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Using the smart health management services and devices among China's adults and the influencing factors: A mixed-methods study ☆

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ABSTRACT

Background: As the emerging of structural imbalance characterized by surging demand and insufficient high-quality supply in China's health management system, smart health management services become a novel measure to address this gap. Smart health management services refer to the health monitoring, assessment and intervention with support of information communication and artificial intelligence technologies.

Objective: To systematically analyze the current status, needs, and influencing factors of the using of smart health management services and devices among China's adults, thereby providing evidence support and suggestions for its development.

Methods: A mixed-methods design was employed, combining quantitative and qualitative research methods. In the quantitative section, participants aged 18 years and above were selected by a stratified cluster random sampling method, their intentions and behaviors in utilizing smart health management services were analyzed by structural equation model (SEM).

In the qualitative research section, 13 interviewees were selected for semi-structured, one-on-one interviews, the findings were analyzed by grounded theory coding. Quantitative and qualitative findings were integrated using an explanatory sequential mixed-methods framework.

Results: A total of 2786 adults participated the questionnaire survey with a response rate of 96.07 %. Of them, 13 participants agreed to attend the semi-structured, one-on-one interviews. The main findings are as follows: (1) 37.7 % of the adult participants used smart health management devices. The use rate presents decline with increasing age, and lower use among older adults. (2)The demand for smart health management systems shows a diversified trend, and significant differences between age groups. Overall, participants believe that certain basic functions of the smart health systems, such as health monitoring, are needed, and they hope that it can answer questions raised by users. Qualitative study further revealed that participants' needs for smart health systems are in line with Maslow's Hierarchy of Needs, which includes needs at various levels from "basic life safety and health security" to "active learning and self-actualization." Young participants prefer the support function for basic preventive activities and optimization of lifestyle; older participants then are more concerned about whether the system has practical functions for disease management. (3)The average using willingness was moderately high (62.68 ± 20.65). In the SEM, behavioral attitude emerged as the strongest predictor of willingness of use(β=0.568, $P < 0.001$), followed by subjective norms ($\beta = 0.103$, $P < 0.001$) and media motivation ($\beta = 0.094$, $P < 0.001$). Electronic health literacy exerted significant indirect effects on both willingness ($\beta = 0.045$, $P < 0.001$) and behavior (β=0.051, $P < 0.001$) via media motivation, while perceived behavioral control influenced them indirectly ($\beta = 0.014$ and 0.016, both $P < 0.001$). Living in urban areas positively affected both willingness($\beta = 0.056$, $P < 0.001$) and behavior ($\beta = 0.125$, $P < 0.001$). Health insurance coverage significantly promoted willingness ($\beta = 0.039$, $P < 0.001$). (4)Qualitative findings revealed multiple barriers to using, including high costs, product quality concerns, discomfort during using, and security issues. Attitudes toward smart health management devices were polarized, positive or negative evaluations stemmed directly from experience, perceived benefits, and device intelligence level, whereas neutral users tended to discontinue use due to a lack of perceived value. In addition, personal beliefs and cultural values strongly influenced individuals' acceptance.

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Conclusion: The study identified a distinct pattern of "high wish and low use" among adults regarding smart health management services. Both using behavior and demand pattern exhibited clear age-specific differences and were shaped by a number of factors. To bridge the gap between willingness to use and actual using behavior, future efforts should focus on age-appropriate design, precision implementation, and collaboration with primary care facilities, thereby enhancing adults' capacity for actively managing their health.

With population aging, improved health literacy, increased chronic diseases, and growing willingness and capacity to pay for healthcare services, the demand for health management emerged among residents in China. However, due to limitations in the number and competency of healthcare professionals and the constraints of conventional service delivery models, the supply of high-quality health management services remained insufficient.[1] This imbalance between expanding demand and limited supply prioritized smart health management. Evidence suggests benefits of information-driven health management models, including disease risk prediction, preventive interventions, and health behavior modification.[2] According to market data, the core market size of digital health management in China is projected to reach 241.8 billion Chinese Yuan(CNY) by 2024, driving an overall market value exceeding 1.2 trillion CNY.[3]

Smart health management represents a novel model that senses, analyzes, and integrates information across monitoring, assessment, and intervention of health based on next-generation technologies on information, communication, artificial intelligence (AI), and bioinformatics. The model enables intelligent, adaptive responses to the health needs of individuals and populations[1] with significant benefits.[4] For example, socially assistive robots can play a valuable role in elderly care by providing emotional and physiological support, cognitive training, and social engagement.[5] Existing studies found that middle-aged and older adults' willingness to use smart wearable devices is influenced by behavioral attitudes, perceived behavioral control, and subjective norms.[6]

However, current research focused on older adults, lacking research on younger and middle-aged populations. Moreover, most studies were based on technology acceptance perspective, ignoring social-ecological factors, such as individual skills, family and peer support, social cultural, and policy environment. Additionally, the reliance on quantitative methods made researchers difficult to capture individuals' subjective experiences, contextualized behaviors, and the motivational mechanisms underlying adoption, these factors are embedded in personal narratives and can only be explored through qualitative research. To address this gap, we employ an explanatory sequential mixed-methods design, integrating quantitative and qualitative researches to explore the using patterns and influencing factors of smart health management services and devices among China's adults, to support multi-level strategies that enhance the using of smart health management services and devices.

Theoretical framework and hypotheses

Theoretical framework

This study adopts the Theory of Planned Behavior (TPB)[7] as core framework to examine the mechanisms shaping individuals' willingness and behavior of smart health management services use. The TPB identifies behavioral attitude, subjective norms, and perceived behavioral control as determinants of behavioral willingness.[7] In the digital health context, individuals' capabilities and motivators may serve as important antecedents of these determinants.[8,9] This study introduces two key variables: eHealth literacy, reflecting individuals' ability to apply health information within digital environments; and media motivation, representing the intrinsic drive to utilize digital media tools. Incorporating these variables enables a more comprehensive exploration of the psychological pathway from individual traits to behavioral outcomes, thereby enhancing the explanatory power of the TPB for digital health behaviors. The overall theoretical framework is illustrated in Fig. 1.

To contextualize these mechanisms within broader social and environmental structures, this study further integrates the Social Ecological Theory (SET)[10,11] to organize theoretical models systematically from micro, *meso*, and macro levels. Micro level focuses on individual attributes and competencies, including knowledge, skills, attitudes, and self-efficacy,[10] this level includes eHealth literacy, media motivation, behavioral attitude, and perceived behavioral control in this study to capture individual factors of health behavior. Meso level emphasizes the influence of immediate social factors, such as family, peers, and community networks,[10] subjective norms are situated at this level to evaluate the influence of family and peers on individual health behaviors. Macro level encompasses sociocultural and policy contexts such as place of residence and health insurance coverage,[10,12,13] which are also included in this study as control variables.

Research hypotheses

Electronic health(eHealth) literacy refers to an individual's ability to use information and communication technologies to improve health outcomes, and can be a predictor of individuals' adoption of eHealth technologies.[14,15] Older adults with lower cognitive abilities and limited health literacy were reported struggle to obtain and interpret useful health information via the internet in previous study,[8] making it difficult for them to benefit from digital health advancements.

Meanwhile, individuals' willingness and motivation of digital access behavior by media, internet, or smart devices are also crucial factors in eHealth services adoption.[9] These findings suggest significant predictive roles of both eHealth literacy and media motivation in the willingness and behavior of adopting eHealth services, however, the internal mechanisms of synerge effect on individual health decisions remained to be explored.

Based on this, the following hypotheses are proposed:

H1. Media motivation positively predicts willingness(H1a) and behavior(H1b) of smart health mManagement services and devices use.

H2. eHealth literacy positively influences willingness and behavior mediating by media motivation.

Behavioral attitude is a major determinant of willingness in TPB,[7] perceived trust is a key component of behavioral attitude, affecting the adoption of information technology. Previous studies showed that the greater trust of older adults in smart elderly care services (i.e., the stronger positive attitude) was related to greater willingness of use.[16] Similarly, trust significantly affects users' willingness to adopt AI-assisted health decision-making tools.[17]

Hence, the following hypotheses are proposed:

H3. Behavioral attitude positively predicts behavioral willingness.

H4. Behavioral attitude mediates the relationship between media motivation and willingness.

Perceived behavioral control, another central factor in the TPB, refers to an individual's perceived control in performing a given behavior.[7] Self-efficacy is often used as a key dimension of perceived behavioral control.[18] Studies suggested that higher perceived behavioral control increased the likelihood of older adults adopting wearable health devices.[6] Similarly, higher self-efficacy enhances the likelihood of accessing online health information,[19] and boosts users' perceived usefulness of mobile health services, thereby increasing willingness of use.[20]

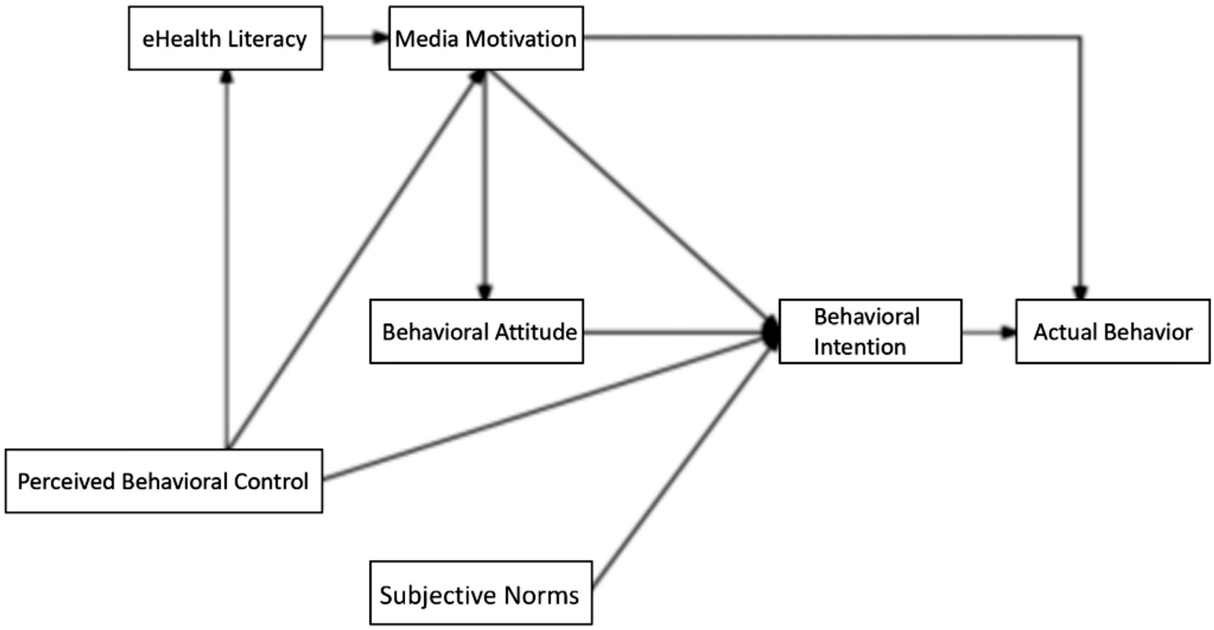

Fig. 1. Schematic diagram of the theoretical framework.

Based on this, the following hypotheses are proposed:

H5. Perceived behavioral control positively predicts willingness.

H6. Perceived behavioral control positively predicts eHealth literacy.

H7. Media motivation mediates the relationship between perceived behavioral control and willingness.

Subjective norm, another core TPB construct, refers to an individual's perception of comments from significant others (e.g., family, peers, colleagues) on a specific behavior.[7] Prior research indicated that subjective norms positively influenced wearable health technology adoption among middle-aged and older adults.[6] Social influence also increased willingness to use smart elderly care services.[21] Accordingly, the following hypothesis is proposed:

H8. Subjective norm positively predicts willingness.

Participants and methods

Participants

In the quantitative research section, 2786 adults aged 18 years and above were selected from 15 provinces, municipalities, and autonomous regions across China. Inclusion criteria were as follows: Aged 18 years or older; Able to complete the questionnaire independently or with assistance from investigator; informed and voluntarily to participate. The qualitative research section involved one-on-one semi-structured interviews designed to obtain in-depth and comprehensive insights. A total of 13 adults were recruited from both urban and rural areas in Beijing, Shanxi, Shaanxi, and Liaoning provinces (or municipalities). Interviews were conducted both online and offline.

Methods

Study design

This study adopted an explanatory sequential mixed-methods design integrating quantitative and qualitative researches. In the quantitative research section, a cross-sectional survey was employed to assess the current status of smart health management service and device use among adults, as well as to identify key influencing factors. The qualitative research section consisted of one-on-one semi-structured interviews with adults aged 18 years and older.

Ethical approval for this study was obtained from the Ethics Committee of Shandong Provincial Hospital (Approval No SWYX:2023–198). All participants were informed of the study purpose and participated voluntarily.

Sample source

The participants for quantitative research were collected using a stratified cluster random sampling approach. The required sample size was estimated based on the standard formula for cross-sectional surveys, with a 95 % confidence level. According to national survey data from 2021, the prevalence of smart wearable device usage among residents in China was 13.3 % ($P = 0.133$) .[22] The margin of error (ε) was set at 0.02, with a design effect of 2.0, and an anticipated response rate of 80 %. Under these parameters, the minimum sample size required was calculated to be 2 770 participants. To ensure national representativeness, stratification was performed according to the four geographic regions defined in the Seventh National Population Census of China—the eastern, central, western, and northeastern regions.[23] A proportional allocation method was applied based on the population size of each region. In total, 15 provinces (including municipalities and autonomous regions) were randomly selected to serve as representative areas across the four strata. The sample size within each province was further proportionally distributed according to the province's share of the regional population. Each cluster consisted of approximately 50 participants. The number of clusters required per province was determined by its allocated sample size. Within each province, clusters were selected randomly, followed by random sampling of individuals within clusters to achieve the target sample. After adjustment for design and non-response, the final effective sample size was 2900 participants, distributed across 58 clusters.

The qualitative research section adopted a purposive sampling strategy to capture maximum diversity and obtain in-depth information. Age was selected as a primary sampling dimension, while residential type was considered to identify potential differences associated with varying environmental contexts. Interviewees were recruited based on recommendations from community workers and online social media platforms to ensure the interviewees met the eligibility criteria and were likely to contribute rich, multifaceted perspectives. The processes of participant recruitment and data analysis were conducted iteratively, adhering to the principle of thematic saturation, refers to interviews continued until the addition of new participants no longer generated novel or meaningful themes.[24] Ultimately, 13 participants were included in the qualitative research section.

Questionnaire survey

The questionnaire survey was performed between September and December 2023 through the Wenjuanxing online platform. In each participating province, the research team collaborated with randomly selected communities or neighborhood committees to identify on-site survey locations. Under the supervision of trained investigators, participants completed the electronic questionnaire in person.

The questionnaire was developed based on a systematic review of relevant literature and refined through expert consultations with specialists in health education and social medicine to ensure content validity. Upon completion, investigators reviewed each questionnaire on-site to check for missing or inconsistent responses. All data were double-entered independently by two researchers and subsequently verified by the research team. The final version comprised following sections:

General Information: A self-designed demographic section was used to collect general sociodemographic characteristics, including age, gender, educational level, per capita monthly household income, marital status, presence of chronic disease, occupation, living arrangement (living alone or not), type of residence (urban/rural), and health insurance coverage. eHealth Literacy: eHealth literacy was assessed using a 5-item scale developed by Lee J,[25] Norman CD,[26] and Guo S.[27] Each item was rated on a 5-point Likert scale (1 = “strongly disagree” to 5 = “strongly agree”), with higher scores indicating greater eHealth literacy. The Cronbach’s α coefficient in this study was 0.951, demonstrating excellent internal consistency.

Media Motivation: Media motivation was measured using a 3-item standardized scale, with each item rated on a 5-point Likert scale (1 = “strongly disagree” to 5 = “strongly agree”). Higher scores reflected stronger motivation to engage with digital media and devices. The Cronbach’s α coefficient for this scale was 0.887.

Perceived Behavioral Control: Perceived behavioral control was assessed using the New General Self-Efficacy Scale–Short Form (NGSES-SF), developed by Chen G[28] and Xiao F,[29] which captures a core dimension of self-efficacy within the TPB framework.

The scale includes 3 items, each rated on a 5-point Likert scale (1 = “strongly disagree” to 5 = “strongly agree”). Higher scores indicate stronger perceived control over performing the behavior. The Cronbach’s α coefficient in this study was 0.921.

Subjective Norm: Subjective norm was operationalized using perceived social support, measured by the Perceived Social Support Scale–Short Form (PSSS-SF) developed by Zhang Fan et al. .[30] This scale includes 3 items, each rated on a 7-point Likert scale (1 = “strongly disagree” to 7 = “strongly agree”), with higher scores reflecting stronger perceived social support and subjective norm. The Cronbach’s α coefficient was 0.883.

Behavioral Attitude: Behavioral attitude was measured using perceived trust, captured by a single item-“To what extent do you trust smart health management devices to provide reliable health information?” Responses were recorded on a 0–100 scale (0 = “not at all trustworthy” to 100 = “completely trustworthy”). Higher scores represent more positive attitudes toward smart health technologies.

Demand for Smart Health Management Services: Service demand was assessed through a multiple-choice question: “Which types of health services would you like smart health management devices to provide?”

Willingness to Use Smart Health Management Services: Willingness was conceptualized as participants’ acceptance tendency toward specific smart health service functions, measured across five core service scenarios. Each item was rated on a 0–100 scale (0 = “completely unacceptable” to 100 = “completely acceptable”). The five items assessed willingness to: accept remote medical consultation services; pay for online medication consultation services; use smart elderly care systems; use intelligent nursing systems; receive home nursing services via online nurse appointment platforms. The total willingness score was calculated as the mean of the five item scores: Total Score=Sum of All Item Scores/5.

Behavior to Utilize Smart Health Management Services: Usage behavior was defined as the active and sustained adoption of smart technologies for health management. Specifically, it referred to participants’ use of smart health monitoring devices (e.g., smart wristbands, smartwatches, smart body-fat scales) and associated mobile applications, excluding standalone health apps not linked to smart devices. Usage was measured by a single multiple-choice item: ”Which smart health monitoring devices are you currently using?” Responses were coded as follows: 1 = Not using any; 2 = Using one device type; 3 = Using two device types; 4 = Using three or more device types.

Interview and analysis

The one-on-one semi-structured interviews were conducted between May 2024 and March 2025. The interview guide included: (1)Basic demographic; (2)Personalized needs for smart health management services; (3)Experience and use of smart health management services; (4)Preferences regarding smart health management service delivery models and feedback for improvement. Interviews were conducted both online and offline to accommodate participants. After obtaining the consent of the respondents, all offline interviews were conducted in quiet and private community meeting rooms or in the respondents’ homes and were recorded in real time. To ensure the completeness of the data, while recording, the interviewers would manually record and supplement key information for subsequent verification. Online interviews were conducted via Tencent Meeting or WeChat voice calls. All interviews were audio-recorded in full, with each lasting approximately 30 min on average. Interviewers maintained a neutral and non-directive stance to ensure the authenticity and reliability of participants’ responses. Following each interview, the recordings were transcribed verbatim, and the textual data were organized for analysis. NVivo 12 software was used for coding and thematic analysis. Based on the principles of Grounded Theory, a three-level coding process (open coding, axial coding, and selective coding) was employed to identify key themes and patterns.[31]

Statistical analysis

In the quantitative analysis, continuous variables conforming to a normal distribution were expressed as mean ± standard deviation(SD), while categorical variables were summarized as frequencies and percentages. Univariate analysis was employed to examine differences in willingness and behavior of smart health management services use across demographic subgroups. For continuous variables, *t*-test and one-way analysis of variance (ANOVA) were applied to compare group means, followed by Student–Newman–Keuls (SNK-q) post hoc tests for pairwise comparisons. For categorical variables, the chi-square test was used to assess group differences. Structural equation modeling (SEM) was employed to identify key determinants, the model fit indicators included: Comparative Fit Index (CFI) > 0.90, Tucker–Lewis Index (TLI) > 0.90, Root Mean Square Error of Approximation (RMSEA) < 0.08, Standardized Root Mean Square Residual (SRMR) < 0.08. All data analyses were performed using SPSS version 27.0 and RStudio version 4.4.1. All statistical tests were two-tailed, and a P-value < 0.05 was considered statistically significant.

Table 1
Sociodemographic Characteristics of the Study Participants.

Variable	Total	Willingness			Behavior			
		Average score ($\bar{x} \pm s$)	t/F	P	No	Yes	$\chi 2$	P
	2786	62.68 ± 20.65						
Age group			3.41	0.009			107.61	<0.001
Youth	1472(52.8)	63.93 ± 20.68			798(54.2)	674(45.8)		
Middle-aged	583(20.9)	61.87 ± 20.37			377(64.7)	206(35.3)		
Silver Youth	346(12.4)	61.65 ± 21.40			257(74.3)	89(25.7)		
Silver Middle-aged	261(9.4)	60.06 ± 20.14			206(78.9)	55(21.1)		
Silver Longevity Elderly	124(4.5)	59.91 ± 19.81			97(78.2)	28(21.8)		
Gender			-2.07	0.039			8.89	0.003
Male	1386(49.7)	61.86 ± 21.12			825(59.5)	561(40.5)		
Female	1400(50.3)	63.48 ± 20.16			910(65.0)	490(35.0)		
Education level			21.57	<0.001			271.89	<0.001
Junior high school or below	749(26.9)	59.44 ± 20.49			639(85.3)	110(14.7)		
High school or vocational	582(20.9)	60.85 ± 21.98			376(64.6)	206(34.5)		
College or above	1455(52.2)	65.07 ± 19.89			720(49.5)	735(50.5)		
Monthly household income per capita (CNY)			11.96	<0.001			66.46	<0.001
≤3000	652(23.4)	54.52 ± 21.47			479(73.5)	173(26.5)		
3000~6000	1258(45.2)	61.45 ± 20.57			791(62.9)	467(37.1)		
≥6000	876(31.4)	61.69 ± 20.88			465(53.1)	411(46.9)		
Marital status			8.45	<0.001			39.42	<0.001
Unmarried	846(30.4)	65.01 ± 19.69			457(54.0)	389(46.0)		
Married	1782(64.0)	61.50 ± 21.07			1162(65.2)	620(34.8)		
Divorced/Widowed	158(5.7)	64.49 ± 19.99			116(73.4)	42(26.6)		
Chronic disease			-0.45	0.657			2.96	0.085
No	1832(65.8)	60.78 ± 21.70			1120(61.1)	712(38.9)		
Yes	954(34.2)	59.91 ± 19.62			615(64.5)	339(35.5)		
Occupation			15.51	<0.001			145.57	<0.001
Student	451(16.2)	68.14 ± 18.09			273(60.5)	178(39.5)		
Employed	1206(43.3)	62.69 ± 20.75			615(51.0)	591(49.0)		
Retired	424(15.2)	61.43 ± 20.54			328(77.4)	96(22.6)		
Other (unemployed/flexible)	705(25.3)	59.90 ± 21.47			519(73.6)	186(26.4)		
Living alone			0.06	0.952			17.65	<0.001
Yes	493(17.7)	62.73 ± 20.21			266(54.0)	227(46.0)		
No	2293(82.3)	62.66 ± 20.75			1469(64.1)	824(35.9)		
Place of residence			4.56	<0.001			82.82	<0.001
Urban	2032(72.9)	63.76 ± 20.41			1162(57.2)	870(42.8)		
Rural	754(27.1)	59.75 ± 21.03			573(76.0)	181(24.0)		
Health insurance			-2.14	0.032			0.18	0.668
Yes	2639(94.7)	62.87 ± 20.58			1641(62.2)	998(37.8)		
No	147(5.3)	59.13 ± 21.76			94(63.9)	53(36.1)		

Results

Basic characteristics of participants

A total of 2900 questionnaires were distributed, among which 2786 were valid, resulting in a response rate of 96.07 %. The participants were categorized into six age groups based on the classification scheme commonly used in epidemiological and health management research on chronic diseases in China[32] and the most recent guidelines from the Chinese Standards for Age Classification of the Silver Population[33]: Youth (18–44 years), Middle-aged (45–54 years), Silver Youth (55–64 years), Silver Middle-aged (65–74 years), Silver Elderly (75–89 years), Longevity Elderly (≥90 years). As only two participants were aged ≥90 years, they were combined with the Silver Elderly group (75–89 years) into a unified category: Silver and Longevity Elderly (≥75 years). The average age of participants was (43.9 ± 16.5) years, with 50.3 % identifying as female. The majority (52.2 %) held an associate degree or higher. Among the participants, 1782 (64.0 %) were married. Univariate analysis showed statistically significant differences in both willingness and behavior of smart health services use across age, gender, educational level, Per capita monthly, household income, marital status, occupation and place of residence(all $P < 0.05$). In addition, health insurance coverage significantly influenced participants' willingness to use smart health services ($P = 0.032$) (see Table 1).

A total of 13 interviewees were included in the qualitative study, among whom 10 were urban residents and 11 were female (84.6 %). The mean age of interviewees was 48.2 years, and 7 (53.8 %) held an associate degree or higher. Detailed demographic information is presented in Appendix Table 3.

Smart health management services use

Using behavior

Overall, 62.3 % of participants reported not using any smart health monitoring devices. Among the devices used, smartwatches were the most commonly adopted (21.1 %), followed by smart wristbands (15.4 %) and smart body fat scales (14.5 %). Age-stratified analysis revealed that the youth group (18–44 years) had the highest usage rate at 45.8 %, with smartwatches (24.4 %), smart wristbands (19.8 %), and body fat scales (18.1 %) being the most frequently used types. By contrast, the Silver Middle-aged group (65–74 years) and the Silver and Longevity Elderly group (≥75 years) showed high non-use rates of 78.9 % and 78.2 %, respectively. In addition, emerging technologies such as EEG headbands were rarely utilized(≤1.8 %)(see Table 2).

Service demand

The investigation results indicated that the most commonly desired services were health Q&A support (46.2 %) and sleep monitoring with alerts (46.0 %), these preferences highlight interest in health information access and basic quality of life. The notable demand for chronic disease management services (43.4 %) and physical activity tracking with reminders (41.2 %) reflects emphasis on proactive health interventions and long-term condition management. In contrast, participants had low demand for scenario-specific features, such as eye protection

Table 2
Usage of Smart Health Monitoring Devices Among Adults.

Age group	Using Situation										
	Not used	Smart watch	Smart band	Smart body-fat scale	Smart belt	Smart running shoes	Brainwave device	Smart socks	Smart T-shirt	Smart necklace	Smart helmet
Total	1735 (62.3)	588 (21.1)	429 (15.4)	404 (14.5)	61 (2.2)	49 (1.8)	39 (1.4)	49 (1.8)	29 (1.0)	19 (0.7)	19 (0.7)
Youth	798 (54.2)	359 (24.4)	291 (19.8)	266 (18.1)	40 (2.7)	35 (2.4)	27 (1.8)	23 (1.6)	20 (1.4)	15 (1.0)	14 (1.0)
Middle-aged	377 (64.7)	127 (21.8)	78 (13.4)	82 (14.1)	9 (1.5)	7 (1.2)	3 (0.5)	7 (1.2)	5 (0.9)	1 (0.2)	2 (0.3)
Silver Youth	257 (74.3)	50 (14.5)	32 (9.2)	35 (10.1)	8 (2.3)	4 (1.2)	2 (0.6)	0 (0.0)	1 (0.3)	3 (0.9)	1 (0.3)
Silver Middle-aged	206 (78.9)	34 (13.0)	22 (8.4)	17 (6.5)	4 (1.5)	2 (0.8)	4 (1.5)	8 (3.1)	3 (1.1)	0 (0.0)	2 (0.8)
Silver Longevity Elderly	97 (78.2)	18 (14.5)	6 (4.8)	4 (3.2)	0 (0.0)	1 (0.8)	2 (1.6)	2 (1.6)	0 (0.0)	0 (0.0)	0 (0.0)

reminders (32.7 %). In addition, 22.7 % of respondents reported no need for any smart health services. Age-stratified analysis indicated that the youth group demonstrated the strongest demand for preventive and lifestyle-oriented services, with high interest in sleep monitoring and reminders (51.7 %) and physical activity tracking with reminders (47.1 %). In contrast, middle-aged and older adults were more concerned with health consultations and chronic disease management. "Answering health-related questions" and "managing chronic diseases" were top priorities across the Silver Youth, Silver Middle-aged, and Silver and Longevity Elderly groups. The proportion of participants reporting “no need” for any smart health services exhibited a U-shaped trend across age groups: it was lowest among the youth group (17.3 %), peaked in the Silver Middle-aged group (33.0 %), and then declined slightly in the Silver and Longevity Elderly group (26.6 %). The service demands were detailed in Appendix Table 4.

The qualitative analysis revealed a four-level model of demand for smart health management services: (1)Basic health security and daily living support, such as health record reminders, household assistance services, basic health monitoring functions, location tracking and emergency calling, and remote monitoring, which were identified as basic demands by most interviewees; (2)Emotional connection and social engagement, such as emotional support and recreational activities, reflecting participants’ desire for smart health services to enhance quality of life; (3)Personalized health management, such as tailored services, indicating expectations for targeted one-on-one service; (4)Advanced demand including advanced health management services and information education. Detailed coding results are presented in Appendix Table 5.

Influencing factors of smart health management services and devices use

Willingness scores

The average willingness score for using smart health management services among all participants was (62.68 ± 20.65). Among the different age groups, the youth group exhibited the highest willingness for use, with a mean score of (69.93 ± 20.68), whereas the Silver and Longevity Elderly group showed the lowest willingness, with a mean score of (59.91 ± 19.81). When examining specific services, participants showed highest score in the adoption of smart elderly care systems (68.21 ± 25.25) and lowest score in the adoption of paid online medication consultation services(50.16 ± 28.65). Detailed scoring results are presented in Appendix Table 6.

Influencing factors of willingness and behavior of use in SEM

SEM showed good overall model fit. All absolute fit indices were below the conventional threshold of 0.08, including Standardized Chi-square = 865.362, Degrees of Freedom (df) = 173, χ^2/df = 5.00, Root Mean Square Error of Approximation (RMSEA) = 0.038 (90 % CI: 0.035–0.040), Standardized Root Mean Square Residual (SRMR) = 0.050. Incremental fit indices showed Comparative Fit Index (CFI) = 0.982, Tucker–Lewis Index (TLI) = 0.978, indicating excellent goodness-of-fit and meets the standards for SEM. The estimated path coefficients are presented in Table 3.

Behavioral attitude was the strongest predictor of willingness (β = 0.568, P<0.001), thereby supporting Hypothesis H3. Both subjective norms (β = 0.103, P<0.001) and media motivation (β = 0.089, P<0.001) had significant positive effects on willingness, supporting Hypotheses H8 and H1a, respectively. Regarding behavior, media motivation emerged as the most influential predictor (β = 0.103, P< 0.001), confirming Hypothesis H1b. Perceived behavioral control did not have a significant direct effect on willingness (β = 0.033, P = 0.167), thus Hypothesis H5 was not supported. However, perceived behavioral control had significant indirect effects on willingness through eHealth literacy (β = 0.290, P< 0.001) and media motivation (β = 0.153, P<0.001), confirming Hypotheses H6 and H7. Urban residence positively influenced both willingness (β = 0.056, P<0.001) and behavior (β = 0.125, P<0.001). Health insurance coverage significantly enhanced behavioral willingness (β = 0.039, P< 0.001).

The mediation analysis revealed that, eHealth literacy had a significant indirect effect on both willingness (β = 0.045, 95 %CI[0.619, 1.389]) and behavior (β = 0.051, 95 %CI[0.028, 0.067]) through media motivation, thereby supporting Hypothesis H2. Perceived behavioral control also exerted indirect effects on both willingness (β = 0.014, 95 %CI [0.184, 0.554]) and behavior (β = 0.016, 95 % CI [0.020, 0.028]) via media motivation, confirming Hypothesis H6. Media motivation influenced willingness indirectly through behavioral attitude (β = 0.086, 95 % CI [1.522, 2.817]), providing support for Hypothesis H4. Importantly, a significant chain mediation pathway was identified: eHealth literacy → media motivation → behavioral attitude → willingness(β = 0.043, 95 % CI [0.661, 1.254]), revealing a multi-level psychological mechanism of eHealth literacy driving intention to adopt smart health management services. Detailed mediation effects are presented in Table 4.

Qualitative findings on influencing factors of willingness and behavior of use

Through stepwise coding of qualitative interview transcripts, three core categories emerged that expanded and enriched the key influencing factors identified in the quantitative analysis:

(1) Perceived behavioral control

This category is mainly reflected in perceived usage barriers and objective challenges.

Perceived usage barriers included two initial categories: limited technical convenience and accessibility(e.g., “Wearing a smartwatch while sleeping is uncomfortable”, preferences for smaller, less obtrusive devices), and safety concerns(health risk and AI-related privacy breaches).

Table 3
Test of the Path Relationships.

Path	β	S.E.	Z	P
Behavioral attitude → Using willingness	0.568	0.016	29.402	<0.001
Subjective norm → Using willingness	0.103	0.393	4.568	<0.001
Place of residence → Using willingness	0.056	0.677	3.852	<0.001
Health insurance policy → Using willingness	0.039	1.324	2.711	0.008
Usage intention → Using behavior	0.073	0.001	4.528	<0.001
Place of residence → Using behavior	0.125	0.036	6.803	<0.001
Perceived behavioral control → eHealth literacy	0.290	0.029	12.520	<0.001
Perceived behavioral control → Media motivation	0.153	0.025	6.514	<0.001
Perceived behavioral control → Using willingness	0.033	0.644	1.381	0.167
eHealth literacy → Media motivation	0.499	0.024	18.124	<0.001
Media motivation → Behavioral attitude	0.152	0.661	6.632	<0.001
Media motivation → Using willingness	0.089	0.456	4.828	<0.001
Media motivation → Using behavior	0.103	0.021	5.046	<0.001

Table 4
Test of the Mediating Effect.

Mediation Path	β	boot*S.E.*	95 %CI
eHealth literacy → Media motivation → Using willingness	0.045***	0.210	(0.553,1.363)
eHealth literacy → Media motivation → Using behavior	0.051***	0.010	(0.028,0.067)
Perceived behavioral control → Media motivation → Use intention	0.014***	0.094	(0.184,0.554)
Perceived behavioral control → Media motivation → Use behavior	0.016***	0.005	(0.010,0.028)
Media motivation → Behavioral attitude → Using willingness	0.086***	0.329	(1.522,2.817)
eHealth literacy → Media motivation → Behavioral attitude → Using willingness	0.043***	0.153	(0.661,1.254)

Notes: *** indicates $P < 0.001$;

Objective challenges included two initial categories: Product quality issues such as bugs, crashes, and system instability; Cost concerns such as premium features hidden behind paywalls, limiting accessibility (e.g., “You have to pay for a membership to see detailed reports”).

(2) Behavioral attitudes

This category focused on interviewees’ varying attitudes, including three initial categories.

Negative attitudes: Some users found the services insufficiently intelligent and only capable of handling basic tasks.

Positive experiences: The user themselves and observing others were satisfied with the services.

Neutral views: Some users expressed ambivalence or eventual disinterest, often due to a lack of noticeable benefit.

(3) Microsystem influences

This category reflected on users’ beliefs and cognitive perceptions, including three initial categories.

Technology resistance: some older users intentionally avoided overreliance on technology, preferring to stay mentally active (e.g., “I want to keep my brain sharp—I don’t want to depend on devices”).

Social avoidance behaviors: Younger users tended to prefer technology-mediated alternatives to conventional approaches, expressing a preference for smart aging solutions rather than (e.g., “I’d rather have a robot caretaker than live in a nursing home”).

Lack of awareness or information access approaches: Some interviewees revealed limited knowledge to smart health services.

Detailed coding categories can be found in Appendix Table 7.

Mixed-methods results on influencing factors of willingness and behavior of use

The integrated findings from both the quantitative and qualitative research sections is presented in Table 5.

Discussion

Overall Usage of Smart Health Monitoring Devices Remains Suboptimal, with Age-Based Disparities

The overall adoption rate of smart health monitoring devices among adult residents in China is 37.7 %, indicating potential for improvement. A notable age-related disparity was observed, with device usage decreasing with age. It was also reported that older adults had low awareness with smart health care and low usage rate of wearable devices(13.9 %) in previous study.[34]

This low adoption rate may be caused by: (1)Older adults lack digital skills to engage with smart technologies, leading to low willingness and behavior rate to utilize; (2) Conflict with established routines and concerns over autonomy cause psychological resistance to adoption.

Demand for Smart Health Management Services Progresses from Basic Life Support to Higher-Level Self-Actualization, with Distinct Age-Stratified Patterns

Our Findings reveal the overall pattern of adult users’ demand shifting from basic life support to higher level service, with age-based disparities. The quantitative results indicate that users’ primary demands are widely accessible functions, such as basic health information support and vital sign monitoring. In contrast, qualitative interviews revealed a four-level demand model ranging from basic life management to advanced self-realization. This model demonstrates the hierarchy and diversity of demands. A core finding of this study is age-stratified demand. Younger users are digital natives, they show a stronger preference for services related to preventive care, lifestyle optimization, and self-monitoring, consistent with their higher technology adoption, stronger health awareness, and focus on self-improvement during this life stage. In contrast, older adults, particularly those in the silver and longevity age groups, showed greater interest in practical functions such as chronic disease management, safety surveillance, and health consultation. These findings underscore the necessity of life-course-oriented product and service design, where smart health systems are personalized to align with the unique needs and capacities of different age cohorts. Moreover, qualitative research findings indicate emotional and psychosocial demands of smart health management services, such as emotional connection and personalized support, which were shown to play a critical role in user satisfaction and behavioral willingness to continue use. This suggests that merely enhancing technical functionality is not sufficient. To effectively engage users over time, smart health man-

Table 5
Results of the Integrated Analysis of Exploratory Sequence-Mixed Methods Studies.

Theme	Results		Consistency	Integrated Interpretation
	Quantitative Results	Qualitative Findings		
Usage intention	The mean score of using willingness was (62.68 ± 20.65)	Six interviewees expressed willingness to use, while three were unwilling	Consistent	The overall willingness to use smart health management services was moderately high. Most participants showed a positive attitude, although some still had reservations.
Influencing factors of using willingness and behavior	1. Behavioral attitude, subjective norm, and media motivation were the main influencing factors of using willingness. 2. Perceived behavioral control and eHealth literacy affected willingness and behavior indirectly through media motivation. 3. A chain mediation effect was observed along the path eHealth literacy → media motivation → behavioral attitude → willingness to use.	1. Behavioral attitude influenced both willingness and behavior. 2. Perceived barriers and objective challenges (e.g., "not convenient," "not smart enough," "extra cost required") were key obstacles to willingness to use. 3. Social perceptions such as "technology lacks human touch" or "I don't like to bother others" also shaped user behavior.	Expanded	Behavioral attitude emerged as a statistically significant factor in quantitative analysis; qualitative findings further revealed that usage barriers can lead to negative attitudinal shifts, thereby reducing willingness and behavior. The value of eHealth literacy is realized through media motivation, which serves as a mediator transforming literacy into willingness and behavior. However, objective barriers (e.g., usability, accessibility) or negative attitudes may interrupt this transformation chain. Personal beliefs and cognition significantly influence users' willingness to adopt smart health management services.

agement services must integrate emotionally resonant, socially responsive, and individually tailored elements into their core design.

Willingness toward smart health management services use is moderately high, with attitude, subjective norm, and media motivation as key predictors

This study found that willingness to utilize smart health management services among adults in China was at a moderately high level. While most participants expressed positive willingness, a proportion still reported concerns and reservations. Quantitative results revealed that behavioral attitude was the strongest predictor of willingness to use, consistent with previous findings that older adults with more favorable attitudes toward wearable technologies are significantly more likely to adopt them.[6] Qualitative interviews indicated that positive attitudes were rooted in satisfactory usage experiences, while negative attitudes stemmed from perceptions that the products were "not smart enough" or had "no obvious benefits". These findings suggest that improving using experience and emphasizing practical value can boost users' trust and willingness to adopt. The qualitative data also identified microsystem-level factors. For example, some older adults rejected smart devices in favor of "exercising their brains," while some younger users favored smart health technologies as a means to avoid face-to-face interactions, these insights underscore the complex interplay between sociocultural beliefs, personal values, and behavioral motivations.

Quantitative results demonstrated significant indirect effects of perceived behavioral control, mediated by both eHealth literacy and media motivation. Qualitative findings elaborated on this mechanism, identifying objective challenges such as concerns about cost, perceptual barriers such as device discomfort, complexity of use, and privacy/security concerns.

This study identified a significant chain mediation pathway: eHealth literacy → media motivation → behavioral attitude → willingness. Individuals with higher eHealth literacy are more motivated to use health-related media, which enhances their attitudes toward smart health technologies, ultimately leading to stronger willingness to utilize. This pathway aligns with prior findings, for instance, one study reported that knowledge of smart elder care significantly influenced adoption via changes in attitude.[35] This suggests that digital health education and publicity may be effective in enhancing adults' digital health literacy and intrinsic motivation for media use, to influence their behavioral attitudes and actual behavioral transformation.

At the meso-system level, subjective norm emerged as a positive predictor of willingness, highlighting the influence of social networks on adoption behavior. Recognition and endorsement of smart health services by family members, friends, and "digital reciprocation" from adult children can significantly enhance intention of use, especially among digitally marginalized populations. At the macro-system level, both residential location and health insurance were identified as significant contextual predictors, emphasizing the foundational role of robust digital infrastructure and inclusive policy environments in promotion of smart health services.

Integrate proactive interventions and data in primary care services

The prominent "high wish–low use" gap along with its complex factors has important implications for the improvement of primary care system in China. First, primary care practitioners(PCPs) can serve as key facilitators by recommending smart health devices that are user-friendly, cost-effective, and functionally relevant, tailored to patients' age and digital literacy levels. In routine consultations, clinicians can demonstrate core functions such as blood pressure and heart rate monitoring to reduce anxiety associated with unfamiliar technology. Second, smart health monitoring data should be systematically integrated into clinical workflows to overcome the current fragmentation between device use and medical care. Given the high demand identified for chronic disease management and health consultation, general practitioners(GPs) can encourage patients to share device-generated health data and assist in its interpretation. For example, during follow-up visits, PCPs can proactively review recorded trends in blood pressure, glucose levels, or sleep patterns, using this information to inform clinical assessments and treatment decisions. This approach can enhance the perceived value of smart monitoring tools for patients and encourage their engagement. Finally, PCPs should focus on digitally marginalized groups, including rural residents, individuals with low income, limited education, older adults, and promote smart health management services.

Research limitations

This study has several limitations. First, the quantitative research section adopted a cross-sectional design and can't draw causal inferences between the variables. Second, there is potential for sampling bias in the quantitative research section. Notably, the sample had a higher proportion of participants with tertiary education compared to the general population, this discrepancy may be attributed to non-response bias, whereby individuals with higher educational attainment tend to exhibit greater interest in health-related topics and a stronger willingness to participate in surveys, while those with lower education levels may be less inclined to engage. Third, the study primarily focused on commonly adopted smart health products, such as smartwatches, fitness bands, and body fat scales. It did not examine the emerging wave of advanced, AI-powered health technologies, including large language model (LLM)-based health assistants, generative AI tools, and algorithm-driven personalized health planning systems. Finally, while this study developed and validated an extended model based on TPB to identify the mechanism of smart health management services adoption. Although the study adopted a layered analytical perspective of SET, it did not fully operationalize or empirically test meso- and macro-level factors emphasized in SET. Future research should aim to integrate environmental and structural variables to develop a more comprehensive, multi-level explanatory model.

Conclusion

In summary, this mixed-methods research analyzed the use and influencing factors associated with smart health management services and devices among China's adults, and provided suggestions on promotion of smart health services and the integrated application in primary care system from the perspectives of individual, communities and primary care.

Declarations

Not applicable.

Authors' contributions

Conceptualization, Z.Xin.; Methodology, Z.Xin.; Data curation, Z.Xin., W.Y., Z.Xu., C.P,; Formal analysis, Z.Xin.; Funding acquisition, not applicable; Project administration, not applicable; Resources, not applicable; Supervision, S.X.; Validation, S.X.; Writing—original draft, Z.Xin.; Writing—review and editing, S.X. All authors have read and agreed to the published version of the manuscript.

Ethical approval and consent to participate

The study received approval from Ethics Committee of the Shandong Provincial Hospital (Approval No SWYX:2023–198).

Consent for publication

Not applicable.

Availability of data and materials

Not applicable.

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Competing interests

All authors declare that there are no competing interests

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cgpj.2025.100089.

Appendix

See Appendix Tables 1, 2, 3, 4, 5, 6, 7.

1. Results of confirmatory factor analysis and reliability and validity tests.

Scale	Item	Factor loading	SE	P	Average variance extracted (AVE)	Composite reliability (CR)
eHealth literacy	eHealth Literacy 1	0.898		***	0.779	0.931
	eHealth Literacy 2	0.906	0.014	***		
	eHealth Literacy 3	0.917	0.020	***		
	eHealth Literacy 4	0.821	0.024	***		
	eHealth Literacy 5	0.833	0.024	***		
Media motivation	Media motivation 1	0.804		***	0.602	0.864
	Media motivation 2	0.809	0.042	***		
	Media motivation 3	0.786	0.041	***		
	Media motivation 4	0.804	0.044	***		
	Media motivation 5	0.677	0.032	***		
	Self efficacy 1	0.897		***	0.796	0.921
Self efficacy	Self efficacy 2	0.890	0.029	***		
	Self efficacy 3	0.894	0.024	***		
Social support	Social support 1	0.808		***	0.719	0.885
	Social support 2	0.904	0.033	***		
	Social support 3	0.833	0.034	***		

2. Results of Discriminant Validity Analysis.

Scale	eHealth literacy	Media motivation	Self efficacy	Social support
eHealth literacy	0.883			
Media motivation	0.560	0.776		
Self efficacy	0.306	0.323	0.848	
Social support	0.262	0.285	0.686	0.892

3. General information of participants for qualitative research.

ID	Interview location	Area type	Gender	Age (years)	Education level	Self-care ability	Living alone	Health status	Economic condition	Hypertension	Diabetes	Other chronic diseases
L1	Daxing District, Beijing	Rural	Female	72	High School	Independent	No	Fair	Fair	No	Yes	No
L2	Xicheng District, Beijing	Urban	Female	64	High School	Independent	No	Fair	Fair	Yes	No	Achalasia
L3	Daxing District, Beijing	Rural	Female	77	Middle School	Independent	No	Fair	Fair	Yes	Yes	Mental disorders; Fundus lesions
L4	Daxing District, Beijing	Rural	Female	60	Middle School	Independent	No	Fair	Fair	Yes	Yes	Lumbar spine disease
L5	Pudong District, Shanghai	Urban	Female	32	Bachelor's	Independent	Yes	Good	Good	No	No	No
L6	Taiyuan, Shanxi Province	Urban	Female	24	Master's	Independent	No	Good	Good	No	No	No
L7	Taiyuan, Shanxi Province	Urban	Female	74	Middle School	Independent	No	Fair	Fair	Yes	Yes	Hyperlipidemia
L8	Xianyang, Shaanxi Province	Rural	Female	58	High School	Independent	No	Fair	Fair	No	No	Lumbar spine disease
L9	Xianyang, Shaanxi Province	Urban	Female	34	Associate Degree	Independent	No	Good	Good	No	No	No
L10	Xi'an, Shaanxi Province	Urban	Male	25	Bachelor's	Independent	Yes	Good	Good	No	No	No
L11	Xi'an, Shaanxi Province	Urban	Male	25	Master's	Independent	Yes	Good	Good	No	No	否
L12	Xi'an, Shaanxi Province	Urban	Female	28	Associate Degree	Independent	No	Good	Good	No	No	No
L13	Dalian, Liaoning Province	Urban	Female	32	Bachelor's	Independent	Yes	Good	Good	No	No	No

4. The desired smart health management services for adults.

Age group	Desired smart health management services								
	No need	Medication monitoring & Reminders	Sleep monitoring & reminders	Personalized diet plans	Hydration reminders	Vision protection reminders	Exercise monitoring & reminders	Chronic disease management	Health consultation
Overall	633 (22.7)	1015 (36.4)	1281 (46.0)	1052 (37.8)	1048 (37.6)	911 (32.7)	1147 (41.2)	1209 (43.4)	1288 (46.2)
Young adults	255 (17.3)	527 (35.8)	761 (51.7)	655 (44.5)	645 (43.8)	586 (39.8)	693 (47.1)	627 (42.6)	683 (46.4)
Middle-aged Adults	145 (24.9)	207 (35.5)	254 (43.6)	187 (32.1)	195 (33.4)	164 (28.1)	233 (40.0)	252 (43.2)	261 (44.8)
Silver young	114 (32.9)	122 (35.3)	125 (36.1)	103 (29.8)	103 (29.8)	81 (23.4)	107 (30.9)	149 (43.1)	161 (46.5)
Silver middle-aged	86 (33.0)	97 (37.2)	91 (34.9)	67 (25.7)	72 (27.6)	53 (20.3)	76 (29.1)	113 (43.3)	120 (46.0)
Silver long-lived	33 (26.6)	62 (50.0)	50 (40.3)	40 (32.3)	33 (26.6)	27 (21.8)	38 (30.6)	68 (54.8)	63 (50.8)

5. Coding results of demand for smart health management services.

Core category	Main category	Initial category	Original data (excerpt)
Meeting physiological and safety needs	Basic medical and health services (26) Life assistance and convenience services (21) Safety and emergency response (6)	Health record reminders (17) Household living services (15) Basic health management functions (9) Location tracking(5) Remote monitoring (1)	"I need health management services, such as timely health alerts and health monitoring information. If there is anything abnormal with my body, I hope to have an initial consultation and then receive some medical and health advice." (L7) "I hope to receive medication reminders." (L1) "I need health care services. If I encounter any health issues that I don't fully understand, I hope I can consult about them." (L6) "A smart robot is enough — one that can cook and clean and provide daily living services." (L12) "I hope there is a function that can track the location of older adults so that our children can know our movements in real time. If there is a fall or sudden incident, it can immediately make an emergency call to handle it." (L6)
Achieving social and emotional connection	Psychological and emotional support (7)	Spiritual comfort (5) Entertainment activities (2)	"At this age, the focus is on health, and then listening to music that can soothe emotions and promote psychological relaxation." (L4) "If there is an intelligent Q&A robot, I hope it can provide some spiritual comfort and chat with me." (L10) "I hope it can provide services that address psychological and mental needs." (L8)
Respecting individualized needs	Personalized services (6)	Customized services (6)	"For example, in the future, it could formulate personalized healthy lifestyle plans based on an individual's physical condition, covering diet, daily routine, and all aspects of life." (L10) "For example, I could input the vegetables I want to eat today into the smart device, and it could analyze whether the nutrition is reasonable based on my previous health records and then customize my menu according to my dietary habits." (L7)
Empowering self-realization	Advanced health management (6) Information and educational support (1)	Advanced medical health management (6) Obtain information (1)	"I need disease consultation services, just like having a family doctor." (L13) "Most apps or smart devices simply suggest going to the hospital when you feel unwell. But your body may not have reached that level yet. So I hope it can provide good improvement recommendations when the condition is still mild, such as in a sub-health state." (L5) "I hope it can monitor brain activity, such as EEG, to measure levels of anxiety, depression, and stress." (L11) "I hope the smart robot can provide social hot topics and health science information, as well as interesting news about finance, technology, and other fields." (L11)

6. Acceptance intentions of smart health management services for adults.

Age group	Total score of willingness to use smart health management services	Type of Willingness to Use Smart Health Management Services				
		Acceptance of smart elderly care system	Acceptance of smart nursing system	Acceptance of app-based home nursing services	Acceptance of remote consultation	Acceptance of paid online medication consultation services
Overall	62.68 ± 20.65	68.21 ± 25.25	67.89 ± 25.04	65.15 ± 26.02	61.96 ± 27.14	50.16 ± 28.65
Young adults	69.93 ± 20.68	69.46 ± 25.39	69.21 ± 24.82	65.97 ± 26.10	63.37 ± 26.67	51.64 ± 28.66
Middle-aged adults	61.87 ± 20.37	67.82 ± 24.69	67.26 ± 24.26	64.52 ± 25.84	61.14 ± 26.10	48.60 ± 28.82
Silver young adults	61.65 ± 21.40	66.90 ± 25.37	66.50 ± 26.33	65.87 ± 26.23	60.86 ± 27.65	48.13 ± 29.64
Silver middle-aged adults	60.06 ± 20.14	65.09 ± 25.23	64.68 ± 25.68	63.14 ± 24.81	57.65 ± 27.42	49.76 ± 26.98
Silver older adults	59.91 ± 19.81	65.48 ± 25.32	65.89 ± 25.56	60.49 ± 27.27	61.36 ± 28.84	46.32 ± 27.67

7. Coding results of factors affecting the willingness and behavior of using smart health management services.

Core category	Main category	Initial category	Original data (excerpt)
Perceived behavioral control	Perceived barriers (21)	Low convenience and accessibility of technology (15) Safety concerns (6)	"It is inconvenient to wear the smartwatch while sleeping; it feels uncomfortable. If the device were smaller and had less presence, it would be better." (L12) "I am concerned about the system having bugs that could potentially threaten users' physical health." (L5)
	Objective challenges (7)	Product quality issues (5) Price concerns (2)	"The biggest concern is the privacy leakage risk related to AI." (L10) "These apps require a paid membership to access detailed health reports, so I would not continue using them.
Behavioral attitude	Attitude and evaluation of use (46)	Negative evaluation (17) Positive user experience (11) Neutral attitude (8)	"I am quite satisfied myself, and based on my observation of friends, family, and colleagues, users who actively engage with smart health management services are generally highly satisfied." (L12) The user experience is rather average. After using it for a while, I don't open it very often anymore. (L5) "It is not smart enough. It can only handle basic Q&A and cannot provide deeper decision-making support." (L5)
Microsystem	Beliefs and cognition (9)	Technology rejection (3) Avoidance of offline social interaction (4) Lack of awareness and information access (2)	"I want to exercise my brain; I don't want to rely too much on electronic devices." (L4) "I prefer smart elderly care. I don't want to live in a nursing home where others manage me, but a robot can act as my steward." (L7) "I think acceptance of new things and personal cognition are still insufficient." (L11)

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