A Structural Equation Model Approach to Enhance Chinese Older Adults' Intention Towards Using AI Assistants in Nursing Care Units

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health marketing, older adults, nursing management, artificial intelligent, nursing care

ABSTRACT
The growing significance of artificial intelligence in nursing care underscores the need to understand its adoption factors. The paper deals with the factors influencing the adoption of AI assistants in nursing care units. This research collect 552 older adults participants stay in nursing homes across ten major Chinese cities within a convinient sampling method. The data were analyzed using descriptive analysis, confirmatory factor analysis (CFA), and structural equation modeling (SEM). The findings reveal that perceived ease of use, service quality, and self-efficacy significantly impact the intention to use AI assistants, with attitude acting as a key mediator. Notably, perceived usefulness directly affects adoption intentions without mediation by attitude. Furthermore, the digital divide moderates the strength of these relationships, with individuals possessing higher digital literacy demonstrating stronger intentions to adopt AI technologies. These results highlight the importance of service quality, ease of use, and digital access in driving AI adoption in older adults care. The findings provide insights for healthcare administrators and policymakers to enhance AI integration and address digital literacy gaps in nursing care units.

JEL I1, O3, C3

INTRODUCTION

As the aging population in China continues to expand rapidly, with individuals aged 60 and over representing 19.8% of the total population and those 65 and older accounting for 14.9% at the end of 2022, the country faces intensifying challenges in eldercare (Liu, 2023). This demographic shift has spurred substantial growth in the eldercare industry, with investment in the sector increasing significantly from 2019 to 2022. Concurrently, advancements in technology have given rise to the smart eldercare industry, incorporating innovations such as big data, AI, and remote medical services, which are becoming increasingly vital in addressing the complex needs of this age group (Liu, 2023). However, despite these advancements, the adoption of AI-assisted technologies in nursing care remains suboptimal among older adults.

Nursing care units play a critical role in the healthcare system by providing essential support to older adults who require assistance with daily activities or continuous medical care (Liu et al., 2020). These units offer indispensable services such as bathing, dressing, eating, and healthcare management, making them vital for older adults care, particularly in the context of a rapidly aging global population. In China, where the older adults population is expanding at an accelerated pace, especially in urban areas (Feng et al., 2020), the demand for these services has grown significantly.

The traditional family support structure has shifted, with fewer extended families living together and younger generations often unable to provide the necessary care due to work commitments (Sánchez-Hernández et al., 2019). As a result, nursing care units have become increasingly important in ensuring that older adults receive both medical attention and the daily support they need to maintain their quality of life.

However, traditional care models in nursing care units are struggling to meet the expanding needs of the elderly population. To address these challenges, the integration of Artificial Intelligence (AI) technologies into older adults care is emerging as a transformative solution. AI has the potential to significantly improve the efficiency and quality of care by automating routine tasks, enhancing patient monitoring, and enabling personalized care plans (Li et al., 2024). For instance, AI systems can monitor vital signs, predict health risks, and provide real-time alerts to caregivers, enabling faster and more accurate responses to emergencies. Additionally, AI can streamline administrative tasks, such as scheduling and record management, allowing caregivers to dedicate more time to direct patient care (Rony et al., 2024). Despite these benefits, challenges such as the digital divide and concerns over data privacy and AI reliability continue to hinder the widespread adoption of these technologies, particularly among older adults unfamiliar with digital tools (Mobsite et al., 2024; Singh et al., 2024). Hence, this study aims to explore the interaction between AI technology and nursing care, with a particular focus on the factors influencing the adoption of digital technologies by older adults.

LITERATURE REVIEW

Recent studies on the integration of AI into older adults care in China has demonstrated its potential to improve care quality through innovations like real-time health monitoring, predictive analytics, and personalized care planning, particularly as nursing care units face increasing demand (Yun & Yu, 2021). However, despite the increased availability of AI tools, their adoption remains limited due to inadequate staff training, high implementation costs, and resistance from older adults who are unfamiliar with or distrustful of AI technologies (Yu et al., 2023; Zhai et al., 2023). The existing research gap lies in the lack of comprehensive studies that explore how these technological, sociocultural, and psychological factors intersect to hinder AI adoption in older adults care settings.

When users perceive AI technologies as reliable, responsive, and empathetic, their intention to adopt these technologies increases. The SERVQUAL model has been widely used to examine this relationship, showing that high service quality enhances user satisfaction and strengthens their intention to continue using the technology. In older adults care settings, studies like Song et al. (2022) have demonstrated that perceived service quality directly correlates with the consistent use of AI-driven services.

Service quality is a key determinant of attitudes towards AI assistants. High-quality service—defined by reliability, responsiveness, and empathy—creates positive user experiences, leading to more favorable attitudes toward AI technologies. The SERVQUAL model, developed by Raza et al. (2020), has been widely used to examine how service quality influences customer satisfaction and attitudes in various industries. In the context of AI in older adults care, studies like Zhao et al. (2022) show that when AI systems are perceived as providing reliable, responsive service, users develop more positive attitudes towards their adoption.

Perceived usefulness plays a critical role in influencing the intention to use AI assistants, as individuals are more likely to adopt technologies they believe will enhance care delivery or daily activities. This relationship is well-established in the technology acceptance literature, with perceived usefulness consistently identified as a key predictor of usage intention. Yang et al. (2021) expanded TAM, emphasizing how perceived usefulness directly impacts behavioral intentions. In older adults care, Wang and Wu (2022) found that older adults and caregivers are more inclined to adopt AI assistants when they believe these tools will improve care quality and life.

Perceived usefulness is a crucial factor in shaping attitudes toward AI assistants in nursing care units. When older adults and caregivers perceive significant benefits, such as improved care quality, safety, and efficiency, they are more likely to develop positive attitudes toward AI technologies. Originally introduced by Davis (1989), perceived usefulness is one of the most critical determinants of user attitudes toward new systems, a notion further reinforced by Venkatesh and Davis (2000). In older adults care, Lin et al. (2023) confirm that the perceived usefulness of AI assistants significantly influences positive attitudes toward their adoption.

When a technology is perceived as easy to use, individuals are more likely to adopt and utilize it, a core principle of TAM. Venkatesh and Davis (2000) further demonstrated that perceived ease of use not only influences attitudes but also directly impacts behavioral intention, particularly with new or complex technologies. In nursing care units, where users may have varying experience levels with AI, the perceived simplicity of the technology is critical. Amin et al. (2024) confirm that user-friendly AI systems in older adults care significantly increase the intention to use them.

When older adults and caregivers find AI technologies easy to use, they are more likely to develop positive attitudes toward them. Rooted in the TAM, perceived ease of use is a key determinant of technology adoption. Davis (1989) noted that user-friendly technologies are more likely to be embraced, as they require minimal effort to learn and operate. In older adults care, where digital literacy levels vary, intuitive AI interfaces are essential. Tian et al. (2024) show that user-friendly AI systems foster more positive attitudes among caregivers and older adults users.

Self-efficacy directly influences the intention to use AI assistants, as individuals who believe in their ability to effectively use these technologies are more likely to adopt them. This relationship is well-documented in technology adoption literature, where self-efficacy consistently predicts behavioral intention. In older adults care settings, where AI can initially appear complex, self-efficacy plays a pivotal role. Jallad et al. (2024) show that caregivers with high self-efficacy are more inclined to integrate AI assistants into their care practices, driven by their confidence in mastering these tools.

Rooted in Bandura's social cognitive theory, self-efficacy refers to an individual's belief in their ability to successfully use technology. When caregivers and older adults users have high self-efficacy, they are more likely to develop positive attitudes toward AI assistants due to their confidence in effectively interacting with these technologies. Bandura (1977) highlighted self-efficacy as a key determinant of motivation and behavior, influencing technology adoption. Jia and Tu (2024) show that enhancing self-efficacy through training and support leads to more favorable attitudes toward AI in older adults care.

According to TAM, attitude mediates the relationship between perceived usefulness, perceived ease of use, and behavioral intention. A positive attitude toward AI assistants, influenced by perceptions of their usefulness and ease of use, strengthens the intention to use them. This relationship has been consistently supported by studies on technology adoption, including research by Davis (1989) and Venkatesh and Bala (2008). In nursing care units, where AI adoption can significantly impact care quality, a positive attitude from caregivers and older adults users is essential.

TAM posits that perceived usefulness directly influences attitude, which in turn shapes behavioral intention. This mediating role has been validated in numerous studies, where the link between perceived usefulness and intention is channeled through the user's attitude. Venkatesh and Davis (2000) showed that users who find a technology useful are more likely to develop a positive attitude, leading to a stronger intention to adopt it. In nursing care units, perceived benefits of AI assistants—such as enhanced care quality—translate into favorable attitudes, boosting the intention to use these technologies.

High service quality in AI technologies—characterized by reliability, responsiveness, and empathy—can strongly influence users' attitudes, leading to a greater intention to adopt these technologies (Zeithaml et al., 1988). The SERVQUAL model has been key in explaining how service quality impacts user behavior, with attitude acting as a mediator. In older adults care settings, the quality of AI services is crucial in shaping positive attitudes, which subsequently drive the intention to use these technologies (Zhu et al., 2023).

The ease with which a technology can be used directly influences a user's attitude, which in turn affects their intention to adopt the technology. Perceived ease of use is a key determinant of both attitude and behavioral intention. Venkatesh and Bala (2008) confirmed that when users find a technology easy to use, they are more likely to develop a positive attitude, which strengthens their intention to adopt it. In nursing care units, where the user-friendliness of AI assistants is critical, this relationship is particularly relevant. If caregivers and older adults users perceive AI as easy to use, their positive attitude will likely lead to a greater intention to adopt it in daily care.

Bandura (1977) suggests social cognitive theory, individuals who believe they can effectively use a technology are more likely to intend to use it. In older adults care settings, where the perceived usefulness of AI significantly influences self-efficacy, this relationship is critical. Lambert et al. (2023) indicate that when AI technologies in nursing care are seen as highly beneficial, users' confidence in using them increases, leading to a stronger intention to adopt these tools.

The digital divide, which refers to the gap between those with access to modern information and communication technology and those without, can significantly impact technology adoption. In the context of AI in nursing care units, this divide may affect how perceived usefulness translates into the intention to use AI technologies. For individuals with limited access, skills, or resources, even if they perceive AI as useful, their intention to adopt these technologies may be lower. Studies by Bao and Lee (2024) suggest that the digital divide moderates the relationship between technology perceptions and adoption intentions, highlighting the importance of addressing this gap for equitable AI adoption in healthcare.

While service quality is a key determinant of user satisfaction and subsequent technology adoption, its impact on intention may vary depending on an individual's position within the digital divide. Users with greater access to digital resources and higher digital literacy are more likely to translate perceived high service quality into a stronger intention to use AI assistants. In contrast, those on the disadvantaged side of the digital divide may not fully appreciate the benefits of high service quality due to limited digital skills or access, weakening the relationship between service quality and usage intention. Fisk et al. (2023) highlight how digital disparities can influence the effectiveness of service quality in promoting technology adoption.

Perceived ease of use is a critical factor in technology adoption, especially among older adults with varying levels of digital literacy. The digital divide can influence how ease of use impacts the intention to adopt AI technologies. Those with limited access to technology or lower digital literacy may struggle to perceive AI as easy to use, even if designed to be user-friendly, weakening the positive impact of perceived ease of use on adoption intentions. Bertolazzi et al. (2024) emphasize that the digital divide can exacerbate challenges in perceiving and using technology, particularly in healthcare.

Self-efficacy, or the belief in one's ability to use technology effectively, is a key predictor of technology adoption, but this relationship can be affected by the digital divide. Individuals with limited technology access or lower digital literacy may experience reduced self-efficacy, weakening their intention to use AI assistants, even if they feel confident in other areas. This highlights how the digital divide creates barriers to adoption by undermining self-efficacy. Ebekozien et al. (2024) stress that addressing the digital divide is essential for boosting self-efficacy and ensuring equitable technology access in healthcare. Based on the literature review, the following hypotheses are formulated (Figure 1):

H1: Service quality positively affects the intention to use AI assistant.

H2: Service quality positively influences attitudes towards AI assistants.

H3: Perceived usefulness positively affects the intention to use AI assistant.

H4: Perceived usefulness positively influences attitudes to use AI assistants.

H5: Perceived ease of use positively influences the intention to use AI assistants.

H6: Perceived ease of use positively influences attitudes to use AI assistants.

H7: Self-efficacy positively influences the intention to use AI assistants.

H8: Self-efficacy positively influences attitudes to use AI assistants.

H9: Attitude to use AI assistants positively influences the intention to use AI assistants.

H10: Attitude to use AI assistants mediates the relationship between perceived usefulness and the intention to use AI assistants.

H11: Attitude to use AI assistants mediates the relationship between service quality and the intention to use AI assistants.

H12: Attitude to use AI assistants mediates the relationship between perceived ease of use and the intention to use AI assistants.

H13: Self-efficacy mediates the relationship between perceived usefulness and the intention to use AI assistants.

H14: The digital divide moderates the relationship between perceived usefulness and the intention to use AI assistants.

H15: The digital divide moderates the relationship between service quality and the intention to use AI assistants.

H16: The digital divide moderates the relationship between perceived ease of use and the intention to use AI assistants.

H17: The digital divide moderates the relationship between self-efficacy and the intention to use AI assistants.

Based on the explaination，figure 1 portrays the conceptual framework for this study.

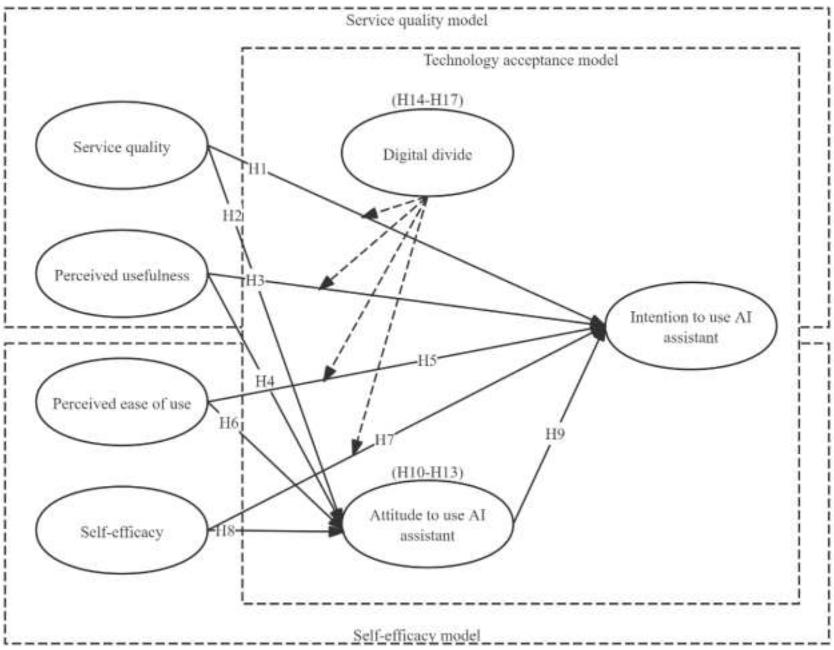

Figure 1 Research model

AIMS

This research aims to explore the factors influencing the adoption intention to use AI assistants in nursing care units among Chinese older adults, focusing on the roles of service quality, perceived usefulness, perceived ease of use, and self-efficacy. Specifically, it examines how these factors directly affect attitudes and intentions toward using AI assistants and investigates the mediating role of attitudes in enhancing usage intentions. Additionally, the study assesses how the digital divide may moderate these relationships, potentially impacting the effective implementation and acceptance of AI technology in healthcare settings. This comprehensive approach aims to provide insights into the dynamics between technology acceptance and user readiness, facilitating better integration strategies for AI in nursing care environments.

METHODS

This study employs a structured quantitative approach, focusing on data collection, questionnaire design, and data analysis. Primary data were gathered through a structured questionnaire distributed across nursing care units in ten major cities in China, including Beijing, Shanghai, Shenzhen, and Guangzhou. Participants were selected using purposive sampling, with assistance from nursing home staff to ensure the relevance of the sample to the study's focus on AI adoption in older adults care. The data collection period lasted two months, resulting in 552 valid responses from nursing care staff and residents.

Table 1 delineates the primary demographic characteristics of the participants involved in the study. The majority of respondents fall within the 70-89 age bracket, comprising 63.4% of the total. This is followed by those aged 55-69, who constitute 27.7% of the sample. The smallest group consists of individuals aged 90 and above, representing 8.9% of the participants. The gender distribution is nearly balanced, with 47.5% male and 52.5% female. Participants were sampled from major Chinese cities, with Chengdu (12.0%), Chongqing (11.2%), and Shenzhen (10.9%) having the highest representation. Educationally, 37.3% hold a bachelor's degree, 35.7% a master's, and 17.9% a PhD. Regarding nursing home stay, 27.9% have been there less than a year, and 25.5% between 3-5 years.

Table 1 Essential Information

		Frequency	Percent
Age	55-60	153	146
	61-65	172	132
	66-70	178	177
	71-75	49	70
	75+	27	27
Gender	Male	262	47.5
	Female	290	52.5
	Beijing	53	9.6
	Shanghai	49	8.9
	Shenzhen	60	10.9
	Guangzhou	54	9.8

City of Residence	Tianjin	47	8.5
	Chongqing	62	11.2
	Hangzhou	50	9.1
	Chengdu	66	12.0
	Xi'an	53	9.6
	Wuhan	58	10.5
	Beijing	53	9.6
Educational Background	Higher school	50	9.1
	Bachelor Degree	206	37.3
	Master Degree	197	35.7
	PHD	99	17.9
Duration of Stay in Nursing Home	Less than 1 year	154	27.9
	1-3 years	131	23.7
	3-5 years	141	25.5
	More than 5 years	126	22.8

The questionnaire delineated comprises a comprehensive array of 105 items, systematically organized into nine distinct sections to capture a broad spectrum of data pertinent to the adoption and efficacy of AI assistants in nursing care settings. The initial section solicits basic demographic information across five categories including age, gender, urban residency, educational attainment, and duration of residency within nursing facilities, which provides foundational context for subsequent analyses.

The second segment assesses the perceived usefulness of AI assistants, incorporating four items modeled after Hanjaya et al. (2019) to evaluate the practical benefits perceived by the elderly. This is followed by an extensive evaluation of service quality in the third section, which encompasses 26 items adapted from Amin and Isa (2008). These items are designed to scrutinize various dimensions of service delivery such as tangibility, reliability, responsiveness, assurance, and empathy, which are critical in gauging the qualitative aspects of AI-assisted services. In the fourth part, perceived ease of use is measured through four additional items also derived from Hanjaya et al. (2019), focusing on the user-friendliness of AI technologies for elderly users. Subsequent to this, the fifth section explores attitudes towards the use of AI assistants, providing insights into the subjective receptivity of elderly residents towards technological aids in their daily care routines. The sixth section addresses self-efficacy with six items sourced from Humaidi et al. (2021), assessing the confidence of the participants in their ability to utilize AI technologies effectively without external aid. The seventh segment tackles the digital divide, employing four items from Sánchez-Torres (2019) to explore disparities in digital access and literacy among the elderly, which can significantly impact the adoption and utilization of digital solutions in healthcare. The penultimate section gauges the intention to use AI assistants, through four items that determine the likelihood of continued engagement with AI services for personal care and daily needs. Finally, the ninth section, designated as Supplementary Materials, serves as a repository for additional aids or instructions provided to assist participants in understanding or completing the questionnaire.

Each item throughout the questionnaire employs a 5-point Likert scale ranging from "strongly disagree" to "strongly agree", ensuring a uniform metric for response quantification and facilitating subsequent analytical procedures to derive meaningful conclusions from the aggregated data.

Following data collection, several analyses were conducted. Descriptive analysis was used to summarize the demographic characteristics of the respondents. Reliability and validity analyses were performed to assess the internal consistency and validity of the constructs. Confirmatory factor analysis (CFA) was conducted to verify the measurement model, while structural equation modeling (SEM) was applied to examine the relationships among perceived usefulness, service quality, perceived ease of use, self-efficacy, digital divide, attitude, and the intention to use AI assistants in nursing care units. This structured methodology ensures a comprehensive evaluation of the factors influencing AI adoption in older adults care.

RESULTS

Table 2 presents the reliability statistics for the study variables, measured by Cronbach's α, a standard indicator of internal consistency. A Cronbach's α value above 0.7 is considered acceptable, while values exceeding 0.8 indicate good reliability. The study variables demonstrate high reliability across all constructs. Perceived usefulness (α = 0.931), service quality (α = 0.968), and self-efficacy (α = 0.869) show excellent reliability. Perceived ease of use (α = 0.829), attitude toward AI assistants (α = 0.812), and intention to use AI assistants (α = 0.829) also display strong reliability. The digital divide (α = 0.712), though slightly lower, remains within the acceptable range, confirming the consistency of the scale items.

Table 2 Reliability Statistics

Study variables	Number of questions	Cronbach's α
Perceived usefulness	4	0.931
Service quality	26	0.968
Perceived ease of use	4	0.829
Attitude to use AI assistant	4	0.812
Self-efficacy	6	0.869
Digital divide	4	0.712
Intention to use AI assistant	4	0.829

Table 3 presents the results of the Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity, which assess the suitability of the data for factor analysis. The KMO value of 0.960 is well above the recommended threshold of 0.6, indicating excellent sampling adequacy. Bartlett's Test of Sphericity is significant ($p < 0.001$), with a large chi-square value (18856.233), indicating that the correlation matrix is not an identity matrix, thus confirming the data's suitability for factor analysis.

Table 3 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.960**
Bartlett's Test of Sphericity	Approx. Chi-Square	18856.233
	df	1326
	Sig.	.000

When the model meets the criteria of $\chi2/df < 3$, RMSEA < 0.08, GFI > 0.9, AGFI > 0.85, NFI > 0.9, TLI > 0.9, and CFI > 0.9), the model fit is considered good. Table 4 shows that the model fitting indices for this study align with these standards, with $\chi2/df = 1.284$, RMSEA = 0.023, GFI = 0.909, AGFI = 0.900, NFI = 0.915, TLI = 0.979, and CFI = 0.980. These results indicate that the model fits the data well, confirming the robustness of the measurement model.

Table Error! No text of specified style in document. **Measure model fit metrics**

Fit index	**χ2/df**	**RMSEA**	**GFI**	**AGFI**	**NFI**	**TLI**	**CFI**
Reference standards	<3	<0.08	>0.9	>0.9	>0.9	>0.9	>0.9
Result	1.284	0.023	0.909	0.900	0.915	0.979	0.980

Table 5 presents the results of the convergent validity test, which evaluates whether the latent variables are adequately captured by their corresponding observation indicators. Convergent validity is assessed using three key metrics: factor loadings, composite reliability (CR), and average variance extracted (AVE). These metrics help to determine whether the measurement items accurately reflect the constructs they are intended to represent.

The factor loadings for all items across the latent variables are above 0.7, demonstrating strong correlations between the indicators and their respective constructs. This indicates that each indicator is a good representation of its latent variable, confirming that the measurement items are valid measures of the underlying concepts they aim to capture.

In addition, the composite reliability (CR) values for all constructs exceed the 0.7 threshold, demonstrating strong internal consistency. For example, perceived usefulness has a CR of 0.832, while service quality has an excellent CR of 0.968. The average variance extracted (AVE) for all constructs is above 0.5, meeting the standard for convergent validity. For instance, perceived usefulness has an AVE of 0.553, and service quality has an AVE of 0.539, indicating that more than 50% of the variance in the indicators is explained by the latent constructs. These results confirm the model's strong convergent validity across all variables.

Table 5 Convergence Validity

Latent variables	**Observation indicators**	**Factor loading**	**CR**	**AVE**
Perceived usefulness	PU1	0.739	0.832	0.553
	PU2	0.738		
	PU3	0.747		
	PU4	0.751		

Service quality	SQ1	0.703	0.968	0.539
	SQ2	0.760		
	SQ3	0.750		
	SQ4	0.746		
	SQ5	0.714		
	SQ6	0.729		
	SQ7	0.726		
	SQ8	0.716		
	SQ9	0.713		
	SQ10	0.715		
	SQ11	0.704		
	SQ12	0.773		
	SQ13	0.731		
	SQ14	0.719		
	SQ15	0.756		
	SQ16	0.721		
	SQ17	0.735		
	SQ18	0.729		
	SQ19	0.738		
	SQ20	0.750		
	SQ21	0.761		
	SQ22	0.766		
	SQ23	0.740		
	SQ24	0.722		
	SQ25	0.752		
	SQ26	0.709		
Perceived ease of use	PE1	0.753	0.829	0.549
	PE2	0.712		
	PE3	0.766		
	PE4	0.730		
Attitude to use AI assistant	AT1	0.758	0.813	0.521
	AT2	0.685		
	AT3	0.719		
	AT4	0.723		
Self-efficacy	SE1	0.742	0.870	0.527
	SE2	0.688		
	SE3	0.748		
	SE4	0.704		
	SE5	0.725		
	SE6	0.745		
Intention to use AI assistant	IT1	0.727	0.829	0.549
	IT2	0.750		
	IT3	0.722		

	IT4	0.762

Table 6 presents the results of the discriminant validity test, which assesses whether the constructs in the study are distinct from one another. Discriminant validity is evaluated by comparing the square root of the average variance extracted (AVE) of each latent variable with the correlations between constructs. To establish discriminant validity, the square root of the AVE (displayed on the diagonal) should be greater than the correlations with other constructs.

The diagonal values represent the square root of the AVE for each latent variable, and all are above 0.7, indicating strong convergent validity. For example, perceived usefulness has a square root of AVE of 0.744, service quality has 0.734, and intention to use AI assistants has 0.741. The off-diagonal values represent correlations between latent variables, such as the correlation between perceived usefulness and service quality (0.480) and the correlation between perceived ease of use and intention to use AI assistants (0.608). Since all correlations are below the corresponding square root of the AVE, the results confirm that the constructs are distinct from each other, demonstrating that the model meets the criteria for discriminant validity.

Table 6 Discriminant validity test

Latent variables	**1**	**2**	**3**	**4**	**5**	**6**
Perceived usefulness	0.744					
Service quality	0.480 ***	0.734				
Perceived ease of use	0.546 ***	0.489 ***	0.741			
Attitude to use AI assistant	0.485 ***	0.496 ***	0.503 ***	0.722		
Self-efficacy	0.541 ***	0.510 ***	0.523 ***	0.506 ***	0.726	
Intention to use AI assistant	0.617 ***	0.583 ***	0.608 ***	0.603 ***	0.610 ***	0.741

Note: The diagonal is the square root of the corresponding dimension AVE
***: $p<0.001$

Table 7 presents the model fit metrics, indicating how well the hypothesized model fits the observed data. The chi-square/degree of freedom ratio (χ^2/df) is 1.284, which is below the reference standard of 3, suggesting an excellent model fit. The Root Mean Square Error of Approximation (RMSEA) is 0.023, well below the acceptable threshold of 0.08, further confirming good model fit.

The Goodness of Fit Index (GFI) is 0.909, meeting the standard of 0.9, while the Adjusted Goodness of Fit Index (AGFI) is marginally lower at 0.900, still indicating an acceptable fit. The Normed Fit Index (NFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI) all exceed 0.9, with values of 0.915, 0.979, and 0.980, respectively, confirming excellent fit across multiple indices. These results collectively demonstrate that the model provides a strong and reliable fit to the data.

Table 7 Model fit metrics

Fit index	χ2/df	RMSEA	GFI	AGFI	NFI	TLI	CFI
Reference standards	<3	<0.08	>0.9	>0.9	>0.9	>0.9	>0.9
Result	1.284	0.023	0.909	0.900	0.915	0.979	0.980

Table 8 details the results of hypothesis testing for paths within the structural equation model, analyzing the relationships among the latent variables: Perceived Usefulness (PU), Service Quality (SQ), Perceived Ease of Use (PE), Self-Efficacy (SE), Attitude Toward AI Assistants (AT), and Intention to Use AI Assistants (IT). The table provides path estimates, standardized coefficients (β), standard errors (S.E.), critical ratios (C.R.), and p-values (P), along with the support status for each hypothesis. The results indicate that all proposed hypotheses (H1 through H9) are supported, as the paths are statistically significant:

H1, assessing the impact of SQ on IT, shows a positive effect with a coefficient of 0.161 ($p = 0.009$).

H2 and H4 examine the impact of SQ and PU on AT, showing positive effects with coefficients of 0.203 and 0.202, respectively ($p < 0.001$).

H3 demonstrates a significant positive relationship between PU and IT, with a coefficient of 0.217 ($p < 0.001$).

H5 and H6 explore the effects of PE on IT and AT, both supported by significant positive relationships, with coefficients of 0.218 and 0.180 ($p < 0.001$).

H7 and H8 confirm that SE significantly impacts both IT and AT, with coefficients of 0.190 and 0.194 ($p < 0.001$).

H9, assessing the influence of AT on IT, is strongly supported with a coefficient of 0.215 ($p < 0.001$).

This analysis highlights the significant interrelations between service quality, perceived usefulness, perceived ease of use, self-efficacy, attitude, and intention to use AI assistants, confirming the robustness of the model and the reliability of the findings in explaining the adoption of AI technologies in nursing care settings.

Table 8 Direct path effects

Hypothesis	Path	Estimate	β	S.E.	C.R.	P	Results
H1	SQ→IT	0.165	0.161	0.063	2.617	0.009	Supported
H2	SQ→AT	0.210	0.203	0.063	3.320	***	Supported
H3	PU→IT	0.246	0.217	0.060	4.106	***	Supported
H4	PU→AT	0.214	0.202	0.063	3.374	***	Supported
H5	PE→IT	0.207	0.218	0.052	4.003	***	Supported
H6	PE→AT	0.189	0.180	0.049	3.861	***	Supported
H7	SE→IT	0.186	0.190	0.052	3.603	***	Supported
H8	SE→AT	0.185	0.194	0.052	3.570	***	Supported
H9	AT→IT	0.198	0.215	0.049	4.048	***	Supported

Note: PU: Perceived usefulness; SQ: Service quality; PE: Perceived ease of use; AT: Attitude to use AI assistant; SE: Self-efficacy; IT: Intention to use AI assistant.
***: p<0.001

Table 9 provides insights into how attitude toward AI assistants (AT) mediates the relationships between various factors—perceived usefulness (PU), service quality (SQ), perceived ease of use (PE), and self-efficacy (SE)—and the intention to use AI assistants (IT).

H10 (PU → AT → IT) showcases the mediation effect of attitude in the relationship between perceived usefulness and intention to use AI assistants is rejected. The effect size is 0.033, but the 95% confidence interval (-0.002, 0.087) crosses zero, indicating no significant mediation effect. This suggests that while perceived usefulness directly influences IT, attitude does not significantly mediate this relationship.

H11 (SQ → AT → IT) shows the mediation effect of attitude in the relationship between service quality and intention to use AI assistants is supported. The effect size is 0.049, with a 95% confidence interval of (0.014, 0.121), confirming significant mediation. This implies that a positive attitude toward AI assistants strengthens the influence of service quality on the intention to adopt AI technologies.

H12 (PE → AT → IT) presents the mediation effect of attitude between perceived ease of use and intention to use AI assistants is supported. The effect size is 0.042, with a confidence interval of (0.007, 0.098). This indicates that a positive attitude mediates the impact of ease of use, suggesting that when users find AI systems easier to use, their attitude positively influences their intention to adopt the technology.

H13 (SE → AT → IT) showcases the mediation effect of attitude in the relationship between self-efficacy and intention to use AI assistants is supported. The effect size is 0.042, with a confidence interval of (0.009, 0.102), indicating significant mediation. This finding demonstrates that self-efficacy, or users' belief in their ability to use AI effectively, enhances their attitude toward AI, which in turn strengthens their intention to adopt the technology.

Overall, the results highlight that attitude plays a significant mediating role in the relationships between service quality, perceived ease of use, and self-efficacy with the intention to use AI assistants, but not for perceived usefulness.

Table 9 Mediation effect bootstrap test

Hypothesis	Mediation path	Effect size	SE	Bias-Corrected 95%CI		Results
H10	PU→AT→IT	0.033	0.021	-0.002	0.087	Rejected
H11	PU→SQ→IT	0.049	0.025	0.014	0.121	Supported
H12	PU→AT→IT	0.042	0.023	0.007	0.098	Supported
H13	PU→AT→IT	0.042	0.024	0.009	0.102	Supported

Note: PU: Perceived usefulness; SQ: Service quality; PE: Perceived ease of use; AT: Attitude to use AI assistant; SE: Self-efficacy; IT: Intention to use AI assistant.

Table 10 presents the results of the moderating effects analysis, examining how the digital divide (DD) influences the relationships between various constructs and the intention to use AI assistants (IT). Each hypothesis tests the interaction effect, reported with coefficients (Coeff), standard errors (SE), t-values (T), p-values (P), and bias-corrected 95% confidence intervals (CI).

H14, testing the moderating effect of the digital divide (DD) on the relationship between perceived usefulness (PU) and IT, shows a positive coefficient of 0.0800 with a significant t-value of 4.9354 ($p = 0.000$). The confidence interval (0.0481, 0.1118) does not cross zero, supporting the hypothesis.

H15, examining the moderating effect of DD on the relationship between service quality (SQ) and IT, yields a coefficient of 0.0826 with a t-value of 4.7437 ($p = 0.000$). The confidence interval (0.0484, 0.1169) also indicates a significant moderating effect, supporting the hypothesis.

H16 tests the moderating role of DD on the relationship between perceived ease of use (PE) and IT. With a coefficient of 0.0835 and a significant t-value of 5.2637 ($p = 0.000$), the hypothesis is supported, as the confidence interval (0.0523, 0.1147) does not cross zero.

H17 evaluates the moderating effect of DD on the relationship between self-efficacy (SE) and IT, showing a strong effect (coefficient = 0.0960, $t = 5.6182$, $p = 0.000$), with a confidence interval of (0.0624, 0.1295), supporting the hypothesis.

All hypotheses are supported, indicating that the digital divide significantly moderates the relationships between these key variables and the intention to use AI assistants.

Table 10 Moderating effects

Hypothesis	Mv	Path	Coeff	SE	T	P	Bias-Corrected 95%CI		Results
H14	DD	PU→IT	0.0800	0.0162	4.9354	0	0.0481	0.1118	Supported
H15	DD	SQ→IT	0.0826	0.0174	4.7437	0	0.0484	0.1169	Supported
H16	DD	PE→IT	0.0835	0.0159	5.2637	0	0.0523	0.1147	Supported
H17	DD	SE→IT	0.0960	0.0171	5.6182	0	0.0624	0.1295	Supported

Note: PU: Perceived usefulness; SQ: Service quality; PE: Perceived ease of use; AT: Attitude to use AI assistant; SE: Self-efficacy; IT: Intention to use AI assistant; DD:Digital divide.
Mv: Moderating variables; Coeff: Interaction term coefficient.

Figure 2 showcases the relationship among service quality, perceived usefulness, perceived ease of use, self-efficacy, attitude to use AI assistant, and intention to use AI assistant. In this way, this model identifies the mediating role of service quality and attitude to use AI assistants, as well as the moderating role of digital dived.

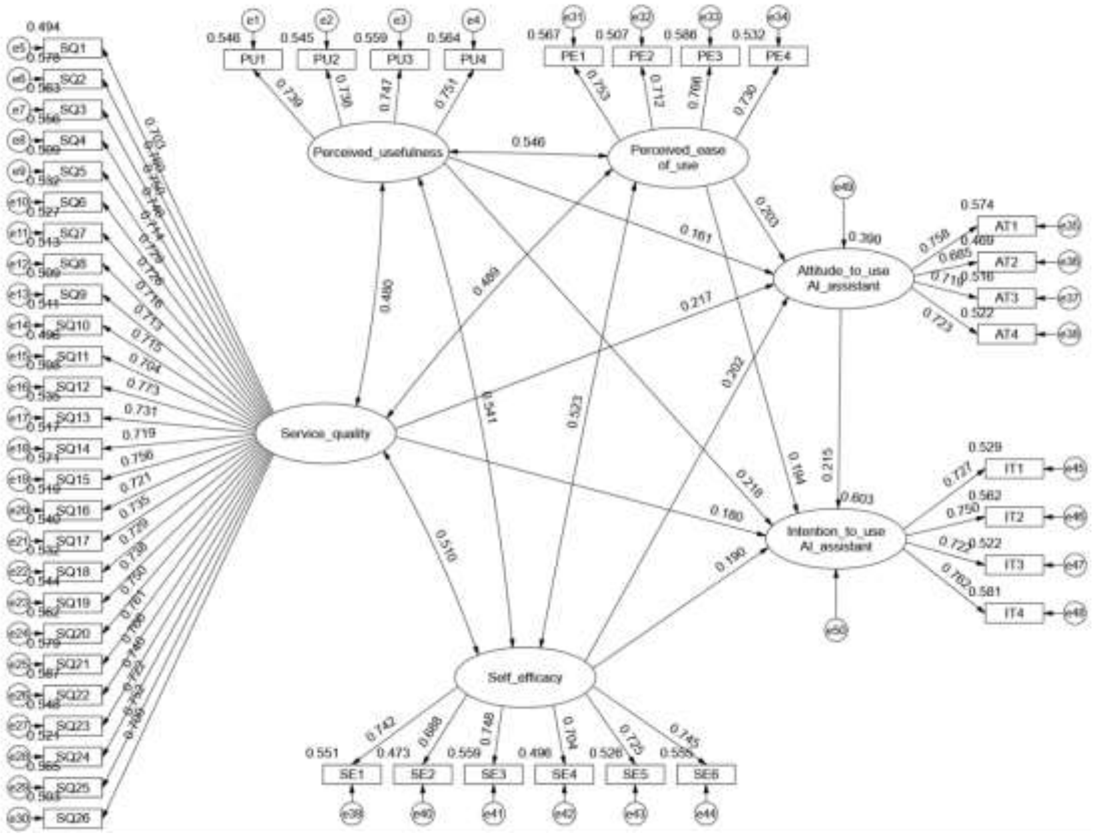

Figure 2 Structural model diagram

DISCUSSION

The findings reveal that perceived usefulness (β = 0.217, p < 0.001), service quality (β = 0.161, p = 0.009), perceived ease of use (β = 0.218, p < 0.001), and self-efficacy (β = 0.190, p < 0.001) significantly influence the intention to use AI assistants in nursing homes. Perceived usefulness had a direct positive effect on AI adoption but did not exhibit a significant mediation effect through attitude (β = 0.033, p = 0.087), indicating that users' direct perception of AI's benefits is the primary driver of adoption. Service quality (β = 0.203, p < 0.001) and perceived ease of use (β = 0.180, p < 0.001) also significantly impacted the intention to use AI assistants, underscoring the need for high-quality, user-friendly AI services. Self-efficacy plays a crucial role, with users who are confident in their ability to operate AI systems being more likely to adopt them (β = 0.194, p < 0.001).

Additionally, attitude mediates the relationships between service quality, perceived ease of use, self-efficacy, and intention to use AI, highlighting that fostering a positive attitude enhances the impact of these factors on AI adoption. This emphasizes the importance of service quality, ease of use, and user confidence, with attitude acting as a key mediator in driving AI adoption in older adults care.

The theoretical implications of this study are grounded in the Technology Acceptance Model (TAM) (Davis, 1989), SERVQUAL model (Zeithaml et al., 1988), and self-efficacy theory (Bandura, 1977), offering contemporary insights into AI adoption in older adults care. The findings confirm several aspects of TAM, particularly the significant effects of perceived ease of use ($\beta = 0.218$, $p < 0.001$) and self-efficacy ($\beta = 0.190$, $p < 0.001$) on the intention to use AI assistants, aligning with Venkatesh et al. (2016). However, contrary to previous research, this study found no mediation effect of attitude between perceived usefulness and intention to use AI ($\beta = 0.033$, $p = 0.087$), suggesting that perceived usefulness directly influences AI adoption without necessarily shaping users' attitudes, diverging from the typical mediation expected in TAM (Al-Maroof et al., 2023). This expands TAM by incorporating service quality and self-efficacy, enriching the model's applicability to AI adoption in healthcare settings. Service quality ($\beta = 0.203$, $p < 0.001$) significantly influences intention to use AI assistants, supporting research highlighting the importance of reliability and responsiveness in AI systems (Alalwan, 2020), while confirming the direct impact of SERVQUAL dimensions on AI adoption, an area underexplored in healthcare technology literature (Prentice et al., 2020).

The role of self-efficacy in influencing AI adoption aligns with self-efficacy theory, confirming that user confidence in operating AI systems is essential for adoption ($\beta = 0.194$, $p < 0.001$) (Tetri & Juujärvi, 2022). This study also adds to the literature by revealing the moderating role of the digital divide. Similar to recent studies (Jokisch et al., 2020; Xu et al., 2024), it emphasizes that digital literacy and access are key barriers to AI adoption, even for users with high self-efficacy. This finding highlights the need to address the digital divide in order to fully realize AI's potential in older adults care (Martínez-Alcalá et al., 2021). Furthermore, the mediation role of attitude between service quality ($\beta = 0.203$, $p < 0.001$), perceived ease of use ($\beta = 0.180$, $p < 0.001$), self-efficacy ($\beta = 0.194$, $p < 0.001$), and intention to use AI assistants underscores the importance of fostering positive attitudes towards AI adoption in older adults care settings. This finding aligns with recent research demonstrating that attitude is a significant determinant of technology adoption (Wu et al., 2020) and suggests that training programs aimed at improving user attitudes will be critical to increasing AI adoption (Zhang et al., 2023).

These findings provide a strong basis for future empirical studies and offer important implications for both theory and practice in AI-driven older adults care. The results offer crucial managerial implications for stakeholders in the healthcare sector, particularly concerning the integration of AI technologies into older adults care. For nursing home administrators, the findings highlight the importance of investing in user-friendly AI systems that improve care quality and streamline operations, while also providing training programs to boost caregivers' and residents' confidence in using these technologies. Caregivers should be encouraged to participate in AI training to increase their ease of use and self-efficacy, improving their willingness to adopt AI tools. Technology developers should focus on creating intuitive, reliable, and responsive AI systems tailored to varying levels of digital literacy. Additionally, policymakers must address the digital divide by implementing initiatives to ensure equitable access to AI technologies and enhancing digital literacy through educational programs. These strategies will foster positive attitudes toward AI adoption and ultimately lead to improved care outcomes in older adults care settings.

CONCLUSION

This study aimed to explore the factors influencing the adoption of AI assistants in nursing care units, focusing on the relationships between perceived usefulness, service quality, perceived ease of use, self-efficacy, attitude, and intention to use AI assistants. The results confirmed that service quality, perceived ease of use, and self-efficacy significantly impact the intention to use AI assistants, with attitude serving as a key mediator. However, perceived usefulness directly influenced intention, with no mediation by attitude, suggesting that users may adopt AI technologies based on perceived benefits alone. The moderating effect of the digital divide further revealed barriers to AI adoption, particularly among individuals with lower digital literacy or limited access to resources, even if other factors such as self-efficacy are high. These findings offer important insights for addressing disparities and improving technology integration in older adults care.

The research extends the technology acceptance model (TAM) and integrating the SERVQUAL model and self-efficacy theory to better understand AI adoption in healthcare. By introducing service quality and the digital divide into the framework, the study offers a comprehensive understanding of how these factors influence AI adoption. It also provides practical recommendations for nursing home administrators, caregivers, technology developers, and policymakers on fostering AI integration in older adults care environments.

Despite its contributions, the study has some limitations. The focus on nursing homes in major Chinese cities may limit the generalizability of the findings to other regions or cultural contexts. Future research should test the model in different geographical and cultural settings to verify its broader applicability. Additionally, the reliance on self-reported questionnaires may introduce bias, and future studies could benefit from longitudinal or mixed-method designs for more comprehensive insights.

Future research should also investigate the long-term impact of AI on older adults residents' quality of life and mental well-being, providing a more holistic understanding of AI's role in healthcare. Exploring emerging technologies like machine learning and virtual reality in elderly care would further expand the scope of AI applications in healthcare.

AUTHOR CONTRIBUTIONS

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Reference

Al-Maroof, R. S., Salloum, S. A., Hassanien, A. E., & Shaalan, K. (2023). Fear from COVID-19 and technology adoption: the impact of Google Meet during Coronavirus pandemic. *Interactive Learning Environments*, *31*(3), 1293-1308.

Amin, M. S., Johnson, V. L., Prybutok, V., & Koh, C. E. (2024). An investigation into factors affecting the willingness to disclose personal health information when using AI-enabled caregiver robots. *Industrial Management & Data Systems*, *124*(4), 1677-1699. https://doi.org/10.1108/IMDS-09-2023-0608

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*. https://doi.org/10.1016/0146-6402(78)90002-4

Bao, H., & Lee, E. W. (2024). Examining the antecedents and health outcomes of health apps and wearables use: an integration of the technology acceptance model and communication inequality. *Behaviour & Information Technology*, *43*(4), 695-716. https://doi.org/10.1080/0144929X.2023.2183062

Bertolazzi, A., Quaglia, V., & Bongelli, R. (2024). Barriers and facilitators to health technology adoption by older adults with chronic diseases: an integrative systematic review. *BMC public health*, *24*(1), 506. https://doi.org/10.1186/s12889-024-18036-5

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340. https://doi.org/10.2307/249008

Ebekozien, O., Fantasia, K., Farrokhi, F., Sabharwal, A., & Kerr, D. (2024). Technology and health inequities in diabetes care: How do we widen access to underserved populations and utilize technology to improve outcomes for all? *Diabetes, Obesity and Metabolism*, *26*, 3-13. https://doi.org/10.1111/dom.15470

Feng, Z., Glinskaya, E., Chen, H., Gong, S., Qiu, Y., Xu, J., & Yip, W. (2020). Long-term care system for older adults in China: policy landscape, challenges, and future prospects. *The Lancet*, *396*(10259), 1362-1372.

Fisk, R. P., Gallan, A. S., Joubert, A. M., Beekhuyzen, J., Cheung, L., & Russell-Bennett, R. (2023). Healing the digital divide with digital inclusion: enabling human capabilities. *Journal of Service Research*, *26*(4), 542-559. https://doi.org/10.1177/10946705221140148

Hanjaya, S. M., Kenny, S. K., & Gunawan, S. F. (2019). Understanding factors influencing consumers online purchase intention via mobile app: perceived ease of use, perceived usefulness, system quality, information quality, and service quality. *Marketing of Scientific and Research Organizations*, *32*(2), 175-205. https://doi.org/10.2478/minib-2019-0035

Humaidi, N., Seman, S. A. A., Imam, A. N. L., Fahrudi, S. F. A. K. J., & Jamil, N. A. (2021). User's Satisfaction Towards Course File Information System (CFIS): The Role of Green IT Attitude, Self-Efficacy and CFIS Training. *Global Business and Management Research*, *13*(4), 207-224.

Jallad, S. T., Alsaqer, K., Albadareen, B. I., & Almaghaireh, D. (2024). Artificial intelligence tools utilized in nursing education: Incidence and associated factors. *Nurse Education Today*, 106355. https://doi.org/10.1016/j.nedt.2024.106355

Jia, X.-H., & Tu, J.-C. (2024). Towards a New Conceptual Model of AI-Enhanced Learning for College Students: The Roles of Artificial Intelligence Capabilities, General Self-Efficacy, Learning Motivation, and Critical Thinking Awareness. *Systems*, *12*(3), 74. https://doi.org/10.3390/systems12030074

Jokisch, M. R., Schmidt, L. I., Doh, M., Marquard, M., & Wahl, H.-W. (2020). The role of internet self-efficacy, innovativeness and technology avoidance in breadth of internet use: Comparing older technology experts and non-experts. *Computers in Human Behavior*, *111*, 106408. https://doi.org/10.1016/j.chb.2020.106408

Lambert, S. I., Madi, M., Sopka, S., Lenes, A., Stange, H., Buszello, C.-P., & Stephan, A. (2023). An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals. *NPJ Digital Medicine*, *6*(1), 111. https://doi.org/10.1038/s41746-023-00874-z

Li, Y.-H., Li, Y.-L., Wei, M.-Y., & Li, G.-Y. (2024). Innovation and challenges of artificial intelligence technology in personalized healthcare. *Scientific Reports*, *14*(1), 18994. https://doi.org/10.1038/s41598-024-70073-7

Lin, G.-Y., Ruan, J.-H., & Wang, Y.-S. (2023). Factors Affecting Family Caregivers' Behavioral Intention to Use Socially Assistive AI Robots for Elderly Care Within Their Own Home Environment. *International Journal of Human–Computer Interaction*, 1-11. https://doi.org/10.1080/10447318.2023.2263247

Liu, Q., Luo, D., Haase, J. E., Guo, Q., Wang, X. Q., Liu, S., Xia, L., Liu, Z., Yang, J., & Yang, B. X. (2020). The experiences of health-care providers during the COVID-19 crisis in China: a qualitative study. *The Lancet Global Health*, *8*(6), e790-e798.

Liu, P. (2023, October 18). Analysis of the current status and development trends of the smart eldercare industry in China: Adapting products and services to meet the needs of the elderly. Retrieved from https://www.huaon.com/channel/trend/933782.html

Martínez-Alcalá, C. I., Rosales-Lagarde, A., Pérez-Pérez, Y. M., Lopez-Noguerola, J. S., Bautista-Díaz, M. L., & Agis-Juarez, R. A. (2021). The effects of Covid-19 on the digital literacy of the elderly: norms for digital inclusion. Frontiers in Education,

Mobsite, S., Alaoui, N., Boulmalf, M., & Ghogho, M. (2024). Feature fusion-based computer vision system for fall and head injury detection trained on a new humanlike doll-based dataset. *Engineering Applications of Artificial Intelligence*, *137*, 109069. https://doi.org/10.1016/j.engappai.2024.109069

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). The impact of artificial intelligence and employee service quality on customer satisfaction and loyalty. *Journal of Hospitality Marketing & Management*, *29*(7), 739-756. https://doi.org/10.1080/19368623.2020.1722304

Raza, S. A., Umer, A., Qureshi, M. A., & Dahri, A. S. (2020). Internet banking service quality, e-customer satisfaction and loyalty: the modified e-SERVQUAL model. *The TQM Journal*, *32*(6), 1443-1466. https://doi.org/10.1108/TQM-02-2020-0019

Rony, M. K. K., Alrazeeni, D. M., Akter, F., Nesa, L., Das, D. C., Uddin, M. J., Begum, J., Khatun, M. T., Noor, M. A., & Ahmad, S. (2024). The Role of Artificial Intelligence in Enhancing Nurses' Work-Life Balance. *Journal of Medicine, Surgery, and Public Health*, 100135. https://doi.org/10.1016/j.glmedi.2024.100135

Sánchez-Hernández, M. I., González-López, Ó. R., Buenadicha-Mateos, M., & Tato-Jiménez, J. L. (2019). Work-life balance in great companies and pending issues for engaging new generations at work. *International journal of environmental research and public health*, *16*(24), 5122. https://doi.org/10.3390/ijerph16245122

Sánchez-Torres, J. A. (2019). Moderating effect of the digital divide of e-commerce. *International Journal of Social Economics*, *46*(12), 1387-1400. https://doi.org/10.1108/IJSE-11-2018-0622

Singh, N., Jain, M., Kamal, M. M., Bodhi, R., & Gupta, B. (2024). Technological paradoxes and artificial intelligence implementation in healthcare. An application of paradox theory. *Technological Forecasting and Social Change*, *198*, 122967. https://doi.org/10.1016/j.techfore.2023.122967

Song, M., Xing, X., Duan, Y., Cohen, J., & Mou, J. (2022). Will artificial intelligence replace human customer service? The impact of communication quality and privacy risks on adoption intention. *Journal of Retailing and Consumer Services*, *66*, 102900. https://doi.org/10.1016/j.jretconser.2021.102900

Tetri, B., & Juujärvi, S. (2022). Self-efficacy, internet self-efficacy, and proxy efficacy as predictors of the use of digital social and health care services among mental health service users in Finland: A cross-sectional study. *Psychology research and behavior management*, 291-303.

Tian, Y. J., Felber, N. A., Pageau, F., Schwab, D. R., & Wangmo, T. (2024). Benefits and barriers associated with the use of smart home health technologies in the care of older persons: a systematic review. *BMC geriatrics*, *24*(1), 152. https://doi.org/10.1186/s12877-024-04702-1

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, *39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Wang, C.-H., & Wu, C.-L. (2022). Bridging the digital divide: the smart TV as a platform for digital literacy among the elderly. *Behaviour & Information Technology*, *41*(12), 2546-2559. https://doi.org/10.1080/0144929X.2021.1934732

Wu, F., Lu, C., Zhu, M., Chen, H., Zhu, J., Yu, K., Li, L., Li, M., Chen, Q., & Li, X. (2020). Towards a new generation of artificial intelligence in China. *Nature Machine Intelligence*, *2*(6), 312-316. https://doi.org/10.1038/s42256-020-0183-4

Xu, S., Khan, K. I., & Shahzad, M. F. (2024). Examining the influence of technological self-efficacy, perceived trust, security, and electronic word of mouth on ICT usage in the education sector. *Scientific Reports*, *14*(1), 16196. https://doi.org/10.1038/s41598-024-66689-4

Yang, K., Choi, J.-g., & Chung, J. (2021). Extending the Technology Acceptance Model (TAM) to explore customer's behavioral intention to use Self-Service Technologies (SSTs) in Chinese budget hotels. *Global Business & Finance Review (GBFR)*, *26*(1), 79-94. https://doi.org/10.17549/gbfr.2021.26.1.79

Yu, H., Zhang, G., & Hjorth, L. (2023). Mobilizing care? WeChat for older adults' digital kinship and informal care in Wuhan households. *Mobile media & communication*, *11*(2), 294-311. https://doi.org/10.1177/20501579221150716

Yun, M. R., & Yu, B. (2021). Strategies for reducing hospital nurse turnover in South Korea: Nurses' perceptions and suggestions. *Journal of Nursing Management*, *29*(5), 1256-1262. https://doi.org/10.1111/jonm.13264

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1988). Communication and control processes in the delivery of service quality. *Journal of marketing*, *52*(2), 35-48. https://doi.org/10.1177/002224298805200203

Zhai, K., Yousef, M. S., Mohammed, S., Al-Dewik, N. I., & Qoronfleh, M. W. (2023). Optimizing clinical workflow using precision medicine and advanced data analytics. *Processes*, *11*(3), 939. https://doi.org/10.3390/pr11030939

Zhang, Y. C., Peng, J., Sun, W. J., Zhang, H. P., & Yang, G. (2023). Analysing Home Pharmaceutical Care Under the Combination of Medical Care and Nursing. *Journal of Multidisciplinary Healthcare*, *16*, 1793-1800. https://doi.org/10.2147/jmdh.S411330

Zhao, Y., Rokhani, F. Z., Sazlina, S.-G., Devaraj, N. K., Su, J., & Chew, B.-H. (2022). Defining the concepts of a smart nursing home and its potential technology utilities that integrate medical services and are acceptable to stakeholders: a scoping review. *BMC geriatrics*, *22*(1), 787. https://doi.org/10.1136/bmjopen-2020-041452

Zhu, Y.-Q., Fang, Y.-H., & Lim, S.-Y. (2023). Investigating drivers of service extension success for a super app. *Computers in Human Behavior*, *149*, 107928. https://doi.org/10.1016/j.chb.2023.107928

SUPPLEMENTARY MATERIALS

Questionnaire

Part I Basic Information

1.Age Group:
□ 55-60
□ 61-65
□ 65-70
□ 71-75
□ 75+

2.Gender:
□ Male
□ Female

3.City of Residence:
□ Beijing
□ Shanghai
□ Shenzhen
□ Guangzhou
□ Tianjin
□ Chongqing
□ Hangzhou
□ Chengdu
□ Xi'an
□ Wuhan

4.Educational Background:
□ Higher school
□ Bachelor Degree
□ Master Degree
□ PhD

5.Duration of Stay in Nursing Home:
□ Less than 1 year
□ 1-3 years
□ 3-5 years
□ More than 5 years

6.Would you be willing to use an AI assistant to assist in your own healing and aging:

□ Yes

□ No

Part II perceived usefulness

Please choose between 1-5 based on your own actual situation, where 1-5 represents "strongly disagree- strongly agree"

Items	1	2	3	4	5
1.Using AI assistants in nursing homes makes it easier for the old adults to access care and services.					
2.AI assistants facilitate quicker responses to the needs and requests of elderly residents.					
3.AI assistants contribute significantly to improving the efficiency and effectiveness of care provided in nursing homes, enhancing the quality of life for residents.					
4.The information and support provided by AI assistants are highly beneficial for the old adults in managing their health and daily activities.					

Part III Service quality

Please choose between 1-5 based on your own actual situation, where 1-5 represents "strongly disagree- strongly agree"

Items	1	2	3	4	5
1.Visually appealing and intuitive interfaces of AI services.					
2.Quick response times for AI-enabled assistance and transactions.					
3.Nursing home offers extended hours for tech support and AI interactions.					
4.AI systems maintain accurate health and personal records.					
5.AI-assisted services are delivered as scheduled.					
6.AI systems effectively address and resolve resident care issues.					
7.Comprehensive range of AI-enhanced care services.					
8.Availability of AI-monitored emergency response systems.					
9.Staff and AI systems are consistently available to address resident needs.					
10.AI-driven responses to resident inquiries are timely and efficient.					
11.AI-enabled services for common tasks are prompt and reliable.					
12.Expansion of AI services to accommodate more residents.					
13.AI interactions are conducted with respect and					

sensitivity.					
14.AI systems and staff are knowledgeable, providing accurate information.					
15.Strict confidentiality of all resident data by AI systems.					
16.AI provides health and wellbeing advice based on data analytics.					
17.AI facilitates remote interaction with family and healthcare providers.					
18.AI services are easily accessible and user-friendly for residents.					
19.24/7 AI monitoring for health and safety.					
20.AI systems are programmed to offer personalized resident care and attention.					
21.AI services are designed to cater to the individual preferences of residents.					
22.Nursing homes offer AI services at competitive rates, ensuring affordability.					
23.AI systems adhere to ethical standards of care without prejudice.					
24.Provision of digital platforms for engaging with community services.					
25.AI investment in resident care products yields measurable improvements.					
26.AI facilitates financial management and support for residents.					

Part IV Perceived ease of use

Please choose between 1-5 based on your own actual situation, where 1-5 represents "strongly disagree- strongly agree"

Items	1	2	3	4	5
1.AI assistants in nursing homes are user-friendly and easy for the old adults to use.					
2.Learning how to operate AI assistants is straightforward for elderly residents.					
3.Interacting with AI assistants is simple and intuitive for users in nursing homes.					
4.It is effortless for the old adults to command AI assistants to perform desired tasks.					

PartVI Attitude to use AI assistant

Please choose between 1-5 based on your own actual situation, where 1-5 represents "strongly disagree- strongly agree"

Items	1	2	3	4	5
1.It is convenient for elderly residents to use AI assistants in nursing homes.					
2.It is beneficial for elderly residents to engage with AI assistants in nursing homes.					
3.It is a pleasant experience for elderly residents to interact with AI assistants in nursing homes.					
4.It is a sensible choice for nursing homes to implement AI assistants for elderly care.					

Part VII Self-efficacy

Please choose between 1-5 based on your own actual situation, where 1-5 represents "strongly disagree- strongly agree"

Items	1	2	3	4	5
1.I can access and utilize the features of AI assistants in nursing homes.					
2.I can freely navigate and interact with AI assistants without confusion.					
3.I can use AI assistants effectively without needing explicit instructions on their functions.					
4.I can solve issues that arise during the use of AI assistants in the care setting.					
5.I can operate AI assistants efficiently with the help of user manuals or guides.					
6.Overall, I am confident in my ability to use AI assistants in nursing homes without any assistance.					

PartVIII Digital divide

Please choose between 1-5 based on your own actual situation, where 1-5 represents "strongly disagree- strongly agree"

Items	1	2	3	4	5
1.I believe that the cost of accessing AI technologies is high.					
2.I think the prices of devices required to use AI assistants are very expensive.					
3.I consider the quality of the connection needed to use AI assistants to be poor, with frequent issues in connectivity and performance.					
4.I think the expense generated annually by using AI-related services is a significant part of my budget.					

PartvIX Intention to use AI assistant

Please choose between 1-5 based on your own actual situation, where 1-5 represents "strongly disagree- strongly agree"

Items	1	2	3	4	5
1.I am likely to engage with AI assistants in nursing homes for care and support.					
2.I intend to continue utilizing AI assistants in nursing homes for my daily needs and care.					
3.I would trust AI assistants in nursing homes to assist me with personal care tasks.					
4.I would not hesitate to interact with AI assistants in nursing homes, providing necessary information to receive personalized care.					