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A Study on Influencing Factors of Mobile Health Application Use Behavior Among Young-Old Adults in Guangzhou Based on the Health Belief Model——A Partial Least Squares Structural Equation Modeling Analysis

Chen Xuejiao[1], Cheok Mui Yee[2]

Universiti Tun Abdul Razak

chen.xuejiao@ur.unirazak.edu.my

ABSTRACT

Global population aging has become a critical public health issue, while China is confronted with the unique "aging before affluence" dilemma and the world's largest elderly population. Mobile health applications serve as cost-effective tools for seniors' chronic disease management and daily health monitoring, yet their adoption rate remains low among urban young-old adults aged 60–74. This study employs the complete six-dimensional Health Belief Model to examine factors affecting mHealth usage behavior among Guangzhou's young-old adults. A total of 400 valid questionnaires were gathered through stratified mixed sampling and analyzed with PLS-SEM. Outcomes indicate perceived susceptibility, self-efficacy, perceived benefits, action cues and perceived severity significantly boost usage, whereas perceived barriers inhibit adoption. The model presents satisfactory fit with R^2=0.443 and SRMR=0.041. This research enriches localized empirical evidence of the Health Belief Model in digital health research for young-old adults and provides targeted optimization references for mHealth developers to improve elderly users' digital health experience.

Keywords: Health Belief Model; Mobile Health Adoption; Young-Old Adults; Population Aging; PLS-SEM

1. INTRODUCTION

1.1 Global and Chinese Population Aging Status

According to 2024 United Nations data, the global population aged 65 and above grows at an annual rate of 2.6%, increasing from 574.2 million in 2013 to 791.4 million in 2023. As the largest developing country worldwide, China's aging rate far exceeds the global average. In 2023, China's population aged 65 and above reached 216.8 million, accounting for 15.4% of the total national population. Unlike Western aging countries, China is characterized by typical "aging before affluence", imposing enormous pressure on the elderly care and public medical service systems (Li & Zhang, 2022). To alleviate the burden of offline medical services and promote healthy aging, China has vigorously promoted smart elderly care and digital mobile health services in recent years.

Integrating multiple functions including real-time health monitoring, online medical consultation, fitness guidance, and chronic disease management, mHealth applications serve as innovative auxiliary tools for community-based and home-based elderly care (Leung & Lam, 2025). Nevertheless, survey data shows that the mHealth application adoption rate among young-old adults aged 60–74 years in first-tier cities such as Guangzhou remains low. As a special transitional age group, young-old adults possess basic smartphone operation skills but suffer from obvious digital adaptation barriers, distinguishing them from disabled oldest-old adults and young and middle-aged groups

(Huang et al., 2024). Clarifying the influencing factors of mHealth use behavior among this group is of great practical significance for promoting the implementation of smart elderly care policies.

1.2 Research Gaps

Three core research gaps exist in current literature, providing solid research motivation for this study. First, there is a research gap in specific age groups. Most existing studies on mHealth adoption generally cover all elderly groups or focus on young populations. Among 126 relevant studies on elderly mHealth, only 7 specifically target young-old adults aged 60–74 years (WHO, 2023). Young-old adults have unique physiological, psychological, and digital usage characteristics, and research conclusions based on general elderly samples cannot accurately explain their behavioral logic (Pang & Zheng, 2023).

Second, the application of the Health Belief Model is incomplete. As a classic theoretical framework for explaining individual health decision-making, the HBM is widely adopted in research on vaccination, cancer screening, and chronic disease medication adherence (Janz & Becker, 1984). However, most existing digital technology adoption studies only select 2 to 4 dimensions of the HBM, lacking empirical verification of the complete six-dimensional original model (Nguyen et al., 2022). Previous studies have confirmed that excluding complete dimensions significantly reduces the explanatory power of the HBM in digital health scenarios, and no prior research has applied the full HBM to explore mHealth adoption among Chinese young-old adults.

Third, localized empirical evidence is insufficient. Existing empirical studies on the HBM and mHealth adoption are mostly based on samples from European, American, and Southeast Asian countries (Acilar & Sæbø, 2025). Constrained by limited pension resources, insufficient digital training, and fragmented community health services, Chinese urban young-old adults present unique behavioral characteristics. It is necessary to re-verify the predictive effectiveness of each HBM dimension combined with China's special national condition of "aging before affluence" (Li & Zhang, 2022).

1.3 Research Objectives and Research Questions

This study aims to systematically examine the direct effects of six core HBM dimensions on mHealth application use behavior among young-old adults in Guangzhou. The specific research questions are proposed as follows:

RQ1: Does perceived susceptibility positively predict mHealth application use behavior among young-old adults?

RQ2: Does perceived severity positively predict mHealth application use behavior among young-old adults?

RQ3: Does perceived benefits positively predict mHealth application use behavior among young-old adults?

RQ4: Does perceived barriers negatively predict mHealth application use behavior among young-old adults?

RQ5: Does self-efficacy positively predict mHealth application use behavior among young-old adults?

RQ6: Do action cues positively predict mHealth application use behavior among young-old adults?

1.4 Research Contributions and Paper Structure

Theoretically, this study empirically verifies the complete HBM in the field of digital health adoption among young-old adults, enriching localized evidence of health behavior theory research in developing countries (Acilar & Sæbø, 2025). Practically, this study clarifies the core driving and inhibiting factors of mHealth use among elderly users, providing practical optimization strategies for mHealth application developers (Leung & Lam, 2025). The remainder of this paper is structured as follows: Section 2 reviews relevant literature and proposes research hypotheses; Section 3 elaborates the research design, sampling methods, and measurement scales; Section 4 presents empirical results based on PLS-SEM; Section 5 interprets research findings, compares with existing literature, and proposes practical implications; Section 6 summarizes the core conclusions, illustrates research limitations, and prospects future research directions.

2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 Theoretical Foundation: Health Belief Model

Proposed by Rosenstock in 1974, the Health Belief Model is a classic framework linking individual health cognition with specific health behavioral decisions (Rosenstock, 1974). It consists of six core dimensions: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, self-efficacy, and action cues. The core logic of the HBM indicates that individuals tend to adopt preventive health behaviors only when they perceive health risks, recognize the value of health intervention behaviors, and are able to overcome behavioral barriers. Individual self-cognition and external environmental cues further motivate behavioral implementation (Champion & Skinner, 2008).

Traditionally, the HBM is mainly applied to offline health behavior research, including infectious disease vaccination, cancer screening, and long-term chronic disease management (Mo et al., 2024). In recent years, several studies have attempted to extend the HBM to digital health technology adoption scenarios, yet most have deleted original model dimensions, resulting in reduced theoretical explanatory power (Valizadeh et al., 2016). For young-old adults, using mHealth applications is essentially a preventive health management behavior, which is highly consistent with the core logic of the HBM. Therefore, this study retains all six original dimensions to construct a complete predictive model

2.2Literature Review and Hypothesis Development

2.2.1Perceived Susceptibility and mHealth Use Behavior

Perceived susceptibility refers to individuals' subjective judgment of the probability of suffering from diseases or health complications (Wang & Li, 2022). Existing public health studies confirm that higher perceived health risk significantly promotes individuals' willingness to implement preventive health behaviors (Zhang et al., 2023). For young-old adults with potential chronic disease risks, subjective disease risk perception motivates them to actively adopt mHealth tools for daily health monitoring. Accordingly, the following hypothesis is proposed:

H1: Perceived susceptibility has a significant positive effect on mHealth application use behavior among young-old adults in Guangzhou.

2.2.2Perceived Severity and mHealth Use Behavior

Perceived severity refers to individuals' subjective cognition of negative consequences caused by diseases, including physical damage, economic burden, and family pressure. (Lee et al., 2021) demonstrated that perceived severity explains 32% of the variance in preventive health behaviors. When mHealth platforms provide personalized risk assessment functions, elderly users' cognition of disease hazards is significantly deepened, leading to increased usage frequency. Most young-old adults worry that untreated chronic diseases will aggravate family care burdens, and mHealth applications can reduce the risk of disease deterioration through real-time monitoring. Accordingly, the following hypothesis is proposed:

H2: Perceived severity has a significant positive effect on mHealth application use behavior among young-old adults in Guangzhou.

2.2.3Perceived Benefits and mHealth Use Behavior

Perceived benefits refer to individuals' cognition of the practical value brought by health intervention tools, including improved medical convenience, reduced medical costs, and enhanced quality of life (Smith, 2021). (Wang,2023) summarized three core values of smart health devices for elderly chronic disease patients: simplifying chronic disease management procedures, facilitating access to professional medical advice, and sustaining improved health status. For urban young-old adults, mHealth applications break the time and space limitations of offline medical services, and higher recognition of practical value promotes continuous usage intention. Accordingly, the following hypothesis is proposed:

H3: Perceived benefits have a significant positive effect on mHealth application use behavior among young-old adults in Guangzhou.

2.2.4 Perceived Barriers and mHealth Use Behavior

Perceived barriers refer to various internal and external factors hindering the implementation of health behaviors, including complex operational procedures, cumbersome interface design, and privacy concerns (Liu, 2022). Wang et al. (2023) pointed out that complicated reservation and report query procedures of telemedicine platforms significantly reduce elderly users' usage intention and force them to return to offline medical treatment. Lacking systematic digital skill training, young-old adults are easily discouraged by complex operations, which constitutes a core psychological barrier to sustained mHealth application use. Accordingly, the following hypothesis is proposed:

H4: Perceived barriers have a significant negative effect on mHealth application use behavior among young-old adults in Guangzhou.

2.2.5 Self-Efficacy and mHealth Use Behavior

Derived from Bandura's social cognitive theory, self-efficacy refers to individuals' confidence in independently mastering specific technical operations (Bandura, 2019). Consistent findings in elderly digital technology research confirm that self-efficacy is a core positive predictor of technology adoption and sustained usage (Hang, 2023). Young-old adults with strong digital operation self-efficacy are capable of overcoming basic operational difficulties such as registration and data query, while those with low self-efficacy tend to abandon usage due to simple operational failures. Accordingly, the following hypothesis is proposed:

H5: Self-efficacy has a significant positive effect on mHealth application use behavior among young-old adults in Guangzhou.

2.2.6 Action Cues and mHealth Use Behavior

Action cues refer to external environmental stimuli that trigger individual health behaviors, including media health science popularization, community lectures, family reminders, and public welfare publicity (Bandura, 2019). Zhang et al. (2022) emphasized that external cues adapted to the cognitive characteristics of elderly users can effectively activate health behaviors. Without external reminders, young-old adults are prone to forgetting regular health recording behaviors, while timely media publicity and family supervision can convert usage intention into actual usage behavior. Accordingly, the following hypothesis is proposed:

H6: Action cues have a significant positive effect on mHealth application use behavior among young-old adults in Guangzhou.

2.3 Conceptual Framework

This study constructs a pure main-effect research framework without moderating variables. The six dimensions (perceived susceptibility, perceived severity, perceived benefits, perceived barriers, self-efficacy, and action cues) are set as exogenous latent variables, and mHealth application use behavior is taken as the sole endogenous dependent variable. Eliminating cross-level moderating factors, this framework focuses on the original core causal relationship of the HBM, constructing a concise and complete baseline model for digital health behavior research among young-old adults.

3. RESEARCH METHODOLOGY

3.1 Research Design and Paradigm

This study adopts a positivist quantitative cross-sectional questionnaire design. The positivist paradigm is suitable for this research, as it can quantify the linear causal relationship between HBM latent variables and mHealth use behavior through standardized questionnaire data. The cross-sectional design collects data at a single time point, which efficiently reflects the current status of mHealth application usage among young-old adults in Guangzhou.

3.2 Research Subjects and Sampling Method

The research subjects are permanent young-old adults aged 60–74 years in Guangzhou, China. Inclusion criteria: aged 60–74 years; mentally sound without cognitive impairment; possessing basic smartphone operation ability; voluntary participation and full understanding of the survey content. Exclusion criteria: elderly individuals with severe visual, physical, or cognitive disorders who are unable to use mobile devices.

A mixed sampling method combining stratified random sampling, institutional snowball sampling, and screening sampling was adopted in this study. First, six main urban districts of Guangzhou were selected through stratification. Second, questionnaires were distributed via snowball sampling relying on community service centers, senior universities, and elderly activity stations in each district. Finally, unqualified respondents were excluded through screening questions at the beginning of the questionnaire. Following the PLS-SEM sampling principle (a minimum of 10 samples per measurement item), the target of over 300 valid samples was set. A total of 400 valid samples were finally obtained, meeting the statistical analysis requirements.

3.3 Measurement Instruments

All measurement items in this study were adapted from mature scales published in peer-reviewed journals, with minor wording revisions tailored to the mHealth usage scenarios of Chinese young-old adults to ensure scale adaptability. All items were rated on a 5-point Likert scale, with 1 representing "strongly disagree" and 5 representing "strongly agree".

1. The six latent variables including perceived susceptibility, perceived severity, perceived benefits, perceived barriers, self-efficacy, and action cues were adapted from mature health behavior scales.

2. mHealth application use behavior was adapted from validated digital health adoption scales.

Each latent variable contains 3 to 4 measurement items, and the complete representative items are presented in the appendix.

3.4 Data Collection Procedure

This study strictly followed standardized quantitative research procedures for questionnaire design and data collection: (1) adapting mature scales according to the research scenario; (2) inviting experts in public health and gerontology to review and revise the initial questionnaire; (3) conducting a pre-survey with partial young-old adults to revise ambiguous items; (4) uploading the final questionnaire to the Wenjuanxing platform; (5) distributing questionnaire links through community elderly institutions; (6) collecting questionnaire data, cleaning invalid samples, and conducting statistical analysis. All respondents provided informed consent before participation, and no personal privacy information was collected throughout the survey to fully protect respondents' privacy.

3.5 Data Analysis Tools

Two software programs were used for data processing in this study:

1. IBM SPSS 26.0: Used for demographic descriptive analysis, data normality test, and preliminary data cleaning.

2. SmartPLS 4.0: Used for two-stage PLS-SEM analysis, including measurement model tests (reliability, validity, common method bias) and structural model hypothesis tests (path coefficient, p-value, coefficient of determination R^2).

4. RESEARCH RESULTS

4.1 Sample Demographic Characteristics

A total of 400 valid samples were collected in this study, covering multiple dimensions including gender, age, education level, and lifestyle of young-old adults in Guangzhou. The sample distribution is balanced and highly representative. Detailed demographic characteristics and proportions are shown in Table 2.

Table 2. Sample Demographic Characteristics (N=400)

Variable	Category	Sample Size (n)	Proportion (%)
Gender	Male	181	45.3
	Female	219	54.8
Age (Years)	60–64	185	46.3
	65–69	130	32.5
	70–74	85	21.3
Education Level	Primary School and Below	85	21.3
	Junior High School	111	27.8
	High School/Technical Secondary School	130	32.5
	Bachelor's Degree and Above	74	18.5
Smartphone Usage Frequency	Multiple Times Daily	268	67.0
	Occasional Use	132	33.0
mHealth Operation Ability	Independent Operation	258	64.5
	Partial Operation Only	142	35.5
Living Arrangement	Living with Spouse and Children	100	25.0
	Nursing Home Residence	89	22.3
	Living with Spouse Only	83	20.8
	Living Alone	64	16.0
	Living with Children Only	64	16.0

4.2 Measurement Model Assessment

This study verified the measurement model quality through reliability, convergent validity, and discriminant validity tests, with core indicators presented in Table 3. In terms of reliability, the Cronbach's α coefficients of all latent variables ranged from 0.846 to 0.893, and composite reliability (CR) values ranged from 0.904 to 0.925, all exceeding the critical standard of 0.7, indicating excellent internal consistency of all scale items. For convergent validity, the average variance extracted (AVE) values of all variables ranged from 0.743 to 0.788, all higher than the threshold of 0.5, proving that all measurement items effectively correspond to their respective latent variables. In terms of discriminant validity, the Heterotrait-Monotrait (HTMT) criterion was adopted. All HTMT ratios between latent variables were lower than 0.38, far below the critical value of 0.90, confirming good independence and discriminability of each latent variable. The overall measurement model is suitable for subsequent structural equation analysis.

Table 3. Reliability and Convergent Validity Test Results

Latent Variable	Cronbach's α	CR	AVE
Perceived Susceptibility	0.872	0.915	0.762
Perceived Severity	0.846	0.904	0.743
Perceived Benefits	0.881	0.918	0.771
Perceived Barriers	0.853	0.908	0.749
Self-Efficacy	0.893	0.925	0.788
Action Cues	0.865	0.912	0.756
Use Behavior	0.877	0.921	0.776

The Harman single-factor test, a widely accepted academic method, was adopted to assess common method bias. Exploratory factor analysis without rotation was performed on all measurement items. The results showed that the first common factor explained only 18.53% of the total variance, far lower than the critical threshold of 40%, indicating no serious common method bias in this study and high reliability of the survey data.

4.3 Structural Model and Hypothesis Testing

The model fitness indicators verified good overall model adaptability: the standardized root mean square residual (SRMR) was 0.041 (lower than the industry standard of 0.08), and the coefficient of determination (R^2) of the dependent variable (mHealth application use behavior) was 0.443, indicating that the six HBM dimensions collectively explained 44.3% of the variance in young-old adults' mHealth use behavior with ideal explanatory power. This study adopted the 5000-time repeated sampling Bootstrap method built in SmartPLS 4.0 to test the significance of each path coefficient. The final hypothesis testing results are shown in Table 4.

Hypothesis	Path Relationship	Path Coefficient (β)	p-value	Test Result
H1	Perceived Susceptibility → Use Behavior	0.359	$p < 0.001$	Supported
H2	Perceived Severity → Use Behavior	0.186	$p < 0.01$	Supported
H3	Perceived Benefits → Use Behavior	0.236	$p < 0.001$	Supported
H4	Perceived Barriers → Use Behavior	-0.174	$p < 0.01$	Supported
H5	Self-Efficacy → Use Behavior	0.316	$p < 0.001$	Supported

H6	Action Cues → Use Behavior	0.205	$p < 0.001$	Supported

Table 4. Path Coefficients and Hypothesis Testing Results

As shown in Table 4, all six original main-effect hypotheses of the HBM were fully supported by empirical data. Significant differences were observed in the influence intensity of each variable on mHealth use behavior. The positive influence ranking is as follows: perceived susceptibility (β=0.359) > self-efficacy (β=0.316) > perceived benefits (β=0.236) > action cues (β=0.205) > perceived severity (β=0.186). Perceived barriers (β=-0.174) serve as the only significant negative influencing factor, acting as the core inhibitor of elderly users' mHealth use behavior.

5. DISCUSSION

5.1 Interpretation of Core Empirical Findings

This study confirms that all six dimensions of the HBM can significantly predict mHealth application use behavior among young-old adults in Guangzhou, verifying the universality of this classic health behavior theory in digital health adoption scenarios. The influence intensity of the six dimensions follows the order: perceived susceptibility > self-efficacy > perceived benefits > action cues > perceived severity > perceived barriers (absolute value).

Perceived susceptibility exerts the strongest positive predictive effect, revealing the unique behavioral logic of Chinese young-old adults: subjective judgment of personal disease risk is the primary driving factor for their adoption of health applications. With aging, young-old adults begin to pay extensive attention to personal health status, and the perception of potential chronic disease risks motivates them to actively use mHealth tools for daily health monitoring and management. This finding is consistent with domestic elderly health studies, indicating that the health behaviors of Chinese elderly groups are primarily driven by risk perception rather than functional value perception.

The positive influence of self-efficacy ranks second, which is in line with the conclusions of Hang (2023). For young-old adults with overall weak digital skills, "operational ability" determines "usage willingness". Elderly users with strong operational confidence can overcome basic operational barriers such as registration and data recording to maintain sustained usage, while those with low self-efficacy tend to abandon usage due to simple operational failures.

Perceived benefits show a moderate positive predictive effect, consistent with the findings of Smith (2021) and Wang (2023). Young-old adults' decisions to use mHealth tools remain highly dependent on practical utility, and intuitive values such as free online consultation and automatic health data recording significantly enhance their usage willingness.

Perceived barriers have a significant negative inhibitory effect, supporting the conclusions of Liu (2022) and Wang et al. (2023). Cumbersome registration procedures, multi-level operation interfaces, and complex function settings are the main reasons for the abandonment of sustained mHealth usage among digitally vulnerable young-old adults.

Action cues and perceived severity show relatively weak positive effects. The limited influence of action cues is mainly attributed to the mismatch between existing online health publicity channels and the daily information acquisition channels of elderly users, as scattered and irregular reminders fail to form continuous behavioral motivation. The weak effect of perceived severity may result from the fact that most young-old adults are in the early stage of chronic diseases, lacking in-depth personal experience of severe disease consequences, thus reducing the behavioral driving force of severity cognition.

5.2 Theoretical Implications

This study presents two core theoretical contributions. First, it empirically verifies the complete six-dimensional HBM in the field of mHealth adoption among young-old adults. Different from existing digital health studies that delete model dimensions and damage theoretical integrity, this study restores the original HBM framework and confirms its robust explanatory power in China's aging scenarios (R^2=0.443). Second, it supplements localized empirical evidence under China's "aging before affluence" national condition. Unlike Western elderly groups with mature digital training systems, Chinese young-old adults face dual dilemmas of limited economic resources and insufficient digital literacy, forming a unique factor influence ranking (perceived susceptibility > self-efficacy > perceived benefits > action cues > perceived severity > perceived barriers). The leading role of perceived susceptibility expands the cross-cultural application boundary of the HBM, indicating that risk perception may exert stronger driving effects than functional value perception among elderly groups in developing countries.

5.3 Practical Implications for Developers

Based on the core driving effects of perceived susceptibility and self-efficacy, targeted optimization suggestions for mHealth application product design are proposed. First, strengthen personalized health risk guidance. Add customized health risk assessment and chronic disease popularization modules on the homepage to awaken the health risk awareness of young-old adults and maximize the driving effect of perceived susceptibility. Second, focus on improving elderly users' digital operation self-efficacy. Build large-font step-by-step operation guide videos, set one-click manual customer service functions, and simplify core function operation paths to help elderly users build operational confidence. Third, highlight core practical functions such as one-click blood pressure recording and free general consultation to strengthen users' value perception. Fourth, comprehensively optimize operational procedures by simplifying registration steps, enlarging fonts, removing redundant pop-up advertisements, and adding one-click return functions to reduce the negative impact of perceived barriers. Fifth, cooperate with community elderly activity centers to carry out offline usage training and health popularization, combining online publicity with offline guidance to strengthen the driving effect of action cues.

6. CONCLUSION

Based on 400 cross-sectional questionnaire data and PLS-SEM, this study systematically explores the predictive effects of six core HBM dimensions on mHealth application use behavior among young-old adults aged 60–74 years in Guangzhou. All six research hypotheses are fully supported. Specifically, perceived susceptibility (β=0.359), self-efficacy (β=0.316), perceived benefits (β=0.236), action cues (β=0.205), and perceived severity (β=0.186) significantly and positively promote mHealth use behavior, while perceived barriers (β=-0.174) significantly inhibit usage behavior. Perceived susceptibility is the core driving factor, followed by self-efficacy, and perceived barriers act as the key inhibiting factor. The model achieves an R^2 of 0.443 and an SRMR of 0.041, indicating excellent overall model fit.

This study enriches the localized empirical evidence of the complete HBM in elderly mHealth research and provides practical optimization references for mHealth application developers. Nevertheless, several limitations exist in this study. First, cross-sectional data cannot reflect the dynamic causal changes of variables. Second, the sample is limited to Guangzhou, restricting the national generalizability of the research conclusions. Third, all data are self-reported by respondents, which may lead to subjective response bias.

Future research can adopt longitudinal tracking surveys to explore the dynamic changes of elderly users' mHealth use behavior, expand samples from multi-level cities nationwide for comparative research, and combine qualitative interviews to explore the in-depth psychological mechanism of digital health usage among young-old adults. In addition, moderating variables such as digital health literacy and social support can be introduced to expand the boundary conditions of the HBM, which is also the core research direction of the supporting SCI paper of this doctoral research.

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