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Effect of older adults willingness on telemedicine usage: an integrated approach based on technology acceptance and decomposed theory of planned behavior model

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Abstract

Background Telemedicine, as a novel method of health management system, has demonstrated to have a significant impact on health levels. However, a challenge persists in the form of low usage rates and acceptance among older adults in China. There are accumulating evidence that willingness will affect the telemedicine usage among older adults. This study investigates factors influencing older users' trust in adopting telemedicine technology, thereby promoting actual use.

Methods A questionnaire survey was conducted with 400 urban seniors aged 60 and above. Drawing from the Technology Acceptance Model (TAM) and the Decomposed Theory of Planned Behavior (DTPB), the author combines elements such as Perceived Usefulness, Perceived Ease of Use, Subjective Norms, Service Environment, Self-Efficacy, Behavioral Intention to Use, and Usage Behavior. The aim is to explore the interrelationships between these factors.

Results Perceived Usefulness (PU) and Service Environment (SE) significantly and positively impact Behavioral Intention (BI) to use telemedicine, with Trust (TR) identified as a crucial mediating variable. Enhancing trust can substantially increase older adults' intention to use telemedicine services. Furthermore, the study reveals a significant relationship between older adults' trust in telemedicine and factors such as Perceived Usefulness (PU), Service Environment (SE), Subjective Norms (SR), as well as Emotional Risk (ER) and Cost Risk (CR), the latter two tending to decrease Trust(TR).

Conclusions This paper constructs and validates a combined model based on TAM and DTPB, comprehensively exploring the potential factors influencing the older adults' intention to use telemedicine. The findings suggest that telemedicine services for older adults should prioritize improving user perception and enhancing trust throughout the service process to effectively increase their willingness to use these services.

Keywords Older adults, Telemedicine, Trust, Willingness to use

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Background

The issue of global population ageing is becoming globally prevalent. According to the latest United Nations World Population Prospects for 2022, projections indicate that individuals aged 65 and older will constitute 10% of the global population. With this figure, this population is anticipated to increase by 16% by 2050 [1]. In China, the challenge of population aging is particularly pronounced. The nation's economic growth and advancements in health care have led to an increase in average life expectancy, marking China's transition into an aging society at an unprecedented pace. By 2020, the population of individuals aged 65 and is expected to reach 190.64 million [2]. A World Bank report suggests that by 2050 individuals over 65 will make up 26% of China's population, with those over 80 comprising 5% [3]. Despite the global trend of increased life expectancy among older adults over the last three decades, their health status has not exhibited significant improvement [4]. The combination of declining physical functions and a rise in chronic ailments necessitates heightened health care and nursing support for older individuals [5]. However, with the growth of the population, the 2015 China Family Development Report reveals that nearly 10% of older adults live alone while 41.9% reside only with their partners. In other words, the older adults lack the necessary conditions for care. The number of empty-nested older adults was in China is on the rise [6], indicating that conventional model of aging at home may be unviable.

The American Telemedicine Association defines telemedicine as "an advanced medical diagnostic system that facilitating the exchange of patients' medical information across different locations through electronic communication means, such as two-way video technology, emails, smart phones, and wireless tools". The aim is to enhance the level of medical diagnostics for patients [7]. Telemedicine encompasses a range of services, including health information management and assessment, medical appointment reminders, health education, health testing, health surveys and data collection [8]. In the United States, telemedicine services flourished with approximately 200 telemedicine networks employing various technological modes. These networks connect more than 3,000 remote sites, benefiting more than 80,000 residents who use telemedicine and health monitoring services [7]. In a 2017 survey conducted by the American Telemedicine Association (ATA) Advisory Board, it was found that 77% of patients preferred online consultations [9].

However, in China, the development of telemedicine is currently ineffective in most regions, with an actual utilization rate of less than 30%. The utilization of telemedicine by older adults is even lower. A study involving African and Hispanic older adults revealed that 63% of them used the telemedicine services to acquire health-related information, surpassing all other activities, such bill payment or products orders [10]. Conversely a study examining telemedicine services use among older adults in a Chinese province found that only 3.1% of obtained disease-related information online [11].

Recent researches have delved into the intentions of older adults to use telemedicine. A study explores the attitudes of women over 50 towards adopting intelligent health services, and identified significant impacts of perceived usefulness, perceived ease of use, and subjective norms on the adoption intentions of older women [12]. Zhang's study examined users' adoption intentions focusing on wearable medical technology focusing on technological attributes (Perceived Convenience, Perceived Irreplaceability, Perceived Trustworthiness, and Perceived Usefulness) [13]. Another study [14] found that the Physician Service Environment and Subjective Norms positively influence patients' adoption intention of online medical services. Trust has emerged as crucial factor in the study of older adults' intentions to use telemedicine services. Meng's study [15] analyzed elderly users' Behavioral Intention to use telemedicine based on a trust transfer model from the users' trust in telemedicine service platforms. Mun Yi [16] studied the initial trust of online health information, and using trust as a mediating variable between perceived information quality and perceived risk. Additional studies by Egea and González [17] indicated that perceived risk significantly affects trust.

However, the relationship between user trust, technical attributes of telemedicine services and older adults' Behavioral Intention to use telemedicine services remains unclear. The specific influential role of user trust as a mediating variable between the technological attributes of telemedicine services and older adults' Behavioral Intention to use them has not been fully discussed. Particularly in China, there is a lack of attention to the older adults, who are most in need of medical resources, in studies on the willingness to use telemedicine services.

The purpose of this study is to investigate how trust affects the willingness of older adults to use telemedicine services and to identify the factors influencing their trust in these services. Understanding these aspects is crucial for addressing the medical challenges faced by older adults.

Literature review and hypotheses

The Technology Acceptance Model (TAM) proposed by Davis et al. in 1989 stands as one of the most influential theories in the realm of information technology adoption research [18]. It primarily investigates how two key determinants, perceived usefulness, and perceived ease of use, collectively influence behavioral intentions. Despite TAM's widespread applicability and logical foundations supported by numerous empirical studies, some research argues that the dimensions within TAM are overly simplistic and lack practicality [19].

However, exploration into information technology adoption extends beyond TAM alone. Both the Theory of Planned Behavior (TPB) [19–21], which shares the same origin as TAM, and the Innovation Diffusion Theory (IDT) [22] from the field of communication studies, have contributed to the theoretical advancement of this field from different perspective.

Behavioral theories rooted in the social cognitive model have gained widespread use, taking a forefront role in predicting and explaining health behaviors [23], social marketing [24], and lifestyle studies [25]. According to Dahl [24] and others classify these Behavioral theories as the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Protection Motivation Theory (PMT), the Health Belief Model (HBM), and the Stages of Change Model. Social cognitive models emphasize assessing people's behaviors and beliefs within a social context [23]. While each model has a distinct focus, they share similar ideas about how people act.

The Theory of Planned Behavior (TPB), an extension of the Theory of Reasoned Action (TRA), was developed by Ajzen in 1990. It is one of the most widely used social cognitive theories for understanding the relationship between intentions and behaviors [26]. According to TPB, Attitudes towards the Behavior, Subjective Norms, and Perceived Behavioral Control (PBC) determine intentions, which subsequently predict behavior [27]. TPB has proven to be one of the most concise models in predicting intentions and various behavioral outcomes [28]. However, it is inherently subjective and lacks universal applicability [29]. To address this, Taylor and Todd proposed the DTPB model, an extension of TPB, which exhibits stronger explanatory abilities compared to the traditional TPB model and finds utility in various fields [30]. The DTPB model breaks down Subjective Norms into social influences from peers and superiors.

In academic circles, research confirms that while these models individually possess explanatory capabilities when applied individually, they also have significant limitations, necessitating integration for enhanced explanatory power [20]. Therefore, by integrating TAM with the DTPB model, we amalgamate the elements such as Perceived Usefulness, Perceived Ease of Use, Subjective Norms, Service Environment, Self Efficacy, Behavioral Intention to Use, and Usage Behavior from both models and investigate their influential relationships.

Within the framework of the Technology Acceptance Model (TAM), the key determinants influencing a user's decision to adopt a technology are Perceived Usefulness and Perceived Ease of Use. Perceived Usefulness is defined by Holden and Karsh [31] as an individual's subjective perception of the extent to which using technology enhances their job performance. In the context of telemedicine, Perceived Usefulness refers to the extent to which users perceive telemedicine services as beneficial for treating diseases. Ahmed MH's [32] study found that the higher older adults' perceive the value and effectiveness of telemedicine platforms, the higher their Behavioral Intention to use telemedicine. Kim's [33] study demonstrated that perceived usefulness positively and significantly influences older users' intention to use telemedicine services. In TAM theory, Perceived Usefulness can directly impact users' Behavioral Intention of use.

Hypothesis 1 (H1): Perceived Usefulness (PU) significantly positively influences on older adults' Behavioral Intention (BI) to use telemedicine.

Furthermore, another variable commonly employed in TAM theory is Perceived Ease of Use, defined as an individual's perception of the required when using a specific technology [31]. In the context of telemedicine, Perceived Ease of Use represents the level of difficulty users perceive when utilizing or learning about telemedicine. It pertains to whether patients find that using telemedicine easy to learn. In TAM theory, Perceived Ease of Use can directly impact both Perceived Usefulness and User Behavioral Intention of Use [34].

Hypothesis 2 (H2): Perceived Ease of Use (PE) significantly positively influences on older adults' Behavioral Intention (BI) to use telemedicine.

Service Environment, as proposed by Ronnie Jia [35], refers to customers' perception of the organizational support they receive when employees provide services at work. Parasuraman [36] defines Service Environment as users' overall assessment of the service received, encompassing perceived quality and objective quality. Schneider [37] considers Service Environment as an organizational context that reflects the employees' behaviors and attitudes toward service recipients influencing users' Behavioral Intention.

Hypothesis 3 (H3): Service Environment (SE) significantly positively influences on older adults' Behavioral Intention (BI) to use telemedicine.

Deng [38] posits that Subjective Norms primarily indicate the influence of the social environment on individual behavior. According to DTPB model's categorization of Subjective Norms, for older adults, these norms mainly encompass social influence factors such as family members, children, and doctors. Research by Lu [39] and others has found that Subjective Norms have a positively impact on users' intentions to use information technology. Ernst's study [40] suggests that both Subjective

Norms and Self Efficacy can influence users' self-usage intentions.

Hypothesis 4 (H4): Subjective Norms (SR) significantly positively influences on older adults' Behavioral Intention (BI) to use telemedicine.

Self Efficacy is an individual's self-assessment of their ability to perform a task [41]. Research by Thomas [42] and others indicates that Self Efficacy has a significant positive impact on individual behavior. Studies by Choi [43] and colleagues found that Self Efficacy significantly influences the intention to accept intelligent medical services. Lim [44] and others have shown that Self Efficacy significantly affects women's intentions to adopt smart health services.

Hypothesis 5 (H5): Self Efficacy (SV) significantly positively influences on Behavioral Intention (BI) of older adults to use telemedicine.

The study of trust issues has always consistently attracted attention across multiple disciplines such as sociology, philosophy, psychology, management, and marketing [45]. Trust serves as a crucial bond between social systems and individuals, especially in the healthcare field, where it is a vital factor in determining the quality of doctor-patient relationships. Zarolia [46] argue that trust is the belief that the other partner will perform behaviors that benefit their partner and will not engage in unintended behaviors to the detriment of the transactional partner. Kautish [47] and Yang [48] define trust (TRU) as users' willingness to act on and perform the information and advice received through an telemedicine service, along with the expectation that the platform will fulfill its responsibilities. In service adoption research, trust is widely regarded as a strong mediating factor influencing service adoption. Akter & D'Ambra [49] consider trust to play an important mediating role between credibility and usage behavior. Studies by Akter & Ray [50] show that user trust has a significant positive impact on continuous usage intentions. Kampmeijer R's study [51] demonstrates that older adults' trust in healthcare and telemedicine is influenced by various factors, including Subjective Norms, Education, Health Level, Gender, Age, Self Efficacy, Service Environment, and more. Yang's research [48] shows that Subjective Norms have a positive impact on Trust.

Hypothesis 6 (H6): Trust (TR) significantly positively influences older adults' Behavioral Intention (BI) to use telemedicine.

Hypothesis 7 (H7): Perceived Usefulness (PU) significantly positively influences trust (TR) telemedicine services among older adults.

Hypothesis 8 (H8): Perceived Ease of Use (PE) significantly positively influences older adults' trust (TR) in telemedicine services.

Hypothesis 9 (H9): Service Environment (SE) significantly positively influences older adults' trust (TR) in telemedicine services.

Hypothesis 10 (H10): Subjective Norms (SR) significantly positively influences older adults' trust (TR) telemedicine services.

Hypothesis 11 (H11): Self Efficacy (SV) significantly positively influences older adults' trust (TR) telemedicine services.

The concept of Perceived Risk, originally rooted in psychology, was extended to behavioral science by Bauer [52]. Numerous studies [53–55] hypothesized that six dimensions social, temporal, financial, physical, functional, and psychological risks could comprehensively explain the overall perceived risk. Hassan [56] categorized perceived risks into eight types: financial, functional, temporal, social, psychological, physical, source, and privacy. These risks are further divided into three categories based on their characteristics. Technical Risk [57] pertains to the possibility that the service obtained by the user after using telemedicine services does not achieve the expected effect. Emotional risk [58] involves the potential theft, leakage, or inappropriate use of user's personal information, along with that the user's personal information will be stolen, leaked, or used inappropriately as well as the possibility of psychological or mental stress when using telemedicine services. Cost risk [59] refers the potential loss of time and money for users when using telemedicine services. Research on the telemedicine user adoption model indicates that perceived remote medical risk significantly influences trust, which, in turn, significantly impacts the intention to use telemedicine. In other words, the higher perceived risk of telemedicine leads to lower trust and reduced willingness to use it for medical consultations. Empirical results from Yang [48] suggests that reducing early perceived risk can rapidly establish consumer trust and usage intentions. Studies by Keith [60] and Kim [61] indicate that trust can reduce the uncertainty and risk individuals experience when using new information technology.

Hypothesis 12 (H12): Perceived technological risk (TER) significantly negatively influences older adults' trust (TR) in telemedicine services.

Hypothesis 13 (H13): Perceived emotional risk (ER) significantly negatively influences older adults' trust in telemedicine services (TR).

Hypothesis 14 (H14): Perceived cost risk (CR) significantly negatively influences older adults' trust in telemedicine services (TR).

Behavioral intention refers to an individual's subjective will to perform a specific action and plays a pivotal role in predicting whether the individual will engage in the target behavior. Holden [62] and others define behavioral intention as the user's subjective willingness to adopt telemedicine services. Research by Teo [63] and others suggests that strong behavioral intentions can drive actual usage behavior. The Theory of Planned Behavior (TPB) posits that the most critical determinant of individual behavior is behavioral intention [64].

Hypothesis 15 (H15): Behavioral Intention (BI) significantly positively influences on older adults' actual usage behavior (UB) of telemedicine services.

To further gain insights into the mechanisms influencing older adults' willingness to use telemedicine services and trust, this study empirically investigated the factors that influence older users' trust in telemedicine and how this, in turn, affects older adults' willingness to use telemedicine services. More specifically, we constructed a relationship model based on Technology Acceptance Theory (TAM) and Deconstructive Theory of Planned Behavior (DTPB) among Perceived Usefulness (PU), Perceived Ease of Use (PE), Service Environment (SE), Subjective Norms (SR), Self Efficacy (SV), Trust (TR), Technological Risk (TER), Emotional Risk (ER), Cost Risk (CR), and Behavioral Intentions of Use (BI) with Use Behavior (UB). In this relational model, there are a total of 15 hypotheses, with 12 of them categorized into three main groups. Hypotheses H1 to H5 represent a set that has a direct effect on BI. Hypotheses H7 to H11 potentially have an indirect effect through TR and BI. Hypotheses H12 to H14 are a set that may have a negative effect on TR.

This study extends the research on trust in telemedicine services among older adults and unveils the mediating mechanism of older adults' Behavioral Intention to use telemedicine services based on TAM and DTPB. Building upon on the above hypotheses and analysis, we propose a conceptual model (see Fig. 1.).

Methods and measures

Aim and participants

This cross-sectional study aimed to explore the relationship between the intention to use and trust in telemedicine services among an older adult population in Shanghai, China, spanning from May 2023 to July 2023, utilizing a questionnaire sample. This study explores the influence of trust on older adults' use of telemedicine services and identifies the factors that affect their trust in these services. Data were gathered through a self-reported questionnaire adapted from prior studies and refined based on heuristic study findings. The questionnaire was developed for this study (see Additional file 2). The questionnaire data were collected from a Tertiary Hospital in Shanghai, China. The survey was distributed through an online platform called Wenjuanxing. Each invited participant received a link to complete the questionnaire, and only those invited could participate. A

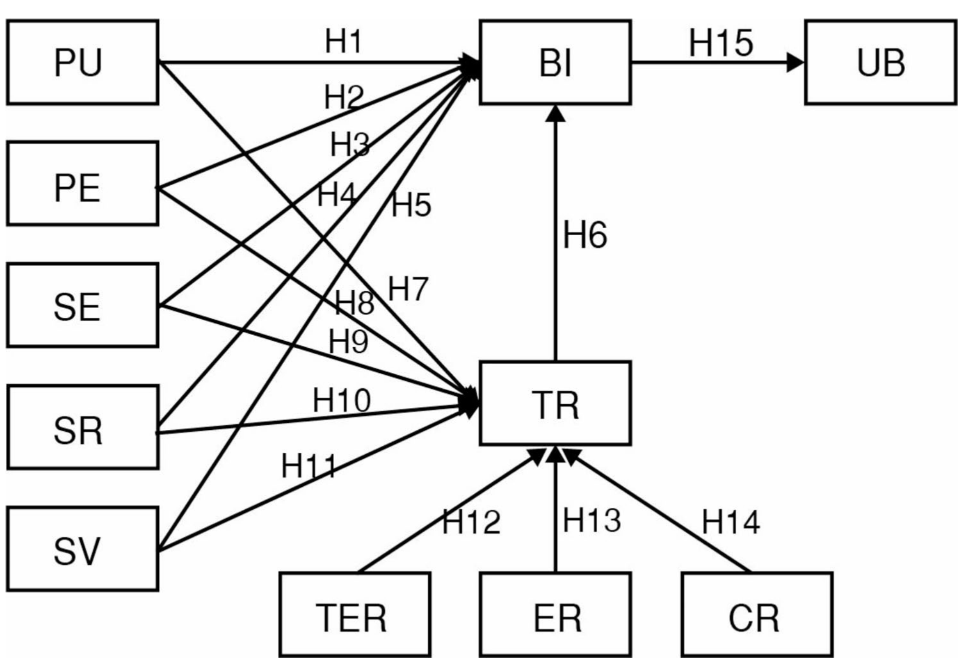

Fig. 1 Conceptual model

total of 548 older adults in Shanghai were surveyed using TAM and DTPB modeling research methods to understand their intentions and behaviors related to telemedicine usage. The questionnaire, distributed from May-July 2023, underwent initial small-scale testing before wider application among the elderly population.

Data collection

A total of 463 questionnaires were collected. Among them, 38 responses were from individuals under the age of 60 and thus did not meet the World Health Organization's definition of older adults. Additionally, 18 responses were excluded due to having over 70% repeated answers, missing values, or extreme values, and 7 questionnaires were excluded because the completion time was less than 60 s. The final data set comprised of 400 effective questionnaires yielding an effective recovery rate of 86.39%. Demographic characteristics are presented in Table 1, with 223 females (55.8%) and 177 males (44.2%) The majority fell within the 60–69 age group (232 or 58.0%), followed by 117 or 29.3% were the 70–79 age group 51 or 12.7% over 80 years. Over 62.8% of participants had a college or higher education level, while 6.7% had a primary education or below. Questions covered age, gender, education, telemedicine use behavior, intention to use telemedicine, perceived risk, perceived usefulness, perceived ease of use, Service Environment, Self Efficacy, and subjective norms. To safeguard participant's privacy the questionnaire did not request names and addresses.

Measure

To ensure the reliability and validity of variables, metrics for each hypothesized variable in this study were derived from measurement items commonly used as theoretical bases in existing literature. These items were then modified and supplemented in alignment with the theoretical foundations relevant to the telemedicine field, and further adjusted to suit the actual usage situations of the older adults. The final questionnaire underwent evaluation by doctors at a Grade 3 A hospital in China. Utilizing a 5-point Likert scale response format (1=completely disagree, 2=disagree, 3=neutral, 4=agree, 5=completely agree), the questionnaire comprised 41 measurement curarized into 12 factors: Demographics, Perceived Usefulness (PU), Perceived Ease of Use (PEU), Service Environment (SE), Subjective Norms (SR), Self Efficacy (SV), Behavioral Intention to Use (BI), Usage Behavior (UB), Trust (TR), Technology Risk (TER), Emotional Risk (ER), and Cost Risk (CR).

Table 1 Demographic characteristics

	Variable Items	*n*	%
Age	60–69	232	58.0
	70–79	117	29.3
	80	51	12.7
Educational Level	Primary and below	27	6.7
	Middle School	122	30.5
	College and above	251	62.8
Genders	Female	223	55.8
	Male	177	44.2

Statistical analysis

Structural Equation Modeling (SEMs) was employed to test the hypotheses based on the theoretical background Initially, descriptive demographic analysis of the sample was conducted using IBM SPSS Statistic 23.0 software package (IBM Corp., Armonk, NY, USA) to analyze the general characteristics. Factor loading and structural equation analysis were then performed using SPSS 23.0 and AMOS 24.0 to validate the measurement model's reasonableness. Subsequently, AMOS 24.0 was used to test each hypothesis proposed in the article, setting the significance level for the structural model at a p-value of less than 0.05.

Whether the data follow a normal distribution is crucial for subsequent analyses. According to Kline (1998), when the absolute value of skewness is less than 3 and the absolute value of kurtosis is less than 10, it indicates that the sample essentially follows a normal distribution. As shown in Table 2 (see Additional file 1), the results for the formal sample demonstrate that the absolute values of skewness for all items are less than 3, and the absolute values of kurtosis are less than 10. Both skewness and kurtosis meet the criteria for a normal distribution, indicating that all items conform to a normal distribution. Therefore, the collected questionnaire data can be directly used for subsequent statistical analyses, such as reliability and validity testing.

From Table 3, it can be observed that the Variance Inflation Factor (VIF) values are all below 3, indicating that there is no collinearity among the variables.

Results

Statistical analysis

The conceptual model underwent confirmatory factor analysis. As presented in Table 4 (see Additional file 1), all items exhibited standardized factor loadings greater than 0.5, with significant and positive residuals. The Composite Reliability (CR) values surpassed 0.7, Average Variance Extracted (AVE) values exceeded 0.5, and Cronbach's Alpha values were greater than 0.7. Consequently, all items met the standards for convergent validity and reliability.

Following the determination of dimension structure and the corresponding question items through validity and reliability analyses, the dimension scores were computed by averaging the scores of individual question

Table 2 Descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PU1	400	1.00	5.00	2.8075	1.21000	-0.018	0.122	-0.883	0.243
PU2	400	1.00	5.00	2.8200	1.18156	0.032	0.122	-0.787	0.243
PU3	400	1.00	5.00	2.8175	1.20325	-0.018	0.122	-0.869	0.243
PE1	400	1.00	5.00	2.7875	1.20456	0.017	0.122	-0.884	0.243
PE2	400	1.00	5.00	2.8150	1.15937	-0.081	0.122	-0.834	0.243
PE3	400	1.00	5.00	2.8350	1.20266	0.025	0.122	-0.803	0.243
SE1	400	1.00	5.00	2.8800	1.12862	-0.078	0.122	-0.738	0.243
SE2	400	1.00	5.00	2.8275	1.20681	0.025	0.122	-0.838	0.243
SE3	400	1.00	5.00	2.7675	1.19037	0.010	0.122	-0.863	0.243
SR1	400	1.00	5.00	2.7975	1.24916	0.024	0.122	-0.958	0.243
SR2	400	1.00	5.00	2.7900	1.21433	-0.005	0.122	-0.886	0.243
SR3	400	1.00	5.00	2.7750	1.18655	-0.037	0.122	-0.876	0.243
SV1	400	1.00	5.00	2.8350	1.20474	0.001	0.122	-0.845	0.243
SV2	400	1.00	5.00	2.8150	1.21427	0.013	0.122	-0.865	0.243
SV3	400	1.00	5.00	2.8800	1.13747	-0.040	0.122	-0.728	0.243
BI1	400	1.00	5.00	2.8250	1.25232	-0.012	0.122	-0.962	0.243
BI2	400	1.00	5.00	2.8350	1.17951	-0.082	0.122	-0.867	0.243
BI3	400	1.00	5.00	2.8475	1.20119	-0.070	0.122	-0.888	0.243
TR1	400	1.00	5.00	2.8675	1.19521	0.001	0.122	-0.867	0.243
TR2	400	1.00	5.00	2.7850	1.19051	-0.017	0.122	-0.838	0.243
TR3	400	1.00	5.00	2.8275	1.22331	0.052	0.122	-0.868	0.243
TR4	400	1.00	5.00	2.8475	1.21776	0.002	0.122	-0.854	0.243
TR5	400	1.00	5.00	2.8775	1.15361	-0.172	0.122	-0.774	0.243
TR6	400	1.00	5.00	2.9225	1.17684	0.003	0.122	-0.816	0.243
TR7	400	1.00	5.00	2.7725	1.20598	0.031	0.122	-0.877	0.243
TR8	400	1.00	5.00	2.7950	1.21518	-0.014	0.122	-0.945	0.243
TR9	400	1.00	5.00	2.8200	1.18156	0.069	0.122	-0.733	0.243
TER1	400	1.00	5.00	3.1825	1.16516	0.041	0.122	-0.776	0.243
TER2	400	1.00	5.00	3.1425	1.18139	0.070	0.122	-0.872	0.243
TER3	400	1.00	5.00	3.1575	1.20263	-0.037	0.122	-0.803	0.243
ER1	400	1.00	5.00	3.1225	1.21910	0.081	0.122	-0.934	0.243
ER2	400	1.00	5.00	3.1550	1.15945	0.005	0.122	-0.744	0.243
ER3	400	1.00	5.00	3.1350	1.21469	0.018	0.122	-0.909	0.243
CR1	400	1.00	5.00	3.0100	1.39634	-0.057	0.122	-1.224	0.243
CR2	400	1.00	5.00	3.0675	1.38301	-0.053	0.122	-1.210	0.243
UB1	400	1.00	5.00	2.6450	1.10091	0.455	0.122	-0.175	0.243
UB2	400	1.00	5.00	2.5725	1.11708	0.609	0.122	-0.200	0.243
UB3	400	1.00	5.00	2.5800	1.10981	0.444	0.122	-0.322	0.243
Valid N (listwise)	400								

Note * $p<0.05$ ** $p<0.01$ *** $p<0.001$,PU= Perceived Usefulness; PEU= Perceived Ease of Use; SE= Service Environment; SR= Subjective Norms; SV= Self Efficacy; BI= Behavioral Intention to Use; UB= Usage Behavior; TR= Trust; TER= Technology Risk; ER= Emotional Risk; CR= Cost Risk

items within each dimension. Subentry correlation analysis was conducted to explore the relationships between dimensions. The correlation coefficient values ranging from −1 to 1, were scrutinized, where the larger absolute value indicated a stronger the correlation between variables. Chiu Haozheng [65] proposed a detailed categorization of correlation coefficients, $|r| = 1$, perfect correlation; $0.70 \le |r| < 0.99$, high correlation; $0.40 \le |r| < 0.69$, moderate correlation; $0.10 \le |r| < 0.39$, low correlation; $|r| < 0.10$, weak or no correlation. Distinct validity analysis was employed to verify whether correlation between different constructs were statistically different. It was crucial to ensure that items in different constructs were not highly correlated, and if they were (0.85 or more), it suggested that these items were measuring the same underlying concept. This typically occurs when construct definitions overlap excessively. The present study utilizes the more rigorous Average Variance Extracted (AVE) method to assess differential validity [66]. For each factor the open root sign of the AVE for

Table 3 Collinearity statistics

	Tolerance	VIF
PU	0.642	1.557
PE	0.707	1.414
SE	0.721	1.386
SR	0.691	1.448
SV	0.707	1.414
BI	0.607	1.646
TR	0.571	1.752
ER	0.733	1.365
CR	0.699	1.430
UB	0.729	1.372

each factor had to be greater than the correlation coefficient of each paired variable indicating differential validity between factors. The diagonal line represents the standardized correlation coefficient for each factor, with the AVE open root sign greater than the off-diagonal line, affirming differential validity. The diagonal downward triangle displays the correlation coefficient (refer to Table 5 for details). Discriminant validity analysis is used to verify whether there is a statistical difference between the correlations of different constructs. Items from different constructs should not be highly correlated; if they are (with a correlation above 0.85), it indicates that these

Table 4 Validation factor analysis results

			Estimate	S.E.	C.*R*.	*P*	Factor Loading	CR	AVE	Cronbach's Alpha
PU1	<---	PU	1.000				0.851	0.897	0.743	0.895
PU2	<---	PU	0.947	0.048	19.781	***	0.825			
PU3	<---	PU	1.062	0.047	22.594	***	0.908			
PE1	<---	PE	1.000				0.785	0.853	0.660	0.852
PE2	<---	PE	1.043	0.064	16.289	***	0.851			
PE3	<---	PE	1.015	0.063	15.992	***	0.799			
SE1	<---	SE	1.000				0.804	0.856	0.664	0.855
SE2	<---	SE	1.092	0.067	16.291	***	0.821			
SE3	<---	SE	1.075	0.065	16.635	***	0.820			
SR1	<---	SR	1.000				0.829	0.852	0.658	0.852
SR2	<---	SR	0.932	0.056	16.750	***	0.795			
SR3	<---	SR	0.926	0.056	16.490	***	0.809			
SV1	<---	SV	1.000				0.801	0.844	0.643	0.843
SV2	<---	SV	1.027	0.062	16.426	***	0.816			
SV3	<---	SV	0.930	0.060	15.429	***	0.789			
BI1	<---	BI	1.000				0.825	0.847	0.648	0.846
BI2	<---	BI	0.920	0.055	16.872	***	0.807			
BI3	<---	BI	0.910	0.056	16.144	***	0.783			
TR1	<---	TR	1.000				0.782	0.939	0.630	0.939
TR2	<---	TR	1.016	0.058	17.501	***	0.797			
TR3	<---	TR	1.045	0.060	17.494	***	0.798			
TR4	<---	TR	1.011	0.060	16.883	***	0.776			
TR5	<---	TR	0.974	0.056	17.280	***	0.789			
TR6	<---	TR	1.010	0.057	17.574	***	0.802			
TR7	<---	TR	1.050	0.059	17.934	***	0.814			
TR8	<---	TR	1.039	0.059	17.638	***	0.799			
TR9	<---	TR	0.994	0.058	17.145	***	0.786			
TER1	<---	TER	1.000				0.788	0.835	0.628	0.835
TER2	<---	TER	1.019	0.067	15.109	***	0.792			
TER3	<---	TER	1.045	0.070	14.901	***	0.798			
ER1	<---	ER	1.000				0.792	0.840	0.636	0.840
ER2	<---	ER	0.964	0.061	15.727	***	0.803			
ER3	<---	ER	1.004	0.066	15.262	***	0.798			
CR1	<---	CR	1.000				0.798	0.811	0.682	0.810
CR2	<---	CR	1.059	0.080	13.223	***	0.853			
UB1	<---	UB	1.000				0.770	0.806	0.581	0.806
UB2	<---	UB	0.972	0.073	13.240	***	0.737			
UB3	<---	UB	1.022	0.075	13.590	***	0.780			

Note* $p<0.05$ ** $p<0.01$ *** $p<0.001$,PU= Perceived Usefulness; PEU= Perceived Ease of Use; SE= Service Environment; SR= Subjective Norms; SV= Self Efficacy; BI= Behavioral Intention to Use; UB= Usage Behavior; TR= Trust; TER= Technology Risk; ER= Emotional Risk; CR= Cost Risk

Table 5 Pearson correlation analysis and discriminant validity

	Mean value	Standard Deviation	1	2	3	4	5	6	7	8	9	10	11
PU (1)	2.815	1.090	0.862										
PE (2)	2.812	1.045	0.425***	0.812									
SE (3)	2.825	1.035	0.342***	0.374***	0.815								
SR (4)	2.787	1.069	0.373***	0.373***	0.394***	0.811							
SV (5)	2.843	1.035	0.401***	0.381***	0.325***	0.416***	0.802						
BI (6)	2.836	1.059	0.449***	0.296***	0.280***	0.277***	0.305***	0.805					
TR (7)	2.835	0.979	0.287***	0.218***	0.279***	0.257***	0.226***	0.454***	0.794				
TER(8)	3.161	1.026	0.022	-0.039	-0.048	0.015	0.000	-0.119*	-0.278***	0.792			
ER (9)	3.137	1.043	-0.007	-0.007	0.087	0.077	0.030	-0.111*	-0.363***	0.388***	0.797		
CR(10)	3.039	1.274	-0.016	-0.010	-0.011	-0.032	-0.080	-0.105*	-0.424***	0.404***	0.436***	0.826	
UB(11)	2.599	0.942	0.333***	0.248***	0.269***	0.288***	0.274***	0.454***	0.259***	-0.006	0.006	0.060	0.762
AVE			0.743	0.660	0.664	0.658	0.643	0.648	0.630	0.628	0.636	0.682	0.581

Note PU=Perceived Usefulness; PEU=Perceived Ease of Use; SE=Service Environment; SR=Subjective Norms; SV=Self Efficacy; BI=Behavioral Intention to Use; UB=Usage Behavior; TR=Trust; TER=Technology Risk; ER=Emotional Risk; CR=Cost Risk

items are measuring the same thing, which usually occurs when the definitions of constructs excessively overlap. This study employs the more rigorous Average Variance Extracted (AVE) method to assess discriminant validity. According to Fornell and Larcker (1981), the square root of the AVE for each factor must be greater than the correlation coefficients of each pair of variables, indicating that the factors have discriminant validity.

In this study, the square roots of the AVE values (shown on the diagonal) are greater than the standardized correlation coefficients outside the diagonal, demonstrating discriminant validity. The correlation coefficients, which are below the diagonal, further support this. Detailed results are shown in the table below. All square roots of AVE are greater than 0.7, and all correlation coefficients are lower than 0.6, indicating good discriminant validity.

In conducting confirmatory factor analysis, several key goodness-of-fit indices are used, including:

Chi-Square Test (χ^2): The chi-square index is the most fundamental test for model fit. However, because the chi-square value is sensitive to sample size, the χ^2/df ratio is used. A smaller value indicates a better model fit.

Goodness-of-Fit Index (GFI): GFI is similar to R-squared in regression analysis, with values ranging from 0 to 1. A value greater than 0.9 is considered ideal. The Adjusted Goodness-of-Fit Index (AGFI) adjusts GFI for degrees of freedom.

Root Mean Square Residual (RMR) and Root Mean Square Error of Approximation (RMSEA): RMR is the square root of the average of the squared differences between the observed and estimated variances and covariances. RMSEA, introduced by Steiger & Lind in 1980, is less sensitive to sample size and more sensitive to model misspecification, making it a preferred fit index. The closer the RMSEA value is to 0, the better the model fit.

Normed Fit Index (NFI), Incremental Fit Index (IFI), and Comparative Fit Index (CFI): NFI is a relative fit index that represents the proportion by which the theoretical model reduces the chi-square value. IFI is an adjustment of NFI that reduces dependency on sample size. CFI addresses the deficiencies of NFI in nested models by comparing the fit of a target model to an independent model, providing a robust estimate of model fit.

Together, these indices provide a comprehensive assessment of model fit, each contributing unique insights into the quality and accuracy of the model.

The model fit results, as presented in Table 6, indicate favorable fit indices. The CMIN/DF is 2.009, while the GFI, AGFI, NFI, TLI, IFI, and CFI all surpassed the standard threshold of 0.9. Additionally, RMSEA is less than 0.08. These fitting indices align with general standards for Structural Equation Modeling (SEM) studies, suggesting the model exhibits a strong fit.

Table 6 Structural model fit

Fitness Index	Acceptable Ranges	Measured Value
CMIN		54.250
DF		27
CMIN/DF	< 5	2.009
GFI	> 0.9	0.977
AGFI	> 0.9	0.945
RMSEA	< 0.08	0.050
IFI	> 0.9	0.974
NFI	> 0.9	0.949
TLI(NNFI)	> 0.9	0.945
CFI	> 0.9	0.973
SRMR	< 0.05	0.047

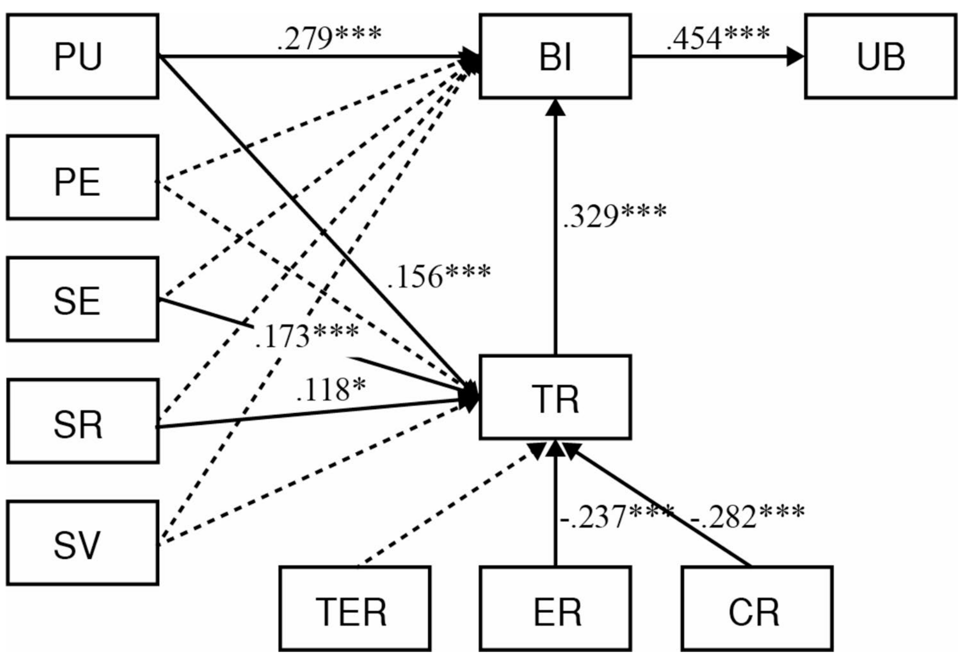

Fig. 2 Structural equation modeling path coefficients

Results of hypothesis testing

Main effects test

Examining the structural equation model results, depicted in Fig. 2 and detailed Table 7. It is evident that Perceived Usefulness (PU) and Trust (TR) exert a significantly positive impact on Behavioral Intention (BI) to use, with effect sizes of 0.279 and 0.329, respectively. Conversely the influences of Perceived Ease of Use (PE), Service Environment (SE), Subjective Norms (SR), and Self Efficacy (SV) on Behavioral Intention (BI) are not significant. This implies that among hypotheses H1-H6, only H1 and H6 are supported.

Moreover, Perceived Usefulness (PU), Service Environment (SE), and Subjective Norms (SR) exhibit significant positive influences on Trust (TR), with effect sizes of 0.156, 0.173, and 0.118, respectively. Emotional Risk (ER) and Cost Risk (CR) demonstrate significant negative impacts on Trust (TR), with effect sizes of -0.237 and −0.282, respectively. However, the effects of Perceived Ease of Use (PE), Self Efficacy (SV), and Technical Risk (TER) on Trust (TR) are not significant. Therefore, hypotheses H7, H9, H10, H13, and H14 are supported, while H8, H11, and H12 are not. Furthermore, Behavioral Intention (BI) exhibits a significant positive effect on Usage Behavior (UB), with an effect size of 0.454, confirming hypothesis H15.

We found that most factors did not have a direct impact on older adults' willingness to use telemedicine. This could be due to two main reasons. First, the current level of telemedicine adoption in China is insufficient. Most users do not have adequate awareness of telemedicine services, which prevents the formation of a direct willingness to use them. Second, the older adult population tends to be skeptical of new technologies such as telemedicine. The results might differ if the study were conducted with a younger demographic.

Table 7 Structural equation modeling path coefficient

				Estimate	S.E.	C.R.	P	Standardized Coefficient	Whether or Not Established
H1	BI	<---	PU	0.272	0.048	5.708	***	0.279	Y
H2	BI	<---	PE	0.054	0.049	1.106	0.269	0.054	N
H3	BI	<---	SE	0.041	0.049	0.836	0.403	0.040	N
H4	BI	<---	SR	0.021	0.048	0.440	0.660	0.021	N
H5	BI	<---	SV	0.078	0.049	1.585	0.113	0.077	N
H6	BI	<---	TR	0.354	0.048	7.441	***	0.329	Y
H7	TR	<---	PU	0.140	0.043	3.292	***	0.156	Y
H8	TR	<---	PE	0.021	0.045	0.476	0.634	0.023	N
H9	TR	<---	SE	0.164	0.044	3.754	***	0.173	Y
H10	TR	<---	SR	0.108	0.044	2.484	0.013	0.118	Y
H11	TR	<---	SV	0.032	0.045	0.708	0.479	0.033	N
H12	TR	<---	TER	-0.064	0.043	-1.482	0.138	-0.067	N
H13	TR	<---	ER	-0.223	0.044	-5.096	***	-0.237	Y
H14	TR	<---	CR	-0.217	0.036	-6.051	***	-0.282	Y
H15	UB	<---	BI	0.404	0.040	10.191	***	0.454	Y

Note * $p<0.05$ ** $p<0.01$ *** $p<0.001$, PU = Perceived Usefulness; PEU = Perceived Ease of Use; SE = Service Environment; SR = Subjective Norms; SV = Self Efficacy; BI = Behavioral Intention to Use; UB = Usage Behavior; TR = Trust; TER = Technology Risk; ER = Emotional Risk; CR = Cost Risk

Table 8 Mediating effect test

	Effect	Point Estimates	Product of Coefficients		Bootstrapping				
					Bias Corrected (95%)		Percentile method (95%)		Two-tailed significance
			SE	Z	Lower	Upper	Lower	Upper	
PU→BI	Direct	0.279	0.051	5.471	0.178	0.378	0.178	0.378	0.001**
	Indirect	0.051	0.017	3.000	0.021	0.088	0.020	0.086	0.001**
	Total	0.331	0.053	6.245	0.222	0.433	0.222	0.432	0.001**
SE→BI	Direct	0.040	0.048	0.833	-0.056	0.135	-0.059	0.133	0.421
	Indirect	0.057	0.018	3.167	0.026	0.096	0.025	0.094	0.001**
	Total	0.097	0.047	2.064	0.007	0.191	0.004	0.188	0.044*
SR→BI	Direct	0.021	0.051	0.412	-0.082	0.120	-0.079	0.122	0.668
	Indirect	0.039	0.017	2.294	0.008	0.074	0.008	0.074	0.017*
	Total	0.060	0.053	1.132	-0.043	0.164	-0.041	0.166	0.253

Note * $p<0.05$ ** $p<0.01$ *** $p<0.001$, PU = Perceived Usefulness; PEU = Perceived Ease of Use; SE = Service Environment; SR = Subjective Norms; SV = Self Efficacy; BI = Behavioral Intention to Use; UB = Usage Behavior; TR = Trust; TER = Technology Risk; ER = Emotional Risk; CR = Cost Risk

Mediation effect test

To investigate the mediating role of Trust (TR), this study employed a Bootstrap mediation effect test to determine the significance of the mediation effect. The validated data finding are presented in Table 8.

In the pathway from Perceived Usefulness (PU) to Behavioral Intention (BI), both the total effect and the indirect effect show confidence intervals that do not include zero, with the Z-values greater than 1.96. This indicates the presence of a mediating effect in the PU to BI pathway. Furthermore, the confidence interval od the direct effect do not include zero, and the Z-value is greater than 1.96, signifying partial mediation with a mediation effect size of 0.051. Therefore, suggests that the positive impact of PU on BI is partially realized through the enhancement of trust (TR).

In the pathway from Service Environment (SE) to Behavioral Intention (BI), both the total effect and the indirect effect exhibit confidence intervals that do not include zero, with Z-values surpassing 1.96, indicating the existence of a mediating effect. The confidence intervals of the direct effect encompassing zero and the Z-value is less than 1.96, rendering the direct effect nonsignificant. This points to full mediation with a mediation effect size of 0.057, suggesting that the positive impact of SE on BI is entirely mediated by enhancing trust (TR).

In the pathway from Subjective Norms (SR) to Behavioral Intention (BI), the confidence intervals of the total effect include zero, and the Z-value is less than 1.96. This suggests an absence of a mediating effect, and the direct effect is nonsignificant indicating no significant relationship between SR and BI.

The results of the mediation effect are shown in Table 9.

Discussion

This study, grounded in a survey of older adults' data and guided by the Technology Acceptance theory, delved into factors influencing older adults' Behavioral Intention

Table 9 Summary of BOOTSTRAP mediation test results

	c total effect	a	b	a*b mediating effect value	a*b (Boot SE)	a*b (z)	a*b (*p*)	a*b (95% BootCI)	c' direct effect	Test Conclusion
PU => TR => BI	0.323***	0.144**	0.354***	0.051	0.019	2.639	0.008	0.016 ~ 0.093	0.272***	intermediary
PE => TR => BI	0.065	0.031	0.354***	0.011	0.019	0.580	0.562	-0.027 ~ 0.048	0.054	insignificant
SE => TR => BI	0.092	0.145**	0.354***	0.051	0.020	2.595	0.009	0.013 ~ 0.092	0.041	Fully intermediated
SR => TR => BI	0.054	0.092	0.354***	0.033	0.018	1.793	0.073	-0.002 ~ 0.069	0.021	insignificant
SV => TR => BI	0.098	0.054	0.354***	0.019	0.018	1.055	0.291	-0.016 ~ 0.056	0.078	insignificant

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

bootstrap type: percentile bootstrap method

to use telemedicine. By amalgamating TAM and DTPB models and employing a mean variable model to scrutinize the path relationships, we discovered that Perceived Usefulness had a significantly positively affected Behavioral Intention to Use. And Service Environment significantly and positively affects Behavioral Intention through the mediating variable of Trust. Notably, Trust emerged as a crucial mediating variable in this relationship, emphasizing the pivotal role of trust in influencing older adults' Behavioral Intention to use telemedicine services.

Perceived Usefulness (PU): Perceived Usefulness, a pivotal variable in the Technology Acceptance Model (TAM), serves as vital indicator for studying users' acceptance of information technology services. Consistent with prior research [32, 33], PU demonstrated a positive influence on older adults' intention to use telemedicine, highlighting its importance, especially among older demographics. Given potential hesitancy towards new technologies [67], tailoring telemedicine services to address the unique needs of older adults, emphasizing convenience, accessibility, and time savings, can enhance their understanding and enhance their understanding and appreciation. Clear communication of telemedicine's functionality and advantages can foster a perception of usefulness [68], increasing the likelihood of acceptance among older adults.

Trust as a mediator

Our findings indicate that both Perceived Usefulness and Service Environment influence older adults' Behavioral Intention to use telemedicine through the mediating role of trust. While PU affects intention through trust mediation, SE exerts its impact on Behavioral Intention through the full trust mediation. This underscores the importance for telemedicine service providers to concentrate on bolstering trust among older adults to enhance their willingness to engage with such services. Trust emerges as a pivotal mediator, aligning with existing research [49, 50, 57]. Telemedicine, being a potentially unfamiliar concept for older adults, may trigger concerns about its effectiveness, safety, and privacy [69]. Trust plays a critical role in allaying uncertainties and instilling confidence in telemedicine's feasibility, effectiveness, and safety, thereby reducing doubts increasing older adults' Behavioral Intention to use telemedicine.

Building on existing research, we conducted a more in-depth study of the factors and pathways that influence trust. Factors Influencing Trust: Perceived Usefulness, Service Environment and Subjective Norms were identified as significant contributors to older adults' trust in telemedicine. Trust in telemedicine was bolstered when older adults perceived its utility in addressing health issues, experienced positive and caring attitudes, and received high-quality services and support. Moreover, positive community and authority endorsements, coupled with supportive subjective norms, were instrumental in enhancing older adults' trust in telemedicine. Shaping Subjective Norms through ensuring telemedicine's utility, providing positive service experiences and fostering a conductive Service Environment are imperative for cultivating trust among older adults in the realm of telemedicine. This may provide some guidance for the development of future standards and policies for telemedicine in China.

Additionally, Emotional Risk and Cost Risk demonstrated significant associations with trust with heightened Emotional Risk and Cost Risk inversely correlated with older adults' trust in telemedicine [70]. The absence face-to-face communication and physical contact in telemedicine may elevate Emotional Risk, leading to emotions like anxiety, restlessness, and worry among older adults. Moreover, the technical requirements and potential expenses associated with telemedicine, such as software and subscription fees, could pose challenges, particularly for older adults with limited financial resources. Effectively addressing Emotional and Cost Risks emerges as a crucial measure for enhancing user trust. This offers a new perspective for the development of telemedicine service software in China. Based on the findings of this study, providers of telemedicine services should prioritize strategies that minimize older adults' Emotional and Cost Risks during the design phase of services. This could potentially enhance the efficiency of building telemedicine service practices targeted at older adults in China.

Finally, our study highlights the significant impact of older adults' Behavioral Intention to use telemedicine on their actual Usage Behavior. The absence of a positive Behavioral Intention may deter older adults from attempting or persisting in the use of telemedicine. Consequently, understanding and fostering a positive Behavioral Intention to use telemedicine among older adults becomes a critical aspect of successful telemedicine implementation.

Limitations

This study, utilized a cross-sectional survey approach, collecting data from 400 questionnaires in China. However, the subjective nature of the variables measured in the questionnaires inevitably introduced a certain level. Future research endeavors aim to enhance objectivity by incorporating experiments that observe objective variables, thus obtaining more accurate and unbiased data.

Furthermore, the scope of this study is constrained by the relatively modest size of the survey and limited by the research sample. The investigation focused on a specific hospital in the Shanghai area, introducing some limitations to the generalizability of the findings. Subsequent research should seek broader data sets to validate the factors influencing older adults' Behavioral Intention to use telemedicine services.

Finally, the majority of the influencing factor variables considered in this paper are drawn from existing studies, with a gap in research on variables not addressed in previous literature. Recognizing this, ongoing research initiatives are underway to delve deeper into the influencing factors of older adults' Behavioral Intention to use telemedicine. This involves an exploration of additional levels and a comprehensive analysis of factors that have not been extensively studied in previous research.

Conclusions

This study developed a comprehensive model of older adults' Behavioral Intention (BI) to use telemedicine services by integrating the TAM and DTPB models. The aim was to explore the factors influencing older adults' intention to use telemedicine. The results underscored that Perceived Usefulness (PU) and Service Environment (SE) significantly and positively influenced Behavioral Intention (BI) to use, with Perceived Usefulness (PU) emerging as the most critical factor shaping older adults' intention to use telemedicine services. Furthermore, Trust (TR) emerged as a pivotal factor influencing older adults' Behavioral Intention (BI) to use telemedicine services, exerting a positive effect on their intention to use these services.

Additionally, the study identified significant relationships between it was shown that Perceived Usefulness (PU), Service Environment (SE), Subjective Norms (SR), Emotional Risk (ER), and Cost Risk (CR) with older adults' Trust (TR) in telemedicine, Emotional Risk (ER) and Cost Risk (CR) were found to reduce Trust (TR).

Consequently, it is imperative for telemedicine services aimed at older adults to focus on enhancing user perception of trust throughout the service process. This involves addressing factors such as Perceived Usefulness, Service Environment, Subjective Norms, Emotional Risks, and Cost Risks in the pre-use stage as well as emphasizing the importance of as Service Environment in the mid-use stage of the telemedicine service process. Such considerations will contribute to a more robust enhancement of older adults' Behavioral Intention to use telemedicine services.

Abbreviations

TAM	Technology Acceptance Model
DTPB	Decomposed Theory of Planned Behavior
IDT	Diffusion Theory
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behavior
PMT	Protection Motivation Theory
HBM	Health Belief Model
PU	Perceived Usefulness
PE	Perceived Ease of Use
SR	Subjective Norms
SE	Service Environment
SV	Self Efficacy
TR	Trust
BI	Behavioral Intention to Use
UB	Usage Behavior
TER	Technological Risk
ER	Emotional Risk
CR	Cost Risk
SEM	Structural Equation Modeling

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Author contributions

Q.T. and Wenjia Li led the conceptualization. Wenjia Li was responsible for data curation and resources. Q.T. and J.G. worked on the formal analysis. The methodology was developed by Wenjia Li and J.G. Wenjia Li and Q.T. validated the study. Q.T., Wenjia Li, J.G., and Wanting Liu conducted the investigation. Q.T. and Wenjia Li were responsible for the software. J.G. and Wanting Liu wrote the initial draft. Wenjia Li and J.T. reviewed and edited the manuscript. The visualization was done by Wenjia Li, J.G., and Wanting Liu. Q.T. supervised the project. J.G. managed the project. Wenjia Li acquired funding. All authors reviewed the manuscript.

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Data availability

"The datasets used or analyzed during the current study are available from the corresponding author on reasonable request."

Declarations

Ethics approval and consent to participate

The Human Research Ethics Committee—Humanities of School of Medicine, Tongji University, approved this study (Ref: ECHTJ 2022-16).The patients/

participants provided their written informed consent to participate in this study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References

1. World Population Prospects. 2022: Summary of Results [https://www.un.org/development/desa/pd/content/World-Population-Prospects-2022]
2. MAJOR FIGURES ON 2020 POPULATION CENSUS OF CHINA. [http://www.stats.gov.cn/sj/pcsj/rkpc/d7c/202111/P020211126523667366751.pdf]
3. Options for Aged Care in China. Building an Efficient and Sustainable Aged Care System (English) [https://documents.worldbank.org/en/publication/documents-reports/documentdetail/171061542660777579/options-for-aged-care-in-china-building-an-efficient-and-sustainable-aged-care-system]
4. WHO. Global strategy and action plan on ageing and health. 2017.
5. Raghupathi W, Raghupathi V. An Empirical Study of Chronic Diseases in the United States: A Visual Analytics Approach. 2018(1660–4601 (Electronic)).
6. Liu H, Zhuang Y, Liang Y, Guo W, Wang Z, Wang H, Wang H, Cai F. China Family Development Report (2015). China Popul Dev Stud. 2017;1(1):98–115.
7. Telehealth. Defining 21st Century Care [https://www.americantelemed.org/resource/why-telemedicine/]
8. eHealth WHOGOf. mHealth: new horizons for health through mobile technologies: second global survey on eHealth. In. Geneva: World Health Organization; 2011.
9. Virtual Visits with Medical Specialists Draw Strong Consumer Demand, Shows S. [https://www.prnewswire.com/news-releases/virtual-visits-with-medical-specialists-draw-strong-consumer-demand-survey-shows-300475757.html]
10. Gordon NP, Hornbrook MC. Older adults' readiness to engage with eHealth patient education and self-care resources: a cross-sectional survey. BMC Health Serv Res. 2018;18(1):220.
11. Sun X, Yan W, Zhou H, Wang Z, Zhang X, Huang S, Li L. Internet use and need for digital health technology among the elderly: a cross-sectional survey in China. BMC Public Health. 2020;20(1):1386.
12. Xue L, Yen Cc Fau - Chang L, Chang L, Fau - Chan HC, Chan Hc Fau - Tai BC, Tai Bc Fau - Tan SB, Tan Sb Fau - Duh HBL, Duh Hb Fau -, Choolani M, Choolani M. An exploratory study of ageing women's perception on access to health informatics via a mobile phone-based intervention. *International journal of medical informatics* 2012(1872–8243 (Electronic)).
13. Zhang M, Luo M, Nie R, Zhang Y. Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology. Int J Med Informatics 2017(1872–8243 (Electronic)).
14. Li C-R, Zhang E, Han J-T. Adoption of online follow-up service by patients: an empirical study based on the elaboration likelihood model. Comput Hum Behav. 2021;114:106581.
15. Meng FA-O, Guo XA-O, Peng ZA-O, Lai KA-O, Zhao XA-O. Investigating the Adoption of Mobile Health Services by Elderly users: trust transfer model and Survey Study. JMIR mHealth uHealth 2019(2291–5222 (Print)).
16. Yi MY, Yoon JJ, Davis JM, Lee T. Untangling the antecedents of initial trust in web-based health information: the roles of argument quality, source expertise, and user perceptions of information quality and risk. Decis Support Syst. 2013;55(1):284–95.
17. Ortega Egea JM, Román González MV. Explaining physicians' acceptance of EHCR systems: an extension of TAM with trust and risk factors. Comput Hum Behav. 2011;27(1):319–32.
18. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 1989;13:319–40.
19. Taylor S, Todd PA. Understanding Information Technology usage: a test of competing models. Inform Syst Res. 1995;6(2):144–76.
20. Mathieson K. Predicting user intentions: comparing the Technology Acceptance Model with the theory of Planned Behavior. Inform Syst Res. 1991;2(3):173–91.
21. Pavlou PA, Fygenson M. Understanding and Predicting Electronic Commerce Adoption: an extension of the theory of Planned Behavior. MIS Q. 2006;30(1):115–43.
22. Moore GC, Benbasat I. Development of an instrument to measure the perceptions of adopting an Information Technology Innovation. Inform Syst Res. 1991;2(3):192–222.
23. Rutter D, Quine L. Changing health behavior: Intervention and research with social cognition models; 2002.
24. Dahl S. Social Media Marketing - Theories and Applications; 2015.
25. Topa G, Moriano JA. Theory of planned behavior and smoking: meta-analysis and SEM model. Subst Abuse Rehabilitation. 2010;1(null):23–33.
26. Croyle RT, Director H, Rimer B, Glanz K. Theory at a glance: a guide for health promotion practice (Second edition). 2005.
27. Ajzen I. The theory of planned behavior. Organ Behav Hum Decis Process. 1991;50(2):179–211.
28. Conner M, Sparks P. The theory of planned behaviour and health behaviours. Predicting health behaviour: research and practice with social cognition models. Maidenhead, BRK, England: Open University; 1996. pp. 121–62.
29. Fishbein M, Ajzen I. Belief, attitude, intention and behaviour: An introduction to theory and research, vol. 27; 1975.
30. Lee YC, Hsieh YF, Guo YB. Construct DTPB model by using DEMATEL: a study of a university library website. Program. 2013;47(2):155–69.
31. Holden R, Karsh B-T. The Technology Acceptance Model: its past and its future in Health Care. J Biomed Inform. 2009;43:159–72.
32. Ahmed MH, Awol SM, Kanfe SG, Hailegebreal S, Debele GR, Dube GN, Guadie HA, Ngusie HS, Klein J. Willingness to use telemedicine during COVID-19 among health professionals in a low income country. Inf Med Unlocked. 2021;27:100783.
33. Kim S, Chow BC, Park S, Liu H. The usage of Digital Health Technology among Older Adults in Hong Kong and the role of technology readiness and eHealth literacy: path analysis. J Med Internet Res. 2023;25:e41915.
34. Lewis JR, Sauro J. Effect of Perceived Ease of Use and usefulness on UX and behavioral outcomes. Int J Human–Computer Interact 2023:1–8.
35. Jia R, Reich BH. IT service climate, antecedents and IT service quality outcomes: some initial evidence. J Strateg Inf Syst. 2013;22(1):51–69.
36. Parasuraman AP, Zeithaml V, Berry L. SERVQUAL: a multiple- item Scale for measuring consumer perceptions of service quality. J Retail 1988.
37. Schneider B, Macey WH, Lee WC, Young SA. Organizational Service Climate drivers of the American customer satisfaction index (ACSI) and Financial and Market Performance. J Service Res. 2009;12(1):3–14.
38. Deng Z, Mo X, Liu S. Comparison of the middle-aged and older users' adoption of mobile health services in China. Int J Med Informatics. 2014;83(3):210–24.
39. Lu J, Yao JE, Yu C-S. Personal innovativeness, social influences and adoption of wireless internet services via mobile technology. J Strateg Inf Syst. 2005;14(3):245–68.
40. Ernst F. Speaking of Health: Assessing Health Communication, strategies for diverse populations. J Natl Med Assoc 2005, 97.
41. Bandura A. Self-efficacy: toward a unifying theory of behavioral change. Adv Behav Res Therapy. 1978;1(4):139–61.
42. Ng TWH, Lucianetti L. Within-individual increases in innovative behavior and creative, persuasion, and change self-efficacy over time: a social–cognitive theory perspective. J Appl Psychol 2016:14–34.
43. Choi Y-N, Kim K-H, Oh S-R. Structural model for users's accepting Smart Health Care services by moderating the user types. J Korea Contents Association. 2015;15:541–54.
44. Lim S, Xue L, Yen CC, Chang L, Chan HC, Tai BC, Duh HBL, Choolani M. A study on Singaporean women's acceptance of using mobile phones to seek health information. Int J Med Informatics. 2011;80(12):e189–202.
45. Luo X, Li H, Zhang J, Shim J. Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: an empirical study of mobile banking services. Decis Support Syst 2010:222–34.
46. Zarolia P, Weisbuch M, McRae K. Influence of indirect information on interpersonal trust despite direct information. J Personal Soc Psychol. 2017;112:39–57.
47. Kautish P, Siddiqui M, Siddiqui A, Sharma V, Alshibani SM. Technology-enabled cure and care: an application of innovation resistance theory to telemedicine apps in an emerging market context. Technol Forecast Soc Chang. 2023;192:122558.
48. Yang Q, Pang C, Liu L, Yen DC, Michael Tarn J. Exploring consumer perceived risk and trust for online payments: an empirical study in China's younger generation. Comput Hum Behav. 2015;50:9–24.

49. Akter S, D'Ambra J, Ray P. Trustworthiness in mHealth Information services: an Assessment of a hierarchical model with Mediating and Moderating effects using partial least squares (PLS). JASIST. 2011;62:100–16.
50. Akter S, Ray P, D'Ambra J. Continuance of mHealth services at the bottom of the pyramid: the roles of service quality and trust. Electron Markets. 2013;23(1):29–47.
51. Kampmeijer R, Pavlova M, Tambor M, Golinowska S, Groot W. The use of e-health and m-health tools in health promotion and primary prevention among older adults: a systematic literature review. BMC Health Serv Res. 2016;16(5):290.
52. Bauer RA. Consumer behavior as risk taking. In: Mark Classics: Selection Influential Articles 1969: 119–27.
53. He L, Park K, Roehl WS. Religion and perceived travel risks. J Travel Tourism Mark. 2013;30(8):839–57.
54. Bashir S, Khwaja MG, Mahmood A, Turi JA, Latif KF. Refining e-shoppers' perceived risks: development and validation of new measurement scale. J Retailing Consumer Serv. 2021;58:102285.
55. Hanafizadeh P, Khedmatgozar HR. The mediating role of the dimensions of the perceived risk in the effect of customers' awareness on the adoption of internet banking in Iran. Electron Commer Res. 2012;12(2):151–75.
56. Hassan AM, Kunz M, Pearson AW, Mohamed FA. Conceptualization and measurement of perceived risk in online shopping. Mark Manage J. 2006;16:138–47.
57. Kuen L, Schürmann F, Westmattelmann D, Hartwig S, Tzafrir S, Schewe G. Trust transfer effects and associated risks in telemedicine adoption. Electron Markets. 2023;33(1):35.
58. Biancone P, Secinaro S, Marseglia R, Calandra D. E-health for the future. Managerial perspectives using a multiple case study approach. Technovation. 2023;120:102406.
59. Yoo B-K, Kim M, Sasaki T, Hoch JS, Marcin JP. Selected use of Telemedicine in Intensive Care Units based on severity of illness improves cost-effectiveness. Telemedicine e-Health. 2017;24(1):21–36.
60. Keith MJ, Babb JS, Lowry PB, Furner CP, Abdullat A. The role of mobile-computing self-efficacy in consumer information disclosure. Inform Syst J. 2015;25(6):637–67.
61. Kim H-W, Chan HC, Gupta S. Value-based adoption of Mobile Internet: an empirical investigation. Decis Support Syst. 2007;43(1):111–26.
62. Holden RJ, Karsh B-T. The Technology Acceptance Model: its past and its future in health care. J Biomed Inform. 2010;43(1):159–72.
63. Teo T, van Schaik P. Understanding the intention to Use Technology by Preservice teachers: an empirical test of competing theoretical models. Int J Human–Computer Interact. 2012;28(3):178–88.
64. Ajzen I. Perceived behavioral control, Self-Efficacy, Locus of Control, and the theory of Planned Behavior. J Appl Soc Psychol. 2002;32:665–83.
65. Haozheng C. Quantitative Research and Statistical Analysis. Chongqing University; 2006.
66. Fornell C, Larcker DF. Evaluating Structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39–50.
67. Lei J, Liang Y, Su Z, Dong P, Liang J, Lin L. Can socially assistive Robots be accepted by older people living alone in the community? Empirical findings from a Social Work Project in China. J Gerontol Soc Work 2024:1–18.
68. Liu S, Zhao H, Fu J, Kong D, Zhong Z, Hong Y, Tan J, Luo Y. Current status and influencing factors of digital health literacy among community-dwelling older adults in Southwest China: a cross-sectional study. BMC Public Health. 2022;22(1):996.
69. Paslakis G, Fischer-Jacobs J, Pape L, Schiffer M, Gertges R, Tegtbur U, Zimmermann T, Nöhre M, de Zwaan M. Assessment of Use and preferences regarding internet-based Health Care Delivery: cross-sectional questionnaire study. J Med Internet Res. 2019;21(5):e12416.
70. Jen W-Y, Hung M-C. An empirical study of Adopting Mobile Healthcare Service: the Family's perspective on the Healthcare needs of their Elderly members. Telemedicine e-Health. 2010;16(1):41–8.

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