0.838
BI3 <- BI	0.760	PE3 <- PE	0.824
BI4 <- BI	0.754	PE4 <- PE	0.792
EE1 <- EE	0.834	SI1 <- SI	0.828
EE2 <- EE	0.804	SI2 <- SI	0.855
EE3 <- EE	0.811	SI3 <- SI	0.765
EE4 <- EE	0.769	SI4 <- SI	0.869
FC1 <- FC	0.874	UB1 <- UB	0.860
FC2 <- FC	0.830	UB2 <- UB	0.862
FC3 <- FC	0.783	UB3 <- UB	0.773
FC4 <- FC	0.839	UB4 <- UB	0.786

4.1.3 Convergent validity

Convergent validity is an essential component of construct validity because it assesses whether multiple theoretically related items or constructs share common variance, with the AVE value being greater than the recommended threshold of 0.5. As shown in Table 4.3, to assess convergent validity, this study calculated the average variance extracted (AVE) of each latent variable.

Specifically, the AVE for BI is 0.620, which is above the threshold, suggesting that BI's items capture a substantial amount of variance. With an AVE of 0.648, the items related to EE explain an adequate amount of the variance, confirming convergent validity for this construct.

The AVE value for FC is 0.692, which is well above the threshold, indicating that the FC construct explains a considerable portion of the variance in its indicators. The AVE for PE is 0.658, indicating that the items related to PE sufficiently explain the variance of the construct.

SI's AVE value is 0.689, confirming that the SI construct explains a good portion of the variance of its items. UB has an AVE of 0.675, demonstrating that the indicators of this construct adequately explain its variance.

The results showed that the AVE of all latent variables exceeded the recommended threshold of 0.5 and coping with 0.620 to 0.689. This is consistent with the guidelines developed by Fornell and Larcker (1981).

Table 4.3 Average variance extracted (AVE)

Construct	Average variance extracted (AVE)
BI	0.620
EE	0.648
FC	0.692
PE	0.658
SI	0.689
UB	0.675

4.1.4 Discriminant validity

4.1.4.1 AVE Square Root Discriminant Method

Discriminant validity is used to assess the differences between all latent variables and to measure the uniqueness of each reflective variable relative to other variables in the model. This form of validity is generally assessed using the Fornell-Larcker criterion, which compares the correlation coefficient value with the squared average variance extracted (AVE) value of the latent variable.

The data results of this study are shown in Table 4.4. When the squared AVE value of each factor (represented on the diagonal) exceeds the AVE value of other factors, the discriminant validity is confirmed (as shown in Table 4.2). This situation indicates that these factors have sufficient discriminant reliability, confirming that each latent variable is different and effectively captures its expected structure.

Table 4.4 AVE Square Root

Construct	BI	EE	FC	PE	SI	UB
BI	0.787					
EE	0.396	0.805				
FC	0.481	0.268	0.832			
PE	0.412	0.369	0.243	0.811		
SI	0.528	0.302	0.500	0.312	0.830	
UB	0.535	0.348	0.420	0.380	0.437	0.821

4.1.5 HTMT Method

HTMT indicates acceptable discriminant validity, with a common threshold of 0.85 (or 0.90 in some fields). If the HTMT value is lower than this threshold, it indicates that the structures are sufficiently different from each other. The data of this study are shown in Table 4.5. From the analysis results, all HTMT values are less than 0.90, and the discrimination is good.

Table 4.5 HTMT

	BI	EE	FC	PE	SI	UB
BI						

EE	0.485				
FC	0.579	0.313			
PE	0.506	0.447	0.288		
SI	0.636	0.359	0.584	0.368	
UB	0.646	0.417	0.488	0.450	0.509

4.2 Structural model evaluation

4.2.1 Variance Accounted For (VAF)

Variance explained (VAF) is a measure used to determine the degree of mediation effect in a model. VAF is calculated as the ratio of the indirect effect to the total effect, which indicates the percentage of the variance of the dependent variable explained by the mediation effect. According to Hair et al. (2017), when VAF is greater than 0.8, it indicates full mediation; when VAF is between 0.2 and 0.8, it indicates partial mediation; and when VAF is less than 0.2, it indicates no mediation.

The VAF values of this study are presented in Table 4.6, and the four different constructs show the degree to which the indirect effect affects usage behavior (UB) through behavioral intention (BI).

1. PE -> BI -> UB: The VAF value of this construct is 0.289, or 28.9%, indicating partial mediation. This indicates that the relationship between PE and UB is partially mediated by BI, which also means that PE affects UB directly and indirectly through BI.

2. SI -> BI -> UB: The VAF value of this construct is 0.400, or 40%, indicating partial mediation. This indicates that SI affects UB directly or indirectly through BI, but the mediation effect is moderate.

3. FC -> BI -> UB: The VAF value of FC is 0.319, or 31.9%, indicating partial mediation. This indicates that FC affects UB directly and indirectly, and BI plays a partial mediation role.

4. EE -> BI -> UB: The VAF of this construct is 0.340, or 34%, also indicating partial mediation. This indicates that EE affects UB directly or indirectly through BI, but the mediation effect is not dominant.

In summary, the VAF values of this study ranged from 28.9% to 40%, indicating the presence of a mediation effect. All constructs showed partial mediation, and BI played a mediating role in the relationship between each independent variable and UB.

Table 4.6 VAF meditation

Construct	Specific indirect effects	Total effect	VAF
PE -> BI -> UB	0.059	0.204	0.289215686
SI -> BI -> UB	0.087	0.217	0.400921659
FC -> BI -> UB	0.071	0.222	0.31981982
EE -> BI -> UB	0.050	0.147	0.340136054

4.2.2 Path coefficient

The path coefficient indicates the strength and direction of the relationship between the latent variables in the structural model. and the p-value determines the statistical significance of these path coefficients. When the p-value is less than 0.05, it indicates that the relationship between the structures is statistically significant (Hair et al., 2017). The p-values of the path coefficient statistics in this study are shown in Table 4.6. The data show that the p-value of each structure in this study is less than 0.05, indicating that each independent variable significantly affects BI or UB, and all paths in the model are statistically significant.

These results of this dissertation support the following hypothesis: the relationship between the structures is meaningful and plays a key role in determining both behavioral intention and usage behavior.

Table 4.7 P-value

Construct	P-value
PE -> BI	0.000
PE -> UB	0.000
EE -> BI	0.000

EE -> UB	0.011
SI -> BI	0.000
SI -> UB	0.002
FC -> BI	0.000
FC -> UB	0.000
BI -> UB	0.000

4.3 Discussion

4.3.1 Review

There are two main questions guiding the research of this dissertation: first, what are the main factors influencing the willingness of community residents to purchase smart elderly care products? Second, how much influence does social influence (e.g. recommendations from family and friends) affect the decision of community residents to purchase smart aged care products?

According to the research of this dissertation, four factors: performance behavior, expected effort, social influence, and convenience conditions all have a negative impact on the willingness of community residents to purchase smart elderly products. Convenience is a decisive factor in their purchase decision.

4.3.2 The hypothesized relationships of the four factors to IB and UB

4.3.2.1 PE and BI and UB

From the result of the structural model, the path from PE to BI has a p-value of 0.000, reflecting significance. This, therefore, implies that user expectancy from the performance of any product significantly might influence one's willingness to use the product. Therefore, performance expectancy in Hypothesis 1 is positive and correlated to behavioral intent. This relationship is highly significant and consistent with prior research by other scholars that older adults are motivated to enhance their quality of life through better services and

convenience provided by smart care products (Wang et al., 2023; Abbad, 2021). Performance expectancy has been cited to be one of the most direct influencing factors on behavioral intent in other contexts, such as in studies of performance in e-learning platforms and enterprise technology (Oyewole, 2018).

Whereas the path from PE to UB has resulted in a p-value of 0.000, hence appearing to be significant and direct, it depicts performance expectancy as also directly influencing usage behavior. Similarly, the performance expectancy in Hypothesis 2 directly affects usage behavior. Among these findings, a hypothesis is reinforced that users are more likely to use the technology when they believe it will improve their performance in managing their health or daily life (Shatta & Shayo, 2021). This is consistent with the UTAUT model and is further supported by research on technology adoption in healthcare settings (AlQudah, A. A., Al-Emran, M., & Shaalan, K. (2021).

Therefore, the two direct assumptions H1 and H2 about performance expectancy are supported by the data, and the assumptions are true, confirming that performance expectancy have a significant impact on behavioral intent and actual usage behavior.

In this study, when community residents believe that smart elderly care products can provide them with tangible benefits, such as providing convenience and improving health management, they are more likely to adopt the technology with the intention and performance expectancy to significantly affect the purchasing behavior of community residents. Because performance expectancy directly affects usage behavior, when community residents believe that purchasing smart elderly care products can help them better enjoy elderly care services, and can also save time and improve convenience, or when innovative elderly care products can promote their elderly care services, purchase willingness and purchase behavior will increase significantly.

4.3.2.2 EE and BI and UB

When exploring effort expectation and behavioral intention, the p-value of the path between effort expectation (EE) and BI is 0.000, showing a significant relationship. This suggests that EE has a significant impact on BI, which means that the expectation of effort, which is

primarily focused on the ease of use of a product or service, plays a crucial role in shaping behavioral intent. Therefore, the effort expectation in hypothesis 3 is positively correlated with the behavioral intention. As with previous studies, work such as Boontarig et al. (2012) agree to support the idea that older adults are more likely to adopt technology if they find it easy to understand and use (McDowd & Birren, 1990; Oyewole, 2018). These findings highlight the importance of ease of use in influencing technology adoption, especially in older populations that may face physical or cognitive challenges (Bozan et al. 2016).

The data results present a p-value of 0.011 for the path from EE to UB, indicating that there is a significant relationship, but compared to the direct relationship between EE and BI, effort expectation has a direct effect on the intention to behave, just a little bit of it, so hypothesis 4 holds. When users can easily operate smart elderly care products, it further reduces their learning curve and the frustration they feel while learning, thus increasing the likelihood that users will continue to use smart products (Boontarig et al., 2012). This also supports the previous finding that effort expectation is an important determinant of technology adoption and use (Oyewole, 2018).

Therefore, both the H3 and H4 hypotheses are supported, suggesting that effort anticipation plays a crucial role in shaping users' intentions and actual behaviors in adopting smart retirement products.

This study shows that when community residents believe that they have the intention to purchase smart elderly care products, the ease of use of the products will have an impact on the intention and actual behavior, which will have a direct impact on their purchases. Especially when they think that learning new technology products is not difficult and they don't have much time to learn. Even some community residents believe that when the products of smart products are easy to operate and can fully understand how to use them after learning, the purchase intention is obvious, which also shows that the expectation of effort also greatly affects the purchase of smart products by community residents. Community residents' perception of the ease of use of smart elderly care products will significantly affect their willingness to adopt smart elderly care products.

4.3.2.3 SI and BI and UB

When exploring social influence and behavioral intention, the p-value is 0.000, and the social influence (SI) in hypothesis 5 has a significant positive effect on behavioral intention. The influence of others, especially family and friends, plays a key role in the decision to adopt smart elderly care products. This agrees with the research by Chen, J., Wang, T., Fang, Z., & Wang, H. (2023) and Yang, Q., et al. (2022), where it is found that social influence acts as a very strong predictor of technology adoption. About smart elderly care products, social pressure and desire to keep up with the social tide have positive impacts on the user's intention. Bozan et al. (2015) also supported that social factors have a significant effect on the use of patient portals, hence supporting the role of social influence in the adoption of health-related technologies.

In the results of this study's data, the p-value was equal to 0.002, thus proving that hypothesis 6 is effective in usage behavior. When residents in a community feel that people around them are using smart elderly care products, they will soon join them. This also agrees with any research on social influence within technology adoption, as it has underlined the function of peers and social norms in shaping behavior (Goldsmith-Pinkham, P., & Imbens, G.W. (2013). Therefore, the hypotheses H5 and H6 of this dissertation are both established, proving that social influence plays an important role in shaping the willingness and behavior of community residents to adopt smart elderly care products.

This study found that when the community learned that people around them talked about using or were already using smart elderly care products, most people would be affected and then have the idea of wanting or deciding to buy them. Some community residents also believed that people who seemed to use smart elderly care products would have stronger abilities than those who did not use them, and this social influence also became a factor influencing them to buy them. And many people believe that if they use smart elderly care products, they can better adapt to the pace of the times and keep up with the development trend of an aging society, which also shows that social factors have an important influence on whether community residents buy smart elderly care products.

4.3.2.4 FC and BI and UB

The p-value of this dissertation is 0.000, which supports the hypothesis that convenience conditions are positively correlated with behavioral intention. Also, the convenience conditions, for example, technical support, the availability of resources, and compatibility with the existing technologies, were also found to have a significant impact on behavioral intention BI. These findings could therefore support the previous research results by Boontarig et al. (2012), who also believed that convenience condition factors would affect the use of e-health service by Thai elderly people. Enough support systems and resources further help the potential and confidence of users in their ability to adopt smart elderly care products and put them into good use. This understanding is also supported by previous literature, including that by Marikyan and Papagiannidis (2021) and Oye et al. (2014), which emphasize the importance of convenience conditions in cultivating user readiness and intention.

Moreover, the influence of behavioral intention as another condition of convenience is supported significantly at a p-value of 0.000 with this perspective that convenience conditions directly influence usage behavior. Convenience conditions support strongly usage behavior UB, in that when the individuals feel they are supported and have most of their resources needed, they continue to use the technology. The findings suggest that convenience is indeed one of the main predictors of using technology and may prove even more so with elderly citizens (Attuquayefio & Addo, 2014).

Thus, the findings of this dissertation, strongly support H7 and H8 that convenience has a significant positive impact on behavioral intention and usage behavior. These findings highlight the key role that support systems, resources, and technology compatibility play in promoting the adoption and continued use of smart elderly care products.

When community residents believe that there are convenient resources to help them use smart elderly care products, they are willing to purchase the product, or when the product is comparable to other technologies and their elderly care is affected by convenience, they are also willing to purchase it. Or when the compatibility of such products is the same as that of products used by family and friends, they can ask them for help when they encounter difficulties in use, which is also one of the decisive factors that influence community residents to purchase smart elderly care products.

4.3.2.5 BI and UB

The last hypothesis of this dissertation is that H9 has a p-value of 0.000, and the results show that behavioral intent is positively correlated with usage behavior. This result is consistent with the Unified Theory of Technology Acceptance and Use (UTAUT) model and confirms the findings of previous studies on technology adoption (Wang et al., 2023; Zacharis & Nikolopoulou, 2022).

The analysis confirms that as community residents become more willing to use smart elderly care products and believe that using the product is a good idea (valuable or able to improve their personal health), they are more likely to convert these intentions into actual use, enhancing their willingness to buy. This relationship between behavioral intent and usage behavior is well documented in the technology adoption literature, especially in the pioneering work of Venkatesh et al. (2003), emphasizing the importance of intent as a key determinant of user behavior. For example, in the case of more and more elderly care products entering the market, compared with other health care products, the willingness of community residents to use smart elderly care products determines the purchase behavior.

4.3.3 Significance

From a practical point of view, these results show that when the ease of use of smart elderly care products is improved, such as the interface is simple and easy to understand, and the system is easy to operate, the purchase rate of smart elderly care products can be improved. Theoretically, they help to have a deeper understanding of purchase intent in the context of smart elderly care products. From a policy point of view, it is helpful for a society or country that has entered an aging population, to have more in-depth research on the elderly market, and to provide reference for policymakers and market researchers to have more ideas in this regard.

Chapter 5 Conclusion

5.1 Limitation

This study is the first time to understand the concept of smart elderly care products, so the selection and classification of products in the smart elderly care market may not be completely accurate. At the same time, this study may not have enough understanding of the variable factors that can be cited in the UTAUT model, and the control between each variable is not accurate enough, so there is still a lack of diversity of influencing factors. In addition, this study only chose a quantitative research method to analyze the factors influencing community residents' purchase of smart elderly care products, but there may be other more suitable research methods to guide this study, and due to time and language limitations, the sample diversity of this study is slightly lacking. As a result, the findings may not be generalizable to some extent. For the above reasons, this report has its own shortcomings.

In addition to the above-mentioned subjective factors, this study also encountered the most prominent problem about community residents. At present, most of the relevant research subjects are specific elderly groups, but there is still a lack of research on other age groups or specific groups, so there are relatively few references for this study. In addition, because the data collection is concentrated in specific regions of China, the collection process and results may show local characteristics, which makes the research results have a certain regional nature, thus limiting the scope of reference.

5.2 Future Prospects

Future research should focus on more specific population characteristics in order to better understand the multiple factors that influence the purchase of smart elderly care products. First of all, it is recommended to consider a longitudinal study in the study, which can observe the long-term effect of time on residents' purchase intentions. Through the survey at different time nodes, we can see more clearly the changes in people's attitudes towards smart elderly products.

In addition, exploring the influence of various factors on purchase intention from different themes or perspectives will be an important direction for future research. For example, research can analyze possible differences in purchase intentions between genders from a gender perspective, and reveal which specific factors have a more significant impact on men or women. Furthermore, the income levels should be taken into consideration. Researchers thus can better explore, with the help of such research, how different income groups prefer smart elderly care products, which group is more likely to buy this kind of products, and how much acceptance is observed within the different income level.

In the future, research should determine the preferences about specific smart elderly care products that the public has and understand consumer behaviors in selecting features, prices, brands, or user experience. This will offer a complete market profile for smart elderly care products that will enable manufacturers to create products in line with consumer demand.

In a nutshell, future studies should be multi-faceted, multi-level, and confirm these findings with more in-depth analyses across different groups, taking temporal factors into consideration. This will fill the gap in the existing literature while providing a wider basis for the formulation of policies and market strategies.

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Annexes

Annex A: The factors affecting the community resident of purchasing smart elderly care products

The factors affecting the community resident of purchasing Smart elderly care products

Hello, I am a second-year master's student, and I am conducting a questionnaire on "The impact of different factors on the purchase of smart elderly care products by community residents". Your answers will be very important to this study, so please help you fill out the questionnaire. This questionnaire is anonymous, and all data is only used for statistical analysis, so please feel free to fill it in. There is no right or wrong question option, please fill in according to your actual situation.
Thank you very much!

1. Gender

- ◯ Woman
- ◯ Man

2. Age

- ◯ 18-30 years old
- ◯ 31-43 years old
- ◯ 44-56 years old
- ◯ Over 57 years old

3. Education background

- ◯ Senior high school and under
- ◯ Junior college
- ◯ Undergraduate college
- ◯ Master's and above

4. Disposable monthly income

- ◯ Below CNY 3500
- ◯ CNY 2501-5000
- ◯ CNY 5001-8000
- ◯ Over CNY 8001

5. Performance Expectancy

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The use of smart elderly care products can help me enjoy elderly care services better	○	○	○	○	○	○	○
I think using smart elderly care products can save time and make daily life more convenient and faster	○	○	○	○	○	○	○
I think using innovative smart elderly care products and technologies can promote healthy elderly care effects	○	○	○	○	○	○	○
I think using smart elderly care products can improve the convenience of elderly care services	○	○	○	○	○	○	○

6. Effort Expectancy

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I can easily learn to use smart elderly care products without spending too much time	○	○	○	○	○	○	○
For me, the operation process of smart elderly care products is simple and easy to understand and use	○	○	○	○	○	○	○
I fully understand and know how to use smart elderly care products	○	○	○	○	○	○	○
For me, the innovative application of smart elderly care products is not a challenge	○	○	○	○	○	○	○

7. Social Influence

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
People around me influence my decision to use smart aged care product	○	○	○	○	○	○	○
People who use smart elderly care products appear to be more capable than those who do not use them	○	○	○	○	○	○	○
I want to keep up with the times, so I will use smart elderly care products because using smart elderly care products is a future trend	○	○	○	○	○	○	○
The use of smart aged care products can improve one's social image	○	○	○	○	○	○	○

8. Facilitating Conditions

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I have the resources to use smart elderly care products	○	○	○	○	○	○	○
I believe that smart elderly care products are comparable to other technolog y	○	○	○	○	○	○	○
I have the skills to use smart elderly care products	○	○	○	○	○	○	○
I can ask friends for help when I encounter difficulties in using smart elderly care products	○	○	○	○	○	○	○

9. Behavioral Intentions

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I think it is a good idea to use smart elderly care products	○	○	○	○	○	○	○
I think using smart elderly care products can improve my personal health	○	○	○	○	○	○	○
I think smart elderly care products are very valuable	○	○	○	○	○	○	○
I will use smart elderly care products in the future	○	○	○	○	○	○	○

10. Use Behavior

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am very willing to use smart elderly care products to manage my heal	○	○	○	○	○	○	○
I am very willing to learn how to use smart elderly care products	○	○	○	○	○	○	○
I prefer smart elderly care products to other health care products	○	○	○	○	○	○	○
I will continue to use smart elderly care products	○	○	○	○	○	○	○