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Bridging the acceptance gap: insights from digital health tools among middle-aged and elderly chronic patients

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Abstract. Digital health technologies exhibit substantial potential in the management of chronic conditions, yet their uptake among middle-aged and elderly patients continues to be notably sluggish, resulting in a prominent "acceptance gap." To unravel the psychological underpinnings of this phenomenon, this study integrates the Health Belief Model (HBM) and the Technology Acceptance Model (TAM) to construct a comprehensive analytical framework. A cross-sectional survey was conducted among 409 chronic disease patients aged 45 and above in an eastern Chinese city, and the proposed integrated model was validated using structural equation modeling. The results demonstrated a good model fit (χ^2/df = 2.78, CFI = 0.93, RMSEA = 0.06). Specifically, perceived usefulness/benefits, perceived severity of disease, and self-efficacy emerged as significant positive predictors of behavioral intention, while perceived barriers exerted a marked negative influence. Social influence and perceived ease of use played crucial indirect roles by enhancing perceived usefulness/benefits and self-efficacy. Notably, the direct effect of perceived susceptibility on behavioral intention was not statistically significant. This study confirms the effectiveness of the integrated model in explaining usage intentions. To bridge the acceptance gap, multi-dimensional strategies are required: optimizing design to improve ease of use and enhance user self-efficacy, clearly conveying the core health values of digital tools in promotional efforts, and actively leveraging recommendations from healthcare professionals to drive adoption.

Keywords: digital health, HBM, technology adoption, chronic disease management, SEM

1. Introduction

The accelerating global aging trend and the rising prevalence of chronic non-communicable diseases represent two of the most pressing challenges confronting public health in the 21st century. According to data from China's National Health Commission, around 79.5% of people aged 60 and over are afflicted with at least one chronic ailment, such as hypertension, diabetes, or coronary heart disease, necessitating long-term, continuous, and often lifelong health management. The traditional hospital-centered passive treatment model faces limitations including strained resources, ineffectiveness, and inadequate accessibility when addressing the needs of such a large chronic disease population. Against this backdrop, digital health tools—encompassing mobile health applications, wearable monitoring devices, electronic personal health records, and telemedicine consultations—have garnered widespread attention from global public health systems [1]. These tools hold

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great promise for improving healthcare accessibility, empowering patients to manage their own health, optimizing the allocation of medical resources, and reducing long-term healthcare costs, thus serving as a key technological enabler for achieving "healthy aging."

However, a striking discrepancy exists between the availability of these technologies and their actual adoption by the target population, a phenomenon termed the "acceptance gap." Market data reveals that while major mobile health platforms in China boast tens of millions of registered users, their monthly active user ratio remains consistently low at approximately 5%. Particularly among the core beneficiary group—middle-aged and elderly chronic disease patients—adoption and sustained usage rates are significantly lower. This exclusion of the population most in need of health management support from the benefits of the digital health revolution risks widening health inequities. Existing research predominantly relies on either the Technology Acceptance Model [2] or the Unified Theory of Acceptance and Use of Technology (UTAUT) [3], approaching the issue from a general information technology adoption perspective and emphasizing the decisive roles of perceived usefulness and perceived ease of use. Nevertheless, for middle-aged and elderly chronic disease patients, adopting digital health tools is not merely a matter of embracing new technology; it constitutes a complex health-related decision closely tied to their own health status. They must carefully weigh the "potential health benefits of tool usage" against the "psychological and time costs of learning new technology, as well as concerns regarding privacy and security." Purely technology-focused adoption frameworks struggle to fully capture and explain the unique psychological mechanisms of this group, including their perceptions of health threats, assessments of disease management effectiveness, and considerations of behavioral transition costs.

To address this research gap, this study adopts the classic Health Belief Model [4] as its core theoretical framework. As a foundational theory in public health, the HBM is widely used to explain and predict individual health behaviors such as vaccination and cancer screening [5]. This study aims to organically integrate the core constructs of the HBM—including health threat perception, perceived benefits and barriers of action, self-efficacy, and cues to action—with the cognitive elements of perceived usefulness and ease of use from the TAM [2], as well as social influence factors from the UTAUT [3], to develop a more comprehensive and explanatory model. The core research question addressed in this study is: For middle-aged and elderly chronic disease patients, how do their perceptions of disease threat, evaluations of the practical value of digital health tools, confidence in their own usage abilities, awareness of potential obstacles, and the influence of their social environment interact to shape their behavioral intention to use digital health tools? The findings of this study are expected to provide solid empirical evidence and theoretical guidance for designing more inclusive, intrinsically motivating, and effective digital health intervention programs and promotion strategies tailored to this population.

2. Literature review and theoretical foundation

2.1. The health belief model and its application in digital health

The Health Belief Model originated in the 1950s to explain why individuals declined to participate in disease prevention programs [4]. Its core premise is that an individual's decision to adopt a specific health behavior is shaped by a comprehensive evaluation of six key factors: (1) Perceived Susceptibility: an individual's subjective evaluation of the likelihood that they may contract a disease or that their existing health condition will deteriorate; (2) Perceived Severity: the degree to which an individual believes a disease may have adverse medical, psychological, and social consequences; (3) Perceived Benefits: the belief in the advantages of engaging in the recommended health behavior; (4) Perceived Barriers: the perception of material, psychological, social, and time costs associated with performing the behavior; (5) Cues to Action: internal (e.g., physical symptoms) or external (e.g., media information, doctor's advice) stimuli that trigger behavioral change; (6) Self-efficacy: an individual's confidence in their ability to successfully perform the behavior and overcome related difficulties [5]. The HBM has been extensively validated in explaining traditional preventive health behaviors [4].

With the rise of digital health, scholars have begun extending the HBM to emerging fields such as e-health and m-health, uncovering interesting contextual differences [6, 7]. For example, in studies focusing on vaccination or screening among healthy populations, perceived susceptibility and perceived severity often serve as important predictors [5]. However, in research examining the adoption of digital management tools by patients with diagnosed chronic diseases, some studies have found that the predictive power of perceived susceptibility diminishes or becomes insignificant [8]. A plausible theoretical explanation is that for individuals already diagnosed with a chronic disease, the cognition "I am already ill" becomes deeply ingrained. Their perception of the risk of disease progression is relatively stable, shifting the focus of decision-making from "whether I might get sick" to "how to effectively manage my existing disease." At this stage, the trade-off between perceived benefits (i.e., whether the tool can effectively support disease management) and perceived barriers (i.e., whether using the tool is cumbersome), along with the assessment of self-efficacy (i.e., whether I can learn to use the tool), becomes more prominent. This provides preliminary justification for the differentiated weighting of various HBM variables in the integrated model proposed in this study.

2.2. The roles of technology acceptance cognitions and social influence

The Technology Acceptance Model is one of the most influential theories for explaining and predicting user acceptance of information systems [2]. Its core logic is concise yet powerful: an individual's behavioral intention to use a technology is primarily determined by two key beliefs—perceived usefulness and perceived ease of use [2]. Perceived usefulness refers to the extent to which a user believes that using a technology will enhance their work or life performance, while perceived ease of use refers to the degree to which a user believes that using the technology will be effortless [2]. In the context of digital health, perceived usefulness is reflected in the tool's ability to help control disease indicators, improve quality of life, and enhance healthcare convenience. Perceived ease of use, on the other hand, is manifested in the intuitiveness of application interfaces, the simplicity of operational steps, and the associated learning costs. Numerous studies have shown that perceived ease of use not only directly affects usage intention but also exerts an indirect influence by positively shaping perceived usefulness [2, 6].

Beyond individual cognition, the impact of the social environment cannot be overlooked. In subsequent theories such as UTAUT, social influence is explicitly identified as a key variable, defined as the degree to which an individual perceives that important others (e.g., family members, friends, doctors) believe they should use the new technology [3]. For middle-aged and elderly individuals, especially those with chronic diseases, professional recommendations from attending physicians and family support from children have proven to be highly effective "cues to action" [8]. This social influence can not only directly increase users' willingness to try a tool but also, more importantly, enhance their trust in the tool's usefulness ("if the doctor recommends it, it must be effective") and boost their sense of self-efficacy ("with family help, I should be able to learn how to use it"), thereby generating multi-level and multi-path promotional effects [3, 9].

2.3. Research gaps and study positioning

Although existing research has provided valuable insights from the perspectives of health behavior science and information technology science [2-4, 6], significant gaps remain. Firstly, there is a lack of sufficient theoretical integration. Most studies apply the HBM [4] or TAM/UTAUT [2, 3] in isolation, failing to develop a theoretical framework that deeply integrates "health behavior decision-making logic" with "information technology adoption logic" to fully capture the uniqueness of decision-making among middle-aged and elderly chronic disease patients. Secondly, research on the mechanisms underlying behavior in this specific population needs to be deepened. Existing studies primarily focus on identifying influencing factors, with insufficient exploration of how these factors interact or whether mediating or moderating effects exist [8]. This study aims to directly address these gaps. By constructing and empirically testing a comprehensive model that integrates the HBM's health threat and efficacy cognitions [4], the TAM's technology utility cognitions [2], and social influence variables from the UTAUT [3], this study seeks to more accurately reveal the internal psychological mechanisms and external action pathways that drive this group to overcome the digital health "acceptance gap." In doing so, it contributes to theoretical interdisciplinary integration and provides more targeted intervention strategies in practice.

3. Theoretical framework and research hypotheses

Based on the aforementioned literature review, this study proposes an integrated theoretical framework (see Figure 1). The framework takes "behavioral intention to use digital health tools" as the ultimate dependent variable. The independent variables include core constructs from the Health Belief Model (perceived susceptibility, perceived severity, perceived barriers, self-efficacy) [4], core constructs from the Technology Acceptance Model (perceived usefulness/benefits, perceived ease of use) [2], and a key social environment variable (social influence) [3]. Given the significant conceptual overlap between "perceived benefits" and "perceived usefulness" in the context of digital health tool adoption, this study merges these two constructs into a single variable—"perceived usefulness/benefits"—to simplify the model and enhance its explanatory power. Furthermore, the model treats perceived ease of use and social influence as important external antecedent variables that may not only directly affect behavioral intention but also, more likely, exert indirect effects by influencing core mediating psychological cognitive variables (e.g., perceived usefulness/benefits, self-efficacy). The model also controls for demographic and disease-related characteristics such as age, education level, and the number and types of chronic diseases.

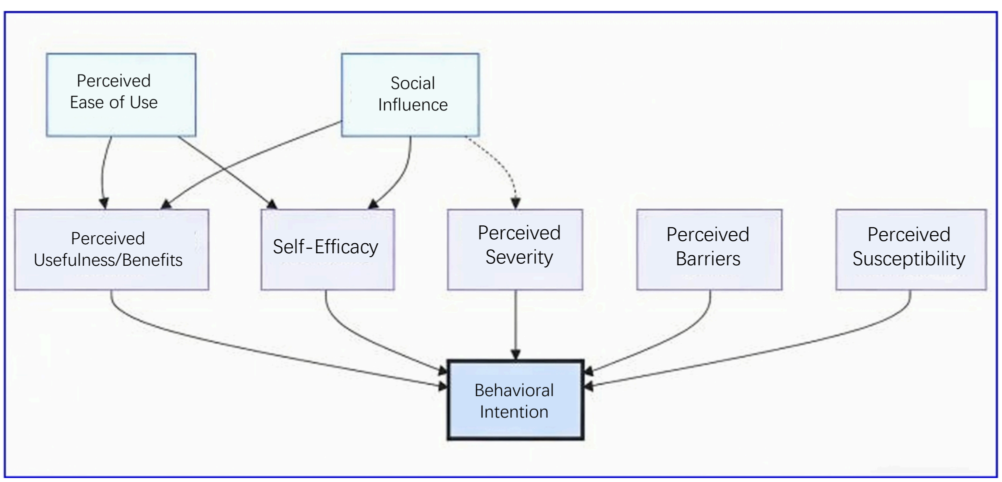

Figure 1. Theoretical model of this study

Note: Arrows indicate the direction of hypothetical relationships between variables. Positive relationships are assumed unless otherwise specified (perceived barriers and social influence on perceived barriers are hypothesized as negative).

Based on this integrated framework, the following research hypotheses are proposed:

H1: Perceived susceptibility has a significant positive effect on the behavioral intention to use digital health tools.

H2: Perceived severity has a significant positive effect on the behavioral intention to use digital health tools.

H3: Perceived usefulness/benefits has a significant positive effect on the behavioral intention to use digital health tools.

H4: Perceived barriers have a significant negative effect on the behavioral intention to use digital health tools.

H5: Self-efficacy has a significant positive effect on the behavioral intention to use digital health tools.

H6: Perceived ease of use has a significant positive effect on perceived usefulness/benefits.

H7: Perceived ease of use has a significant positive effect on self-efficacy.

H8: Social influence has a significant positive effect on perceived usefulness/benefits.

H9: Social influence has a significant positive effect on self-efficacy.

H10: Social influence has a significant negative effect on perceived barriers.

To clarify the operational definitions of each HBM dimension in this study and their corresponding research hypotheses, Table 1 provides a systematic overview:

Table 1. Operational definitions, corresponding hypotheses, and expected directions of HBM dimensions

HBM Dimension	Operational Definition and Manifestation in This Study	Corresponding Hypothesis	Expected Direction
Perceived Susceptibility	The patient's subjective judgment of the likelihood that their existing chronic condition will become poorly controlled, experience an acute episode, or develop serious complications.	H1	Positive
Perceived Severity	The degree to which the patient believes that uncontrolled chronic disease would negatively impact their physical health, daily functioning, family financial burden, and social roles.	H2	Positive
Perceived Benefits	Merged with Perceived Usefulness. Refers to the patient's belief that using a specific digital health tool will help them monitor their condition more effectively, adhere to medical advice, improve health behaviors, and ultimately achieve better health outcomes and convenience.	H3	Positive

Table 1. Continued

Perceived Barriers	The various difficulties the patient perceives in adopting and using digital health tools, including economic costs of purchase/subscription, complexity of learning and operation, time investment, concerns about personal data privacy and security, and frustration associated with technical glitches.	H4	Negative
Self-Efficacy	The patient's confidence in their ability to successfully complete key digital health tool usage tasks—such as downloading, registering, logging in, inputting data, and interpreting reports—independently or with minimal assistance.	H5	Positive
Cues to Action	Manifested through the Social Influence variable. Refers to explicit recommendations, encouragement, modeling, or expectation pressure from the patient's social network (especially doctors, family, peers), constituting external stimuli that trigger consideration and trial use of the tool.	H8, H9, H10	Positive (H8, H9)/Negative (H10)

4. Research methods

4.1. Research design and sampling procedure

This study employed a cross-sectional survey design, collecting data at a single time point using a questionnaire. The survey was conducted in a provincial capital city in eastern China, selected due to its relatively advanced digital infrastructure and well-developed community health service system, which can better reflect the current digital health environment faced by urban middle-aged and elderly chronic disease patients. A combination of convenience sampling and purposive sampling was used. Questionnaires were distributed at the chronic disease management clinics of six large community health centers and four active chronic disease patient community associations.

Inclusion criteria for participants were: (1) aged 45 or above; (2) diagnosed with at least one chronic disease requiring long-term management (primarily hypertension, diabetes, chronic obstructive pulmonary disease, coronary heart disease, etc.) by a secondary or higher-level hospital; (3) clear consciousness, possessing basic Chinese literacy and comprehension skills, and able to complete the questionnaire independently or with minor assistance from investigators; (4) voluntary participation after being fully informed of the study purpose. A total of 435 paper questionnaires were distributed, all of which were returned. After rigorous data cleaning, 26 invalid questionnaires were excluded due to obviously patterned responses, missing key information, or identical answers across all scale items. Ultimately, 409 valid samples were included in the analysis, with an effective recovery rate of 94.0%.

4.2. Measurement tools and variable operationalization

The questionnaire consisted of four parts: Part 1 collected demographic and disease-related information (e.g., age, gender, education level, types and duration of chronic diseases); Part 2 investigated the current status of digital health tool use (e.g., whether they had used such tools, types of tools used, frequency of use); Part 3 included measurement scales for the core latent variables of the study; Part 4 contained acknowledgments and notes. All latent variables were measured using internationally recognized 5-point Likert scales, where 1 denotes "Strongly Disagree" and 5 represents "Strongly Agree."

All scales were adapted from established English-language scales, with semantic equivalence ensured through a "translation-back translation" process. Two experts in public health and psychology assessed the content validity of the scales, and minor adjustments were made to adapt to the cultural context and characteristics of middle-aged and elderly chronic disease patients in China. The measurement of each variable is detailed below:

• Perceived Susceptibility and Severity: Adopted corresponding subscales from Champion's revised HBM scale [5], each consisting of 3 items. For example, a perceived susceptibility item was "I often worry that my [specific chronic disease] may suddenly worsen," and a perceived severity item was "If my [specific chronic disease] is not well controlled, it will seriously affect my daily life."

• Perceived Usefulness/Benefits: Primarily based on Davis's classic TAM scale [2], revised to 4 items for the context of chronic disease management. An example item was "Using a health APP can help me better manage my chronic disease."

• Perceived Barriers: Synthesized from multiple relevant studies [6, 8], forming a 5-item scale covering technical, economic, and psychological dimensions. Example items included "Learning to use these health APPs is too complicated for me" and "I am concerned about the leakage of my health data."

• Self-Efficacy: Selected and adapted 4 items related to technology learning from the General Self-Efficacy Scale [4], with adjustments for digital health tool usage. An example item was "I believe I can master the basic functions of a health APP if I am willing to learn."

• Perceived Ease of Use: Employed Davis's TAM scale [2], consisting of 4 items. An example item was "I think the operation interface of health APPs is clear and easy to understand."

• Social Influence: Referenced the social influence subscale from the UTAUT scale [3], comprising 3 items. Example items included "My attending physician recommended that I use some health management tools" and "My family thinks I should try using health APPs."

• Behavioral Intention: Referenced relevant research [6], measured using 3 items. An example item was "I intend to start using or use a specific health APP more frequently within the next three months."

4.3. Data analysis strategy

Data analysis was performed in three stages using mainstream statistical software:

1. Descriptive Statistical Analysis: SPSS 26.0 was used to conduct descriptive statistics on the sample characteristics, calculate the internal consistency reliability (Cronbach's α coefficient) of each scale, and test for common method bias using Harman's single-factor test.

2. Measurement Model Validation: AMOS 28.0 was used for confirmatory factor analysis to assess the reliability and validity of the measurement model. Evaluation indicators included composite reliability (preferably > 0.7), average variance extracted (AVE, preferably > 0.5), and discriminant validity (tested by comparing the square root of the AVE of each latent variable with its correlation coefficients with other latent variables).

3. Structural Model Analysis: Based on a satisfactory measurement model, AMOS 28.0 was used to construct a structural equation model for path analysis, testing the theoretical model and all research hypotheses (H1-H10). The overall model fit was evaluated using a set of absolute and relative fit indices, including the chi-square to degrees of freedom ratio ($\chi^2/df < 5$), comparative fit index (CFI > 0.90), Tucker-Lewis index (TLI > 0.90), root mean square error of approximation (RMSEA < 0.08), and standardized root mean square residual (SRMR < 0.08) [6].

5. Research results

5.1. Sample descriptive statistics

Analysis of the 409 valid samples revealed an average age of 65.8 years (standard deviation = 7.2 years, range: 45-82 years). Among the participants, 214 were male (52.3%) and 195 were female (47.7%). In terms of educational background, the largest group was those with secondary or technical secondary school education (199 individuals, 48.7%), followed by primary school education or below (28.4%) and college diploma or above (22.9%). Regarding disease burden, 62.0% of patients (254 individuals) suffered from two or more chronic diseases simultaneously, reflecting the high prevalence of comorbidities in this population. In terms of digital health tool usage experience, only 140 participants (34.2%) reported having used at least one type of digital health tool (e.g., WeChat health mini-programs, standalone health APPs, smart wristbands), and most of them used the tools "occasionally" or "only tried them once." This visually confirms the "acceptance gap" phenomenon highlighted in this study.

5.2. Measurement model test results

Confirmatory factor analysis results indicated that the scales used in this study exhibited good reliability and validity. The composite reliability values of all latent variables ranged from 0.78 to 0.92, exceeding the acceptable threshold of 0.7, indicating good internal consistency. The AVE values of all latent variables ranged from 0.51 to 0.73, greater than the critical value of 0.5, demonstrating that the measurement items effectively reflected their corresponding latent variables and confirming convergent validity. Furthermore, the square root of the AVE for each latent variable was greater than its correlation coefficients with all other latent variables, satisfying the requirements for discriminant validity. Harman's single-factor test for common method bias showed that the first unrotated factor explained 38.7% of the total variance, which did not exceed the critical standard of 40%, indicating that common method bias in the study data was within an acceptable range [8].

5.3. Structural model and hypothesis test results

Structural equation modeling analysis showed that the proposed integrated theoretical model fit the data well. All fit indices met or exceeded the recommended standards in the field: $\chi^2/df = 2.78$, CFI = 0.93, TLI = 0.91, RMSEA = 0.06, SRMR = 0.05, indicating a reasonable overall model structure. The specific results of the path analysis (standardized path coefficients, significance levels, and hypothesis verification outcomes) are summarized in Table 2.

Table 2. Results of path analysis and hypothesis testing

Hypothesis	Path Relationship	Standardized Path Coefficient (β)	*P*-value	Test Result
H1	Perceived Susceptibility → Behavioral Intention	0.05	0.241	Not Supported
H2	Perceived Severity → Behavioral Intention	0.14	0.013	Supported
H3	Perceived Usefulness/Benefits → Behavioral Intention	0.32	< 0.001	Supported
H4	Perceived Barriers → Behavioral Intention	-0.18	0.002	Supported
H5	Self-Efficacy → Behavioral Intention	0.25	< 0.001	Supported
H6	Perceived Ease of Use → Perceived Usefulness/Benefits	0.40	< 0.001	Supported
H7	Perceived Ease of Use → Self-Efficacy	0.35	< 0.001	Supported
H8	Social Influence → Perceived Usefulness/Benefits	0.22	0.001	Supported
H9	Social Influence → Self-Efficacy	0.19	0.003	Supported
H10	Social Influence → Perceived Barriers	-0.08	0.112	Not Supported

As shown in Table 2, eight out of the ten research hypotheses were statistically supported (H2, H3, H4, H5, H6, H7, H8, H9). Perceived usefulness/benefits had the strongest positive impact on behavioral intention, followed by self-efficacy. Perceived severity and perceived barriers also had significant effects on behavioral intention, albeit with relatively weaker effect sizes. Notably, the direct effect of perceived susceptibility on behavioral intention was not significant, and social influence did not directly reduce users' perceived barriers as expected. However, as key external antecedents, both social influence and perceived ease of use significantly and positively influenced perceived usefulness/benefits and self-efficacy, thereby exerting important indirect promotional effects on behavioral intention. Overall, the integrated model explained 57.5% of the variance in behavioral intention, demonstrating strong explanatory power [6].

6. Conclusion

This study confirms that the decision-making process of middle-aged and elderly chronic disease patients regarding the adoption of digital health tools is a complex phenomenon influenced by health threat perceptions, technology utility evaluations, self-capacity assessments, and social support. To bridge the "acceptance gap," comprehensive strategies are required: reducing technological barriers through human-centric design, articulating health value clearly through targeted communication, and offering authoritative social incentives by incorporating these tools into the clinical care workflow. Multi-stakeholder collaboration —including involvement from healthcare providers, technology developers, and family members—is essential to ensure that digital health technologies truly benefit those most in need.

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