A Study on the Factors Influencing Older Adults' Willingness to Adopt Health Information in Human-AI Hybrid Interaction Contexts

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Abstract

With the accelerated penetration of AI agents driven by large language models such as ChatGPT and DeepSeek into the healthcare field, human-AI collaborative hybrid interaction has become the mainstream form of online medical services. Against the macro backdrop of an aging society and the rise of the "Silver Economy," it carries significant expectations for enhancing the health and well-being of the elderly population. Therefore, an in-depth exploration of the key influencing factors and mechanisms underlying users' adoption of AI-generated health information holds substantial theoretical and practical value. This study is grounded in the Stimulus-Organism-Response (S-O-R) theoretical framework, integrating the Elaboration Likelihood Model (ELM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to construct a multidimensional theoretical model. Through validation using structural equation modeling, it not only expands the application of human-computer interaction and information adoption theories in the contexts of smart healthcare and aging but also provides empirical evidence and targeted insights for AI health tool designers to optimize age-friendly interactive experiences, as well as for policymakers to establish a scientific and inclusive regulatory and service system for "Internet + Healthcare."

Keywords

Online Healthcare; Human-AI Hybrid Interaction; Health Information Adoption; Silver Economy.

1. Introduction

1.1. Research Background

In recent years, AI agents driven by large language models such as GPT and DeepSeek have rapidly penetrated the healthcare market. Their autonomy, interactivity, and adaptive characteristics have significantly optimized the accessibility of health services, greatly transforming the landscape of health information dissemination and consumption. Based on medical large language models, AI agents can provide round-the-clock online consultation services, recommend diagnosis and treatment plans, and assist users in disease prevention and health management, becoming an important breakthrough point for addressing uneven distribution of medical resources and alleviating supply-demand contradictions.

Meanwhile, Chinese society is undergoing a profound demographic structure transformation. With the acceleration of population aging, the "Silver Economy" has risen to become a national strategic priority [1]. The "Healthy China 2030" Plan Outline clearly points out that in response to the current structural contradiction of "geographic concentration of quality medical

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

resources with weak grassroots coverage" [2], it is necessary to actively promote the application of artificial intelligence in the field of internet healthcare, improve the quality and efficiency of online medical services, and through policies such as the "Opinions on Promoting the Development of 'Internet+Healthcare'," encourage innovative applications of AI technology in disease prevention, online consultation, and health management, building a health information service system covering the entire lifecycle [3].

Under the resonance of policy guidance and technological evolution, hybrid intelligent agents that can interact with both human doctors and AI agents have become a new form of online medical services. The basic concept is to leverage the respective advantages of human doctors and AI agents to complement each other's shortcomings and jointly complete specific medical tasks, thereby improving diagnostic accuracy and treatment efficiency. In this process, users not only need to interact with humans or AI agents but also need to handle the complex relationships constituted by humans and AI agents, fundamentally changing the traditional mode of human-AI interaction [4].

Although AI has demonstrated capabilities surpassing humans in data processing, pattern recognition, and automated services, its "algorithmic rationality" still has essential limitations in dimensions such as emotional resonance, ethical judgment, and clinical intuition. This has prompted the academic and industrial circles to shift toward the research paradigm of "Human-AI Hybrid Agents" [5], namely achieving complementary advantages through human-AI collaboration: AI undertakes repetitive computing and knowledge retrieval tasks, while human doctors focus on emotional communication and complex decision-making, ultimately forming a "1+1>2" synergistic effect.

In the context of an aging society, the elderly population is facing a deep mismatch between high-frequency healthcare needs and the "digital divide." Their functional decline and cognitive barriers result in significant trust barriers and adoption resistance even in human-AI hybrid scenarios. Therefore, exploring how technology can achieve deep alignment between technological dividends and universal health needs through natural, low-barrier interaction logic is an urgent practical pain point that needs to be addressed. The research findings can not only provide direction for technology advancement and optimization for AI tool designers, helping solve medical resource allocation challenges, but also provide scientific basis for policymakers to improve the "Internet + Health" regulatory system, ultimately achieving deep alignment between technological dividends and universal health needs.

1.2. Research Significance

1.2.1. Theoretical Significance

Deeply exploring the adoption willingness of older adults in the context of "human-AI hybrid interaction" not only extends the theoretical application of the S-O-R model in the field of generative AI but also provides solid theoretical support for constructing "Human-AI Hybrid Agents" that better meet the needs of older adults through systematic analysis of the psychological mechanisms and behavioral patterns of older adults during AI interaction.

This study introduces AI technology into the theoretical framework of healthcare service quality management, which helps form a comprehensive and dynamic new paradigm for healthcare service quality management, thereby seizing the initiative in the booming "Silver Economy" market and practically addressing the real pain points of elderly health management.

1.2.2. Practical Significance

At the practical level, the research findings will guide designers to specifically optimize the functional design, interactive interface, and performance of AI tools, improving their usability, reliability, and safety, thereby significantly enhancing older adults' trust and acceptance of AI

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

tools, helping achieve dual improvements in healthcare service efficiency and quality, and alleviating supply-demand contradictions in medical resources.

For policymakers, this study provides relevant basis for improving the “Internet + Health” regulatory system. Policymakers can formulate more forward-looking and scientific regulatory policies based on research findings, effectively regulating the application boundaries and development direction of AI technology in the healthcare field, and safeguarding patients’ rights and medical safety. This will lay a solid foundation for building a health information service system covering the entire lifecycle that is efficient and safe, ultimately promoting the sustainable development of the healthcare industry and making quality medical resources more accessible and inclusive.

2. Literature Review

2.1. Health Information Adoption

Research on health information adoption has mainly conducted systematic exploration around platform differences, population characteristics, and situational dynamics. In terms of methodology, empirical methods such as structural equation modeling, questionnaire surveys, and in-depth interviews are mostly adopted, with theoretical foundations covering the Technology Acceptance Model, Social Cognitive Theory, and Information Adoption Model.

Taking socialized Q&A communities as an example, Li Pengfei (2022) revealed the positive effects of performance expectancy, social influence, and facilitating conditions on adoption and sharing willingness [6]; subsequently, Han Shixi et al. (2023) emphasized the important influence of perceived usefulness, self-efficacy, and outcome expectations on health information adoption willingness in their study of WeChat public platforms [7]; while Yang Qingyang (2023) believed that information quality and source credibility on Weibo platforms directly affect perceived action benefits [8] ; Song et al. (2022) found that on entertainment social platforms like TikTok, health information adoption behavior is driven by "Self-Determination Theory," with users focusing more on content amusement/entertainment value and interactivity [9].

Secondly, research on health information adoption behavior of specific populations has shown a trend of refinement. Chen Hongyu (2024) focused on health anxiety groups, finding that the interaction between information literacy and self-efficacy significantly moderates adoption willingness [10]; Zhang Yuqi (2021) studied rural residents, indicating that health self-efficacy and information channel trust are key drivers of adoption behavior [11]; Qiao Yiru (2023) explored pregnant and postpartum women’s behavior in online health communities, pointing out that information quality, personalized recommendation services, and health homogeneity have significant impacts on satisfaction [12].

At the international level, Mensah (2022) verified the applicability of the TAM model in mobile health services based on Ghanaian data, finding that users in developing countries value perceived ease of use (such as operational simplicity) more [13], while Wu et al. (2025) found that people in developed countries pay more attention to the balance between information quality and privacy protection [14].

In contexts of sudden public health events and information conflicts, users’ health information adoption is dynamically regulated by psychological and behavioral mechanisms such as risk cognition, emotional trust, and the “cognition-behavior paradox.” Han Shixi and Zeng Yueliang (2021) and Yang Lijun et al. (2023) respectively constructed predictive models based on risk cognition and interpersonal influence from crisis contexts [15], revealing that users may exhibit irrational behaviors when adopting health information during emergency events due to panic or social pressure [16]. Cao Po et al. (2022) used SEM and fsQCA methods to point out that in the pandemic information environment, the public’s adoption of corrective health information

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

is both inhibited by cognitive conflict and compensated through emotional trust, demonstrating a dual-path regulatory effect [17].

International research further deepens this dynamic mechanism. Jin et al. (2025) proposed that in the context of health information conflicts, users may experience the "cognition-behavior paradox" phenomenon, that is, although recognizing scientific evidence, they tend to adopt individual narratives, with experience accumulation and information type (authoritative institutions vs. personal experience) becoming key moderating variables [18]; while Bi (2024) verified through the DEMATEL-ISM model that the interaction effect between user characteristics (such as digital literacy) and information conflict intensity determines that in high-conflict scenarios, users rely more on "experience anchoring" rather than rational evaluation [19].

2.2. Scenario-Based Health Information Adoption Mechanisms Under Technological Empowerment

In the diversified context of digital healthcare and health management, a scenario-based turn in health information adoption has emerged. Its core lies in using the dynamic adaptation between technological characteristics and scenario needs to improve user experience and adoption efficiency.

In online diagnosis and treatment scenarios, Zhao Keyi (2024) constructed a social presence and health belief integration model, indicating that the "presence" simulation of doctor-patient virtual interaction (such as real-time consultation feedback) significantly enhances users' trust in diagnosis and treatment information, while health perception threat indirectly drives adoption behavior through risk avoidance pathways [20]. Xu Hao (2025) further integrated UTAUT, health belief, and information adoption models in the study of online consultation platforms, confirming the comprehensive influence of factors such as perceived susceptibility, perceived behavioral benefits, information quality, and source credibility on users' information adoption behavior, providing empirical evidence for interaction optimization in online diagnosis and treatment scenarios [21].

In smart medical and elderly care scenario research, Yang Jinxin (2024) used structural equation and evolutionary game models to reveal that the adoption decisions of elderly patients, doctors, and institutions involve a three-party game, where institutional resource investment and doctor technology training costs are key thresholds for cross-subject collaboration [22].

AI technology-empowered scenario research presents a "function-interaction-ethics" layered deepening characteristic. At the interaction level between AI technology characteristics and user cognition, Lu Xinyuan et al. (2025) found through experimental research that the "interpretability" and "traceability" of medical artificial intelligence can effectively enhance user trust, thereby positively affecting information adoption effectiveness, with users' artificial intelligence literacy playing a key moderating role in this process [23]. Zhang Jinao et al. (2025) found in generative AI (AIGC) health information adoption research that "artificial intelligence literacy" and "health information literacy" together constitute a dual driving mechanism for user adoption behavior, exerting their effects through the mediating paths of perceived system quality and perceived information quality, revealing a new model of compound literacy influence in human-AI interaction [24].

Cross-scenario research on modern health information adoption also shows diversified trends. Regarding health information adoption on social media platforms, Wu et al. (2025) found that the mutual assistance culture formed in Q&A communities can significantly improve health information adoption rates, with this "platform atmosphere effect" being particularly prominent in scenarios requiring long-term support such as chronic disease management [25]. Song et al. (2022) believed that entertainment platforms like TikTok have successfully weakened the serious perception of health information through gamification design, making

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

young users more willing to adopt relevant suggestions, but this "de-seriousness" may simultaneously reduce users' perception of information importance [26].

In rich media scenarios such as short videos and live streaming, research further reveals multiple driving paths of user behavior. Wei Hua et al. (2023) conducted fsQCA analysis based on the MOA framework, finding that health information adoption by users on short video social platforms has three configuration paths: information quality-driven, health literacy-supported self-improvement-driven, and self-efficacy-supported health awareness-driven [27]. Fu Shaoxiong et al. (2023) pointed out from the coping theory perspective that short video users' adoption of false health information is simultaneously affected by the dual-directional influence of perceived information support (opportunity assessment) and perceived risk (threat assessment), with health information literacy playing a key inhibitory role in secondary assessment [28]. Chen Haibo et al. (2024) conducted grounded analysis on the adoption of false information by older adults in online live streaming scenarios, finding that platform information manipulation strategies induce older adults to adopt false information through profit-seeking psychology, human favoritism, and immersive experience, while older adults' cultural confidence and self-efficacy constitute important internal resistance mechanisms [29].

Additionally, in mobile UGC community scenarios, Chen Yini et al. (2022) pointed out that users' "reputation granting" behavior can directly promote subsequent users' information adoption willingness, while "perceived knowledge consensus" provides a basis for users' value judgments, highlighting the key role of social attributes and collective cognition in specific platform scenarios [30]. Xu Xiaojun et al. (2022) further approached from the behavior transformation perspective, verifying the behavioral path from health information "adoption" to "continuous search" in social media, where satisfaction is the core factor driving behavioral continuation, while perceived risk produces continuous negative effects [31].

The adoption mechanisms of mobile health (mHealth) show significant regional differences. Liu et al. (2022) proposed a "push-pull-mooring" model, showing that external triggers such as pandemic policies in developed countries and internal anchoring of personal health habits jointly influence user behavior transformation [32]; while Mensah (2022)'s Ghana study found that users in developing countries rely more on social relationship network recommendations, with this "acquaintance trust" mechanism often being more influential than the technology brand itself [33].

2.3. AI and AIGC Adoption Willingness and Behavior

Research on the impact of AI anthropomorphism on user adoption behavior reveals a multi-layered influence mechanism of "design-cognition-neuroscience," with its development trajectory showing an evolutionary characteristic of "functional optimization-contradiction discovery-emotional deepening."

Initially, research focused on exploring the positive effects and behavioral mechanisms of anthropomorphic design. Abdi (2022) verified through online experiments the promoting effect of service robot anthropomorphism on user recommendation adoption, finding that perceived mind (such as the perception of AI's "thinking ability") and persuasiveness mediating effects are key pathways [34]; Bi (2023) further proved that users' active participation in customizing AI names and appearances can significantly improve adoption rates, proposing the concept of "design sovereignty" [35].

With the continuous improvement and development of AI tools, the complexity and scenario-dependence of their anthropomorphic effects have gradually emerged. In recruitment scenarios, Olszewski (2024) found that excessively high anthropomorphic design (such as human-like facial expressions) instead triggers user aversion, leading to decreased adoption rates, confirming the applicable boundaries of the "Uncanny Valley Effect" in decision-making scenarios [36]; Oh (2024) proposed the "authenticity mediation hypothesis" through

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

information correction experiments, namely that highly anthropomorphic AI indirectly promotes user attitude change by enhancing information credibility, but this effect significantly weakens in health-sensitive topics [37].

In the direction of emotional experience and long-term interaction, Wang Wenqi (2024) found that the anthropomorphic tone design of intelligent voice assistants influences users' continuous usage intention through emotional attachment, with female users being more easily driven by emotional design [38]; Cao Xinyi (2025) found in medical consultation scenarios that the adoption-promoting effect of anthropomorphic design on elderly patients is significantly higher than that on younger groups, attributed to older adults' higher demand for "human-like care," providing evidence for the cross-scenario moderating effect of AI anthropomorphism [39].

2.4. Trust and Adoption of AI Medical Tools

In the healthcare field, users' trust and adoption of AI medical tools presents characteristics of complex game between "functional trust" and "social trust," with the core contradiction lying in the tension between "efficiency-privacy" and "technical rationality-humanistic needs."

In terms of functional trust, Mendel Tamir et al. (2024) pointed out through research on remote monitoring devices that system functionality (such as data collection accuracy) and privacy risks (such as the possibility of health information leakage) constitute key factors that patients must weigh when disclosing information to AI [40]; Wutz et al. (2023)'s integrative review clarified that medical chatbot adoption is mainly dominated by performance expectancy (such as diagnostic efficiency) and effort expectancy (such as operational costs), and revealed that in cross-departmental application scenarios such as chronic disease management, users value long-term data tracking functions more [41]; simultaneously, Zhan et al. (2024) focused on voice assistant research, finding that effectiveness must be improved simultaneously with privacy protection, reducing privacy risks through technologies such as data anonymization, otherwise in sensitive scenarios such as mental health consultation, privacy concerns may completely offset the positive effects brought by technological convenience [42].

In terms of social trust mechanisms, Kim (2024) compared physical health robots (such as diabetes management assistants) with relational health robots (such as emotional support robots), with results indicating that the former can reduce technical uncertainty due to the quantifiability of tasks, thereby gaining higher user trust and directly predicting adoption intention [43]; while Ashish Viswanath Prakash (2024)'s proposed technology trust framework emphasized that perceived anthropomorphism must be combined with explainability (such as transparency of AI decision logic), and excessive anthropomorphism without transparency in accountability easily triggers "technology overreach" anxiety [44].

Additionally, cross-cultural comparative studies show that Chongwu Bi (2024) used the DEMATEL-ISM model to find that users in developing countries (such as India, Ghana) rely more on experience accumulation such as friend and family recommendations to build trust, while users in developed countries (such as the United States, Germany) pay more attention to technology brand reputation; Maram Abdaljaleel (2024)'s survey of Arab university students further revealed that religious cultural concepts have significant constraints on the acceptance of "non-human entities intervening in health decisions" [45].

3. Model Construction and Research Design

3.1. Theoretical Framework and Research Hypotheses

In the context of human-AI hybrid interaction, AI agents are not traditional information retrieval tools but intelligent entities with dual attributes of "information source" and

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

"interaction medium." Therefore, this study is grounded in the S-O-R model, integrating ELM and UTAUT theories to construct a logical closed loop driving users' adoption willingness.

In the transmission path of external stimuli, information quality, as the core element of the central pathway, directly determines users' cognitive judgment of the scientific nature of medical advice; source credibility and reputation characteristics, as driving variables of the peripheral pathway, can effectively reduce the uncertainty caused by information asymmetry; technical anthropomorphism, as an AI-specific interaction characteristic, effectively lowers users' psychological defenses when facing machines by enhancing social presence. The above stimuli together constitute the basic stimulus variables influencing adoption willingness.

In the transmission logic of internal organism, the organism state is the core mediator connecting external technological stimuli and final adoption behavior. Users' subjective evaluation of AI technology interaction simplicity and estimation of actual output value together constitute the most intuitive utility assessment of the organism. When users perceive reduced interaction barriers and improved health benefits, their adoption willingness is significantly activated.

Considering the high-sensitivity particularity of the healthcare field, high levels of risk perception will trigger defensive psychology thereby inhibiting adoption, while a solid trust tendency plays a barrier role, reducing negative interference from uncertainty and ensuring external stimuli transform into final adoption willingness.

Based on the S-O-R model, integrating the Elaboration Likelihood Model and the Unified Theory of Acceptance and Use of Technology, this study analyzes the factors influencing users' health adoption in human-AI hybrid interaction scenarios from three dimensions: stimulus, organism, and response, and constructs the model. Among them, potential factors in stimulus include information quality, source credibility, reputation characteristics, and technical anthropomorphism; potential factors in the organism framework include trust tendency, performance expectancy, effort expectancy, and perceived risk; response factors include users' information adoption willingness. The above factors will have certain effects on users' health information adoption willingness. Integrating the above factors completes the model of factors influencing users' willingness to adopt health information in human-AI hybrid interaction scenarios, as shown in Fig 1.

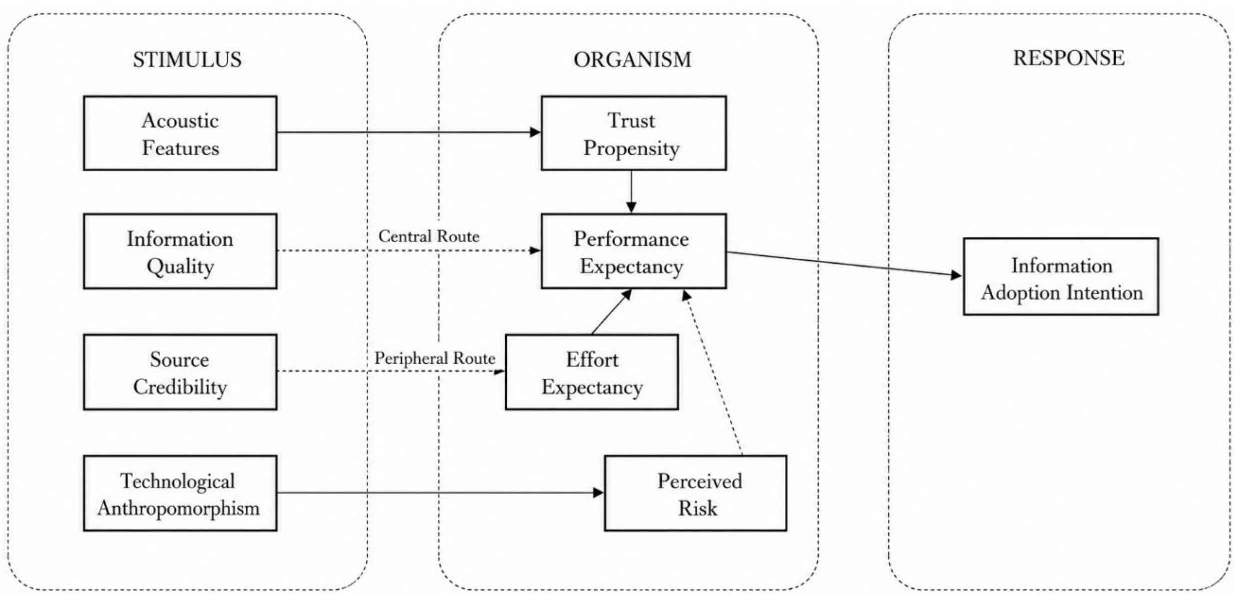

Figure 1. Model of factors influencing users' willingness to adopt health information in a human-AI hybrid interaction scenario

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

Based on the research model, the following hypotheses are proposed:

H1: Information quality positively influences health information adoption willingness

H2: Source credibility positively influences health information adoption willingness

H3: Reputation characteristics positively influence health information adoption willingness

H4: Effort expectancy positively influences health information adoption willingness

H5: Performance expectancy positively influences users' health information adoption willingness

H6: Perceived risk negatively influences health information adoption willingness

H7: Trust tendency positively influences health information adoption willingness

3.2. Variable Measurement Indicators

The research hypothesis model of this paper mainly includes 9 variables: information quality, source credibility, reputation characteristics, technical anthropomorphism, effort expectancy, performance expectancy, trust tendency, perceived risk, and information adoption willingness. The selected variable measurement items are all derived from existing literature. Considering variable validity, some variables have been modified based on original item designs, summarized as follows:

3.3. Data Collection

This study conducted data collection in December 2025 through a combination of online questionnaires and commissioned surveys, targeting elderly groups in China's first-tier and new first-tier cities (including Beijing, Shanghai, Guangzhou, Shenzhen, and Hangzhou). Considering that generative AI intelligent consultation is still a relatively new technology application and the elderly group generally has limited understanding and usage of such applications, video demonstrations combined with scenario descriptions were used before the questionnaire survey to visually present the operational process of generative AI intelligent consultation to respondents.

To ensure data quality and avoid positive bias from information intervention, the introduction process strictly followed the principle of neutrality, ensuring that the obtained data can effectively support the core research on older adults' willingness to adopt health information in human-AI hybrid interaction scenarios.

The data collection results yielded 512 questionnaires, ultimately retaining 417 valid data points, with an effective questionnaire recovery rate of 81.4%. The questionnaire contains 30 scale items, and the valid sample size meets the requirement of 10-15 times the number of scale items, thus enabling further data analysis.

In terms of sample representativeness, the academic objectives of this study focus on path testing of the theoretical model and internal influence mechanism analysis rather than census-style overall description of the national elderly population. According to the academic standards of Structural Equation Modeling (SEM), the valid sample size meets statistical requirements for model fitting and parameter estimation. Therefore, this sample scale has sufficient explanatory power for verifying the theoretical model in human-AI hybrid interaction scenarios. In subsequent research, the sample coverage will be further expanded and stratified sampling methods will be adopted to enhance the universality of research conclusions in regions with different aging degrees.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

Table 1. Variable Measurement Indicators

Variable	Code	Measurement Content
Information Quality	IQ1	I believe the health information provided by interactive AI is scientifically reliable.
	IQ2	Interactive AI can update health recommendations based on the latest medical advances.
	IQ3	AI explains professional medical concepts in plain language.
	IQ4	AI helps me quickly grasp key points of health recommendations through structured presentation (such as point-by-point explanations, table comparisons).
Source Credibility	SC1	I believe the AI platform providing health information (such as DEEPSEEK) has high reputation.
	SC2	I believe the sources of health information marked by AI (such as medical journals, clinical guidelines) are relatively authoritative.
	SC3	The medical knowledge base referenced by AI when generating health recommendations (such as clinical guidelines, authoritative journals) is updated timely and comprehensively covered.
	SC4	The AI platform has undergone rigorous clinical verification or expert review processes before providing health information.
	SC5	The health data marked by the AI platform (such as medical images, medical records) has undergone strict quality control (such as multiple rounds of manual review).
	SC6	The information generated by AI (such as disease explanations, treatment plans) can provide traceable source references (such as citing medical literature).
Technical Anthropomorphism	TA1	AI provides deeper explanations based on my follow-up questions and proactively inquires.
	TA2	Interactive AI dialogue can effectively alleviate my health anxiety (such as using comforting language).
	TA3	AI’s anthropomorphic interaction method (such as emotional support) will enhance my sense of trust.
	TA4	AI can naturally perform turn-taking in conversations.
	TA5	AI can proactively initiate related health topics based on conversation context.
Reputation Characteristics	RC1	I will verify AI recommendations against doctor diagnoses.
	RC2	Doctor recommendations will enhance my willingness to adopt interactive AI health information.
	RC3	Friends and family using interactive AI to obtain health information will influence my choices.
Effort Expectancy	EE1	The process of interacting with AI makes me feel relaxed and efficient.
	EE2	Compared with traditional health management methods (such as consulting materials, consulting doctors), AI saves me a lot of time and effort.
	EE3	When interacting with AI (such as voice dialogue, text input), I don’t need repeated attempts to complete operations.
Performance Expectancy	PE1	I believe the health information generated by AI is practically helpful for my health management (such as disease prevention, medication guidance).
	PE2	Using AI for health monitoring (such as symptom analysis, vital sign tracking) makes me more aware of my own health status.
	PE3	AI’s medication reminder and dosage guidance functions significantly reduce my risk of medication errors.
Perceived Risk	PR1	I believe adopting AI-generated health information may lead to privacy leakage.
	PR2	I worry about being misled by false information during AI interaction, producing incorrect health concepts.
Trust Tendency	TP1	Generative AI is reliable during interaction.
	TP2	Generative AI will keep promises during interaction.
Information Adoption Willingness	AI1	I am willing to accept health viewpoints/recommendations from AI communication.
	AI2	I am willing to adjust health behaviors (such as diet, exercise) based on AI recommendations.

4. Empirical Analysis and Results

4.1. Basic Information Statistical Analysis

Descriptive statistical analysis was conducted on the survey data to understand the basic characteristics of the data. The specific distribution of sample data is shown in Table 2.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

Table 2. Statistical Distribution of Basic Information

Variable Name	Item	Frequency	Percentage (%)
Gender	Male	238	57.1
	Female	179	42.9
Age	60-65 years	153	36.7
	66-70 years	95	22.8
	71-75 years	80	19.2
	75 years and above	89	21.3
Education Level	Primary school and below	175	42.0
	Junior high school and technical secondary school	144	34.5
	High school and junior college	57	13.7
	Undergraduate and above	41	9.8

4.2. Model Evaluation

4.2.1. Measurement Model Reliability and Validity Test

The measurement model reliability and validity test mainly includes internal consistency test and composite reliability test, using Cronbach's Alpha coefficient and CR values for reliability testing. The Cronbach's Alpha coefficient ranges from 0 to 1, with values closer to 1 indicating stronger correlation. Generally, a Cronbach's Alpha coefficient greater than 0.7 indicates good internal consistency of questionnaire items.

The results show that in terms of reliability of the measurement model, the α coefficients of all latent factors are greater than 0.7 (minimum 0.723, maximum 0.982), and the composite reliability indicator CR values are all greater than 0.8 (minimum 0.878, maximum 0.916), indicating that the measurement model has good internal consistency levels and composite reliability.

Validity refers to the degree to which a measurement tool can accurately measure its intended target, improving the credibility of research conclusions. First, the overall KMO of the model is greater than 0.8, and the Bartlett's test of sphericity significance is less than 0.01, indicating that the model has high validity. Second, the factor loadings of all latent factor observation variables are greater than 0.7 (minimum 0.790, maximum 0.910), and AVE values are all greater than 0.5 (minimum 0.716, maximum 0.816), indicating that the measurement model has good convergent validity.

Table 3. Measurement Model Reliability Test

Variable	Items	Cronbach's Alpha	Composite Reliability (rho_c)
AI	2	0.855	0.902
EE	3	0.909	0.912
IQ	4	0.889	0.916
PE	3	0.895	0.883
PR	2	0.879	0.878
RC	3	0.813	0.878
SC	6	0.882	0.882
TA	5	0.879	0.879
TP	2	0.724	0.724

In terms of discriminant validity, according to the Fornell-Larcker Criterion, since the square roots of AVE values for all latent factors are greater than the correlation coefficients between

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

that factor and any other latent factors, the measurement model is determined to have good discriminant validity. Meanwhile, HTMT values are all less than 0.85, further verifying the measurement model's good discriminant validity.

Table 4. Measurement Model Validity Test

Variable	Item	Factor Loading	KMO	AVE
AI	AI1	0.906	0.782	0.782
	AI2	0.863		
EE	EE1	0.881	0.885	0.784
	EE2	0.892		
	EE3	0.884		
IQ	IQ1	0.862	0.697	0.697
	IQ2	0.836		
	IQ3	0.837		
	IQ4	0.805		
PE	PE1	0.884	0.74	0.74
	PE2	0.845		
	PE3	0.851		
PR	PR1	0.882	0.791	0.791
	PR2	0.896		
RC	RC1	0.878	0.728	0.728
	RC2	0.82		
	RC3	0.86		
SC	SC1	0.829	0.626	0.626
	SC2	0.795		
	SC3	0.783		
	SC4	0.807		
	SC5	0.781		
	SC6	0.752		
TA	TA1	0.831	0.674	0.674
	TA2	0.833		
	TA3	0.804		
	TA4	0.835		
	TA5	0.801		
TP	TP1	0.884	0.784	0.784
	TP2	0.887		

Table 5. Fourier-Lackel

	AI	EE	IQ	PE	PR	RC	SC	TA	TP
AI	0.884								
EE	0.346	0.886							
IQ	0.3	0.46	0.835						
PE	0.414	0.489	0.5	0.861					
PR	-0.345	-0.363	-0.344	-0.399	0.889				
RC	0.324	0.262	0.288	0.365	-0.336	0.853			
SC	0.193	0.192	0.14	0.165	-0.185	0.197	0.791		
TA	0.261	0.316	0.282	0.355	-0.289	0.251	0.132	0.821	
TP	0.323	0.358	0.328	0.41	-0.28	0.252	0.141	0.335	0.885

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

Table 6. HTMT

	AI	EE	IQ	PE	PR	RC	SC	TA	TP
AI									
EE	0.434								
IQ	0.38	0.534							
PE	0.53	0.58	0.594						
PR	0.474	0.456	0.432	0.511					
RC	0.42	0.314	0.348	0.448	0.437				
SC	0.241	0.212	0.158	0.191	0.224	0.231			
TA	0.326	0.364	0.323	0.416	0.358	0.297	0.155		
TP	0.447	0.454	0.416	0.531	0.384	0.328	0.173	0.421	

4.2.2. Common Method Bias

Considering that the data collection of this study adopted the questionnaire survey method, there may be common method variance (CMV) between variables. The existence of CMV can amplify correlations between measurements, so Harman's single-factor method was used to assess potential CMV issues. The results showed that there are 9 factors with eigenvalues greater than 1, explaining 72.18% of the variance. The first factor's variance contribution rate is 26.86%, lower than the 40% threshold, indicating that this study does not have serious common method bias and has good explanatory power.

4.3. Structural Model Evaluation

4.3.1. Multicollinearity Test

Table 7. Variance Inflation Factor (VIF)

Item	VIF	Item	VIF
AI1	1.472	PR1	1.511
AI2	1.472	PR2	1.511
EE1	2.182	SC1	2.104
EE2	2.239	SC2	1.789
EE3	2.195	SC3	1.939
IQ1	2.214	SC4	1.967
IQ2	1.935	SC5	2.077
IQ3	1.984	SC6	1.814
IQ4	1.77	TA1	2.024
PE1	2.033	TA2	2.121
PE2	1.825	TA3	1.987
PE3	1.793	TA4	2.186
RC1	1.98	TA5	1.917
RC2	1.59	TP1	1.477
RC3	1.948	TP2	1.477

Multicollinearity refers to the situation where there is high correlation between independent variables in multiple regression models, which may lead to unstable model parameter estimation and difficulty in interpreting the impact of each independent variable, so corresponding tests are needed. The Variance Inflation Factor (VIF) is an indicator commonly used to detect multicollinearity. It can help us measure the degree of correlation between each independent variable and other independent variables. Specifically, for each independent variable, the larger its VIF value, the more significant the linear relationship between that

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

independent variable and other independent variables, indicating more serious multicollinearity problems.

Using SmartPLS4 software to test the VIF values of each item, the results are shown in Table 7. All measurement items have VIF < 5, indicating no multicollinearity problems between variables.

4.3.2. Path Coefficient Test

This study uses the bootstrapping method in SmartPLS3.0, setting the sampling frequency to 5,000 times, to obtain the significance between each latent variable path through calculation. Path coefficients represent the direct relationships between latent variables in structural equation models, which can demonstrate the degree of impact between variables.

In this study, 8 hypothesis relationship paths have P values less than 0.05, obtaining significant results. These are drawn into a path coefficient diagram, as shown in Fig 2.

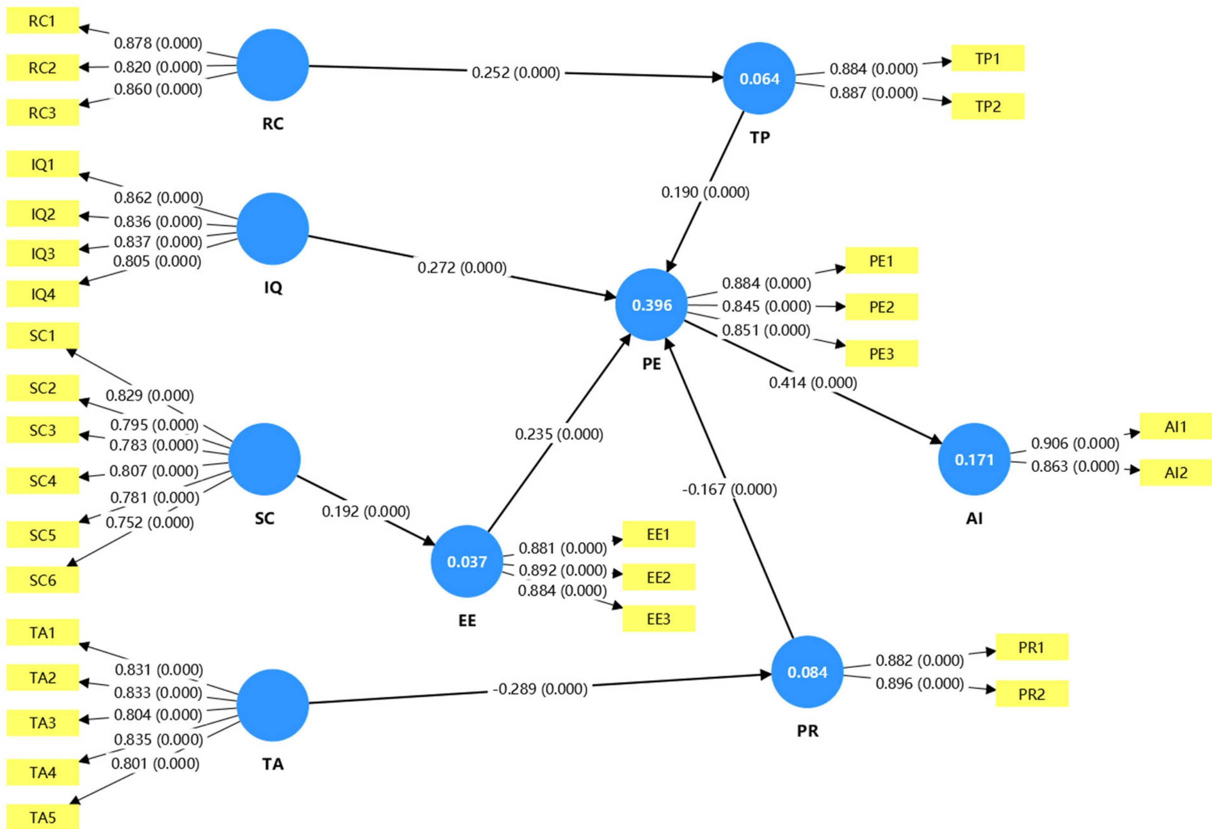

Figure 2. Path coefficient diagram

Table 8. Path Analysis and Significance Test

Path	Sample Mean (M)	T Statistics (	O/STDEV
EE -> PE	0.235	4.393	0
IQ -> PE	0.274	4.95	0
PE -> AI	0.416	9.725	0
PR -> PE	-0.168	3.548	0
RC -> TP	0.256	5.758	0
SC -> EE	0.2	4.381	0
TA -> PR	-0.292	6.474	0
TP -> PE	0.189	4.061	0

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4.3.3. Multiple Mediation Effect Test

The existence of mediating variables can better explain the relationship between dependent and independent variables. The mediation effects of the model are shown in Table 5-6. PE plays significant mediating roles in the relationships between PR and AI, TP and AI, EE and AI, and IQ and AI. Specifically, the effects of PR, TP, EE, and IQ on PE all reach significant levels (path coefficients are -0.069, 0.079, 0.097, and 0.113 respectively, all meeting $p < 0.01$), while the effect of PE on AI is also significant (path coefficient is -0.07, $p < 0.01$).

Table 9. Path Analysis and Significance Test

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (	O/STDEV
PR -> PE -> AI	-0.069	-0.07	0.022	3.194	0.001
RC -> TP -> PE -> AI	0.02	0.02	0.007	2.811	0.005
TP -> PE -> AI	0.079	0.079	0.021	3.672	0
TA -> PR -> PE	0.048	0.049	0.016	2.999	0.003
SC -> EE -> PE	0.045	0.047	0.016	2.859	0.004
SC -> EE -> PE -> AI	0.019	0.02	0.007	2.612	0.009
TA -> PR -> PE -> AI	0.02	0.021	0.007	2.681	0.007
EE -> PE -> AI	0.097	0.098	0.025	3.896	0
IQ -> PE -> AI	0.113	0.113	0.025	4.541	0
RC -> TP -> PE	0.048	0.049	0.015	3.103	0.002

5. Conclusions and Product Development Service Optimization Strategies

5.1. Hypothesis Testing and Research Conclusions

Based on the human-AI hybrid interaction context, this study deeply explored the multiple influencing factors of users' health information adoption willingness, and through empirical analysis revealed the complex interaction mechanisms between these factors. Combining all the above analyses, the hypothesis testing results of this paper can be obtained, summarized as follows:

Table 10. Hypothesis Test Results

Hypothesis	Hypothesis Content	Result
H1	Information quality positively influences health information adoption willingness	Supported
H2	Source credibility positively influences health information adoption willingness	Supported
H3	Reputation characteristics positively influence health information adoption willingness	Supported
H4	Effort expectancy positively influences health information adoption willingness	Supported
H5	Performance expectancy positively influences users' health information adoption willingness	Supported
H6	Perceived risk negatively influences health information adoption willingness	Supported
H7	Trust tendency positively influences health information adoption willingness	Supported

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

The research results indicate that users' health information adoption willingness is not determined by a single factor but is jointly influenced by multiple factors including information quality, source credibility, reputation characteristics, effort expectancy, performance expectancy, perceived risk, and trust tendency.

From the stimulus level, information quality, source credibility, and reputation characteristics, as main factors, have significant positive effects on users' health information adoption willingness. Information quality is the foundation for users to evaluate information value, and high-quality health information can significantly improve users' adoption willingness. Users are more inclined to adopt information that is true, complete, accurate, and clearly expressed, because such information can enhance users' trust and persuasiveness regarding health information, thereby promoting health information utilization and behavior change.

Source credibility reflects the reliability and professionalism of information providers, and information sources with high source credibility are more likely to be relied upon and adopted by users. Especially when users lack professional knowledge, source credibility becomes a key factor in information adoption. Reputation characteristics reflect the cumulative effect of information providers' overall credibility and professionalism in users' minds, and information sources with high reputation are more likely to gain users' trust and adoption.

From the individual user perspective, both effort expectancy and performance expectancy have significant positive effects on users' adoption willingness. This means that when users perceive health information as easy to understand and apply, and able to bring actual health benefits, they are more willing to adopt it. For example, when health information is presented in a simple and understandable form, users don't need to spend too much effort to interpret it, their effort expectancy decreases, and adoption willingness increases; if users believe that adopting certain health information can effectively improve their health status or solve health problems (such as preventing disease through dietary adjustments), their performance expectancy for the information increases, thereby promoting the occurrence of adoption willingness.

Additionally, perceived risk has a negative effect on users' adoption willingness, while trust tendency plays a positive promoting role. When users have doubts about health information, worrying about possible adverse consequences (such as misleading treatment suggestions), their perceived risk increases, inhibiting adoption willingness; conversely, if users have high trust in information providers or platforms, believing that the information provided is reliable and safe, they will more actively adopt health information.

In terms of interrelationships, the study found a positive relationship between effort expectancy and source credibility, that is, the higher the source credibility, the lower the effort expectancy perceived by users. This is because users have more confidence in highly credible information sources, believing that the information provided is easier to understand and use.

Meanwhile, performance expectancy plays a mediating role between multiple factors and information adoption willingness. For example, information quality, effort expectancy, and trust tendency all indirectly influence information adoption willingness through affecting performance expectancy. This indicates that users' expectations of the benefits that may come after information adoption are key factors driving their adoption willingness.

Technical anthropomorphism, as one of the stimulus factors, was also found in the study to indirectly affect performance expectancy and information adoption willingness by influencing perceived risk. Users' perception of AI technology anthropomorphism may increase their risk perception, because users may worry that AI cannot fully understand human needs or may have biases. This risk perception then reduces users' performance expectancy and adoption willingness. Therefore, when designing AI health information tools, it is necessary to fully consider users' perception of technology anthropomorphism and take measures to reduce their risk perception.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

5.2. Practical Suggestions

5.2.1. Building an Age-Friendly Human-AI Health Interaction Ecosystem in the Silver Economy Context

In the context of the booming Silver Economy, AI tool designers should focus on developing health information services that truly match the cognitive characteristics and usage habits of older adults, to improve this group's adoption willingness and usage experience. Designers must first ensure that health information content is accurate, complete, and easy to understand, avoiding excessive professional terminology, using expressions close to users' daily language to convey knowledge, meeting their urgent need for reliable and clear information.

At the same time, information sources should be prominently marked with authoritative endorsements, for example, introducing medical institution certifications or expert review labels to enhance information credibility and older adults' sense of trust. In terms of interactive experience, priority should be given to implementing deep age-friendly design, simplifying operation processes, using large fonts and high-contrast visual presentation, enhancing voice input and feedback functions, and providing auxiliary modes such as "one-click help" and "family collaboration" as much as possible, thereby significantly reducing older adults' usage barriers and cognitive burden, making them feel convenience and respect in the process of obtaining and understanding health information, and effectively improving adoption willingness.

On this basis, designers should establish a continuous iteration mechanism centered on elderly users, continuously optimizing functions and service processes by tracking usage willingness and feedback data, enabling AI tools to dynamically adapt to their changing health needs, thereby achieving deep integration and long-term application in silver health scenarios.

5.2.2. Improving Policy Guidance and Institutional Guarantees for Smart Health and Elderly Care

Policymakers should improve the "Internet + Health" regulatory system based on research conclusions, strengthen the review of health information providers' qualifications, establish information quality evaluation standards and regulatory mechanisms, and severely crack down on the spread of false information.

In the qualification review and supervision process, it is necessary to establish a sound qualification review mechanism for health information providers to ensure the reliability of information sources. Develop scientific and reasonable regulatory standards, strengthen content review of health information service providers, and severely crack down on the spread of false information and misleading content.

In terms of improving information quality evaluation standards, health information should be evaluated from multiple dimensions including accuracy, completeness, timeliness, and ease of use, and these standards should be incorporated into the regulatory scope to ensure that users can obtain high-quality health information.

Policymakers also need to guide technological innovation and application, promoting innovative applications of AI technology in the healthcare field through policy support and incentive measures, improving the efficiency and quality of medical services. At the same time, attention should be paid to privacy and security protection, formulating strict data protection policies to protect users' personal information security and privacy rights, preventing user data from being misused or leaked.

Additionally, strengthen international cooperation and exchange, learn from international advanced experience, promote the internationalization development of China's health information services, and enhance China's influence in the global health information service field. Finally, carry out public education and publicity to improve the public's cognitive level

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

and discernment ability regarding health information, guide the public to reasonably use health information services, and promote the sustainable development of health information services.

6. Conclusion

This reveals that human-AI collaboration is not simple technology acceptance but a complex socio-technical process involving multiple cognitive evaluations. The study places the discussion under the macro vision of aging society and Silver Economy development, not only providing universal design principles for optimizing AI health tools but also highlighting the urgency and special value of targeted adaptation for elderly user groups—they are both "high-demanders" and "vulnerable key groups" for health information adoption. Only by truly understanding and responding to the real needs of older adults can artificial intelligence become a warm force promoting healthy aging and empowering the development of the Silver Economy, ultimately achieving deep integration of technological empowerment and humanistic care.

References

[1] Chen, X. Y., & Guan, L. Y. (2024). The concept, operation mechanism and development prospects of the silver economy. New Economy, 11, 42–54.

[2] State Council. (2016, October 25). Outline of the "Healthy China 2030" Plan. Retrieved March 25, 2025, from http://www.gov.cn/xinwen/2016-10/25/content_5124174.htm

[3] General Office of the State Council. (2018, April 28). Opinions of the General Office of the State Council on Promoting the Development of "Internet + Healthcare". Retrieved July 22, 2022, from http://www.gov.cn/xinwen/2018-04/28/content_5286707.htm

[4] Zhang, S. (2025). Online Medical Human-Intelligence Hybrid Interaction: Theoretical Origins, Paradigm Changes and Frontier Trends. Library and Information Knowledge, 42(5), 79–86.

[5] Liu, H. T. (2024, April 11). From Artificial Intelligence Agents to Hybrid Intelligence Agents. Social Science Weekly, p. 5.

[6] Li, P. F. (2021). A study on users' willingness to adopt and share health information based on socialized question-and-answer communities [Master's thesis]. Chongqing Medical University.

[7] Han, S. X. (2020). A study on factors influencing the willingness of digital youth to adopt health information based on WeChat public platform [Master's thesis]. Huazhong University of Science and Technology.

[8] Yang, Q. Y. (2023). A study on factors influencing the willingness of Weibo users to adopt health information. Medicine and Society, 36(4), 100–105.

[9] Song, S., Zhao, Y. C., Yao, X., Ba, Z., & Zhu, Q. (2022). Serious information in hedonic social applications: affordances, self-determination and health information adoption in TikTok. Journal of Documentation, 78(4), 890–911.

[10] Chen, H. Y. (2023). A study on online health information adoption behavior of people with health anxiety [Master's thesis]. Heilongjiang University.

[11] Zhang, Y. Q. (2020). A study on health information search and adoption behavior of rural residents [Master's thesis]. Nankai University.

[12] Qiao, Y. R. (2024). A study on influencing factors of health information adoption behavior of pregnant and postpartum women in online health communities [Master's thesis]. Jilin University.

ISSN: 2637-6067 DOI: 10.6918/IJOSSER.202608_9(8).0006

[13] Mensah, I. K. (2022). Understanding the drivers of Ghanaian citizens' adoption intentions of mobile health services. Frontiers in Public Health, 10, 906106.

[14] Wu, Q., Yang, X., Su, K., Khakimova, A., Gu, D., & Zolotarev, O. (2025). Adopt or not? The determinants of health information adoption in online question-and-answer communities. Online Information Review.

[15] Han, S. X., & Zeng, Y. L. (2021). A study on the influencing factors of the willingness of digital youth to adopt health information on WeChat public platform under the background of public health emergency. Library Science Research, 6, 83–92.

[16] Yang, L. J. (2022). A study on the prediction of health information adoption behavior of social media users under public health emergency [Master's thesis]. Jilin University.

[17] Cao, P., Liang, Y. Y., & Liu, R. (2022). A study on the willingness of the public to adopt corrective health information under the background of information epidemic - based on SEM and fsQCA method. Modern Information, 42(12), 83–95.

[18] Jin, Y., Zhao, D., Sun, Z., Bi, C., Yang, R., & Deng, S. (2025). Patients' cognitive and behavioral paradoxes in the process of adopting conflicting health information: A dynamic perspective. Information Processing & Management, 62(1), 103939.

[19] Bi, C., Yao, L., Sun, Z., Jin, Y., & Yang, R. (2024). Investigating the determinants of user adoption behavior in the context of conflicting health information: a DEMATEL-ISM model approach. In Proceedings of the 24th ACM/IEEE Joint Conference on Digital Libraries (pp. 1–3).

[20] Zhao, K. Y. (2023). Research on the influencing factors of users' willingness to adopt information in online medical consultation and information service models [Master's thesis]. Jilin University.

[21] Xu, H. (2025). Research on the influencing factors of users' information adoption behavior in online consultation platforms [Master's thesis]. Heilongjiang University.

[22] Yang, J. X. (2023). Research on the influencing mechanism of value subject's willingness to adopt under the smart medical and elderly care service model [Master's thesis]. Hefei University of Technology.

[23] Lu, X. Y., Wang, K. Y., & Zhang, J. A. (2025). The influence of interpretability and traceability of medical artificial intelligence on the effect of user information adoption. Library Forum, 45(12), 120–129.

[24] Zhang, J. A., Lu, X. Y., Wang, D. R., & Cai, X. X. (2025). Research on AIGC health information adoption driven by both artificial intelligence literacy and health information literacy. Library and Information, 4, 83–95.

[25] Wu, Q., Yang, X., Su, K., Khakimova, A., Gu, D., & Zolotarev, O. (2025). Adopt or not? The determinants of health information adoption in online question-and-answer communities. Online Information Review.

[26] Song, S., Zhao, Y. C., Yao, X., Ba, Z., & Zhu, Q. (2022). Serious information in hedonic social applications: affordances, self-determination and health information adoption in TikTok. Journal of Documentation, 78(4), 890–911.

[27] Wei, H., Hu, G. C., & Gao, J. S. (2023). Antecedent configuration study of health information adoption behavior of users on short video social platforms under MOA framework. Information Science, 41(6), 103–112.

[28] Fu, S. X., Sun, L., Deng, S. L., & Zeng, Y. L. (2023). Study on the motivation of short video users' adoption of false health information from the perspective of coping theory. Information and Documentation Work, 44(6), 100–110.

[29] Chen, H. B., Yang, X. W., Chen, P., & Sun, D. Q. (2024). Grounded analysis of false health information adoption behavior of the elderly in the context of online live streaming. Library Forum, 44(9), 152–160.

[30] Chen, Y. N., Zhou, X. Y., Yue, L. X., & Yu, X. N. (2022). Factors influencing the willingness of mobile UGC community users to adopt health information. Library and Information Science, 39(5), 82–95.

[31] Xu, X. J., & Wang, L. (2022). Research on health information adoption and continuous search behavior of social media users. Information Science, 40(8), 152–159.

[32] Liu, Y., Liang, Z., Li, C., Guo, J., & Zhao, G. (2022). An investigation into the adoption behavior of mhealth users: From the perspective of the push-pull-mooring framework. Sustainability, 14(21), 14372.

[33] Mensah, I. K. (2022). Understanding the drivers of Ghanaian citizens' adoption intentions of mobile health services. Frontiers in Public Health, 10, 906106.

[34] Abdi, E., Tojib, D., Seong, A. K., Pamarthi, Y., & Millington-Palmer, G. (2022). A study on the influence of service robots' level of anthropomorphism on the willingness of users to follow their recommendations. Scientific Reports, 12(1), 15266.

[35] Bi, N., & Huang, J. Y. C. (2023). I create, therefore I agree: Exploring the effect of AI anthropomorphism on human decision-making. In Companion Publication of the 2023 Conference on Computer Supported Cooperative Work and Social Computing (pp. 241–244).

[36] Olszewski, S. A. S. (2024). Designing human-ai systems: Anthropomorphism and framing bias on human-ai collaboration. arXiv preprint arXiv:2404.00634. https://arxiv.org/abs/2404.00634

[37] Oh, J., & Lim, S. (2023). How Anthropomorphism of AI Agent Affects Perceived Authenticity: Focus on Correction of Misinformation. Korean Journal of Broadcasting and Telecommunication Studies.

[38] Wang, W. Q. (2024). A study on the influence of human-like design of intelligent voice assistants on users' willingness to continue using them [Master's thesis]. Shanghai International Studies University.

[39] Cao, X. Y. (2023). An empirical study on the influencing factors of users' willingness to adopt artificial intelligence medical consultation [Master's thesis]. Central South University.

[40] Mendel, T., Nov, O., & Wiesenfeld, B. (2024). Advice from a doctor or AI? Understanding willingness to disclose information through remote patient monitoring to receive health advice. Proceedings of the ACM on Human-Computer Interaction, 8(CSCW2), 1–34.

[41] Wutz, M., Hermes, M., Winter, V., & Köberlein-Neu, J. (2023). Factors influencing the acceptability, acceptance, and adoption of conversational agents in health care: integrative review. Journal of Medical Internet Research, 25, e46548.

[42] Zhan, X., Abdi, N., Seymour, W., & Such, J. (2024). Healthcare voice AI assistants: factors influencing trust and intention to use. Proceedings of the ACM on Human-Computer Interaction, 8(CSCW1), 1–37.

[43] Kim, J., Merrill, K., Jin, X., Collins, C., & Xu, K. (2023). Trust, perceived usefulness, and intentions to adopt robotic health advisors for physical and relational health issues. The Social Science Journal, 1–13.

[44] Prakash, A. V., & Das, S. (2024). (Why) Do We Trust AI?: A Case of AI-based Health Chatbots. Australasian Journal of Information Systems, 28.

[45] Abdaljaleel, M., Barakat, M., Alsanafi, M., Salim, N. A., Abazid, H., Malaeb, D., ... & Sallam, M. (2024). A multinational study on the factors influencing university students' attitudes and usage of ChatGPT. Scientific Reports, 14(1), 1983.