

The Impact Mechanism of Social Media on Self-Management Behaviors of Chronic Diseases Among the Elderly in Yulin, Guangxi

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HOW TO CITE:

Zheng Yi, Supalak Fakkham, Sarisak Soontornchai, Hai Li (2026). The Impact Mechanism of Social Media on Self-Management Behaviors of Chronic Diseases Among the Elderly in Yulin, Guangxi. International Journal of Special Education, 41(8s), 415-440

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ABSTRACT:

This study presents a comprehensive quantitative data analysis of the impact mechanism through which social media influences chronic disease self-management behaviors among elderly patients in Yulin, Guangxi, China. Drawing on a structured questionnaire survey of 400 elderly patients across 10 medical institutions, the study employs structural equation modeling (SEM) via SmartPLS 4.1 to examine a theoretically integrated mediation model. Three independent variables Social Media Usage Frequency (SMUF), Health Information Credibility (HIC), and Information Reception Experience (IRE) are examined for their direct and indirect effects on Chronic Disease Self-Management Behavior (CDSMB), with Health Literacy (HL) positioned as the core mediating variable. Results confirm that all seven research hypotheses are statistically supported. The measurement model demonstrates excellent reliability (all Cronbach's $\alpha > 0.90$; all AVE > 0.70) and discriminant validity (all HTMT < 0.85). The structural model reveals high explanatory power ($R^2 = 0.942$), strong predictive relevance ($Q^2 = 0.940$), and acceptable model fit (SRMR = 0.023). Information Reception Experience exhibits the strongest total effect on self-management behavior ($\beta = 0.364$), followed by Health Information Credibility ($\beta = 0.314$) and Social Media Usage Frequency ($\beta = 0.310$). Health Literacy mediates all three pathways significantly, with indirect effects ranging from 0.071 to 0.096. These findings provide empirical evidence for theory-based digital health interventions targeting the elderly population within China's "Healthy China 2030" strategic framework (State Council of the People's Republic of China, 2016).

Keywords: Social media, chronic disease self-management, health literacy, structural equation modeling, elderly, Yulin, Guangxi.

1. Introduction

China's accelerating population aging presents substantial public health challenges. Data from the seventh national census revealed that the population aged 60 and above reached 264 million, comprising 18.70% of the total population (National Bureau of Statistics of China, 2021). Studies show that approximately 75% of Chinese elderly suffer from one or more chronic diseases, with co-morbidity being common, placing heavy burdens on individuals, families, and society (Wang et al., 2020). Simultaneously, China's Internet penetration rate exceeded 77% by the end of 2023, and social media platforms particularly WeChat and Douyin have become pervasive in elderly daily life (CNNIC, 2024). This convergence of aging, chronic disease burden, and digital penetration creates both opportunities and risks for elderly health management.

The "Healthy China 2030" Plan explicitly advocates shifting from disease-centered to people-centered health management, promoting the use of digital technologies to empower primary care and chronic disease control (State Council of the People's Republic of China, 2016). Within this strategic context, understanding how social media influences elderly chronic disease patients' self-management behaviors becomes critically important. However, most existing studies examine simple correlational relationships between social media use and health outcomes, leaving the internal transmission mechanisms particularly the mediating role of health literacy underexplored (Michie et al., 2011; Paakkari & Okan, 2020; Jia et al., 2021).

Despite growing scholarly interest in digital health, theoretical integration remains fragmented. Most existing studies examine either the direct effects of social media use on health outcomes (Wang et al., 2020) or the mediating role of single psychological variables such as self-efficacy (Bandura, 1997). Few have simultaneously modeled multiple dimensions of social media engagement, a multi-faceted health literacy construct, and comprehensive self-management behaviors within a unified

framework. This theoretical gap is particularly consequential for elderly populations, whose information processing patterns differ significantly from younger users due to age-related cognitive, visual, and motor changes (Czaja et al., 2006; Seifert et al., 2021).

Furthermore, the Chinese digital health environment possesses unique characteristics that limit direct generalization of Western findings. WeChat the dominant super-app in China operates on a "strong tie" network structure where health information is primarily shared among family members and close friends, creating distinct credibility dynamics compared to the weak-tie networks of Facebook or Twitter (Lu & Lee, 2021; Montag et al., 2018). Douyin (the Chinese counterpart of TikTok) delivers algorithm-driven short-form health content, whose rapid, emotionally resonant format may differentially affect elderly users' comprehension and recall compared to text-heavy platforms (Brashier & Schacter, 2020; Poquiz et al., 2023). Local cultural factors, including filial piety, trust in authority figures and preference for relational rather than institutional information sources, further moderate how elderly patients perceive and act upon social media health information (Kim, 2022).

This study addresses this gap by constructing and empirically testing an integrated mediation model that links refined social media usage characteristics to self-management behaviors through health literacy. Specifically, it examines three dimensions of social media use (usage frequency, information credibility perception, and information reception experience), a three-dimensional health literacy construct (digital information skills, risk identification skills, and patient-provider empowerment), and three dimensions of self-management behavior (medication adherence, healthy lifestyle adoption, and help-seeking and social support use). The study was conducted in Yulin City, a typical medium-sized prefecture-level city in Guangxi, providing localized empirical evidence with broad generalizability to similar urban contexts across China. This manuscript focuses

exclusively on the quantitative strand of the mixed-methods design, presenting in full the sampling approach, instrument development and validation, descriptive statistics, measurement model analysis, and structural model evaluation. The presentation follows established best practices for PLS-SEM reporting (Hair et al., 2019; Ringle et al., 2015).

2. Literature Review

2.1 Theoretical Foundations

This study integrates three complementary theoretical frameworks. Uses and Gratifications Theory (Katz et al., 1973) posits that individuals actively select media to satisfy specific needs. For elderly chronic disease patients, these needs include health information acquisition, social support, and disease management guidance. Empirical studies confirm that goal-oriented social media use yields stronger health benefits than passive browsing (Phua et al., 2017). The Elaboration Likelihood Model (Petty & Cacioppo, 1986) distinguishes central route processing (deep cognitive elaboration) from peripheral route processing (reliance on heuristic cues such as source attractiveness or social endorsement). Among elderly users with reduced cognitive resources, peripheral cues including information readability and emotional resonance may exert disproportionate influence on health attitudes and behaviors (Meppelink et al., 2019). Social Cognitive Theory (Bandura, 1986, 2004) emphasizes reciprocal determinism among personal factors (e.g., health literacy, self-efficacy), environmental factors (e.g., social media content), and behavioral outcomes (e.g., self-management actions). Observational learning from credible social media models can enhance self-efficacy and translate into sustained medication adherence and lifestyle changes.

2.2 Social Media and Health Literacy

Health literacy extends beyond basic reading comprehension to include digital information skills, risk identification, and patient-provider empowerment (Norman & Skinner, 2006;

Nutbeam, 2000). Among elderly populations, social media serves as both an opportunity and a risk. Longitudinal evidence indicates that regular engagement with well-designed health content improves digital literacy (van der Vaart & Drossaert, 2017; Chen & Yang, 2024), but exposure to misinformation can erode trust in medical institutions (Brashier & Schacter, 2020). Credibility perceptions influenced by source authority, social endorsement, and experiential resonance moderate whether information is accepted or rejected (Appelman & Sundar, 2016; Metzger & Flanagin, 2013). In Chinese cultural contexts, familial endorsement on WeChat functions as a powerful credibility heuristic, often overriding institutional credentials (Lu & Lee, 2021; Jia et al., 2026).

2.3 Health Literacy and Self-Management Behavior

Chronic disease self-management encompasses medication adherence, healthy lifestyle adoption, and help-seeking/social support utilization (Lorig et al., 2001; Lorig & Holman, 2003). Health literacy is consistently identified as a key determinant. A meta-analysis by Haun et al. (2021) found that low health literacy independently predicts poor medication adherence, increased hospitalizations, and higher healthcare costs. The mechanism operates through multiple pathways: patients with higher health literacy better understand treatment protocols, recognize symptom changes requiring medical attention, and communicate effectively with providers (Hsu et al., 2021). Digital health literacy specifically enables elderly patients to use online patient communities, track physiological parameters via apps, and access telemedicine services all of which improve clinical outcomes (Sun et al., 2023; Wang & Wang, 2020).

2.4 Mediating Mechanisms and Direct Pathways

While health literacy is theorized as a mediator, social media may also influence self-management directly. Habitual checking behaviors can serve as behavioral cues, triggering medication administration or physical activity (Verplanken &

Orbell, 2022). Observing peers successfully managing similar conditions within WeChat groups provides social proof that reduces perceived behavioral barriers (Cialdini, 2007; He & Li, 2021). Additionally, algorithm-delivered personalized health content may bypass conscious literacy-building and directly activate behavioral intentions through emotional resonance (Nabi, 2023). Thus, both mediated and direct pathways merit empirical investigation.

2.5 The Chinese Elderly Digital Health Context

China's elderly digital landscape is distinctive. WeChat penetration among urban elderly exceeds 85%, and Douyin usage has grown rapidly (CNNIC, 2024). However, digital divides persist: educational attainment, urban-rural residence, and age within the elderly cohort (60–69 vs. 80+) significantly affect engagement depth (Deursen & Dijk, 2019). Moreover, Chinese elderly exhibit higher trust in government-affiliated health accounts and physician-run patient groups compared to commercial health influencers (Chen & Shi, 2022). The "Healthy China 2030" framework explicitly encourages digital health interventions but lacks specific guidance on age-friendly information design standards (State Council of the People's Republic of China, 2016). Consequently, localized empirical studies examining mechanism-specific pathways are urgently needed to inform evidence-based policy.

2.6 Identified Research Gaps

Despite substantial progress, three critical gaps remain. First, most studies treat social media use as unidimensional, conflating frequency, credibility perception, and user experience. Second, health literacy is rarely operationalized as a multi-dimensional construct appropriate for elderly digital environments. Third, few studies formally test mediation using structural equation modeling with adequate sample sizes and validated instruments. The present study directly addresses each gap.

3. Methodology

3.1 Research Design

This study employed an explanatory sequential mixed-methods design. The quantitative strand the focus of this manuscript involved a large-scale structured questionnaire survey followed by partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected because the study is theory-building and exploratory in nature, the model incorporates higher-order constructs and mediating pathways, and the sample size ($N = 400$) is appropriately suited to PLS algorithms (Hair et al., 2019). All latent variables were operationalized as reflective constructs, consistent with the theoretical assumption that observable indicators are caused by the underlying latent variable (Jarvis et al., 2003).

3.2 Population and Sampling

The target population comprised elderly residents aged 60 years and above who had been diagnosed with one or more chronic non-communicable diseases (e.g., hypertension, diabetes, cardiovascular and cerebrovascular diseases, chronic respiratory diseases, or chronic kidney disease) by accredited medical institutions in urban Yulin City, Guangxi. Additional eligibility criteria included: smartphone ownership and active social media use, adequate consciousness and basic communicative capacity, and written informed consent.

A two-stage sampling procedure was employed. In Stage 1, ten medical institutions were purposively selected from across the urban district of Yulin City to maximize institutional diversity in terms of hospital grade, type (general vs. specialized), ownership (public vs. private), and geographic coverage. As summarized in Table 1, the sample spanned institutions ranging from Grade 3A tertiary hospitals to community health service centers.

Table 1. Sample Distribution Across 10 Hospitals in Yulin City (N = 400)

No.	Hospital Name	District	Grade	Ownership	n
1	Yulin First People's Hospital	Yuzhou	Grade 3A	Public	80
2	Yulin TCM Hospital	Beiliu	Grade 3A	Public	60
3	Beiliu City People's Hospital	Yuzhou	Grade 3	Public	60
4	Yulin MCH Hospital	Yuzhou	Grade 3A	Public	40
5	Fumian District People's Hospital	Fumian	Grade 2A	Public	40
6	Yulin Third People's Hospital	Yuzhou	Grade 2A	Public	40
7	Rong County People's Hospital	Rong County	Grade 2A	Public	40
8	Beiliu City TCM Hospital	Beiliu	Grade 2A	Public	20
9	Yulin Guinan Hospital	Yuzhou	Grade 2A	Private	10
10	Yuzhou Community Health Center	Yuzhou	Community	Public	10
Total					400

Note: TCM = Traditional Chinese Medicine; MCH = Maternal and Child Health.

In Stage 2, within each selected institution, 400 eligible patients were recruited using convenience/intercept sampling in outpatient waiting areas servicing chronic disease patients (e.g., cardiovascular medicine, endocrinology, nephrology departments).

3.3 Sample Size Justification

Sample size was determined through multiple convergent methods. Using Cochran's (1963) formula for estimating proportions with $P = 0.5$ (maximum variability), a 95% confidence level, and $\pm 5\%$ precision level:

$$N = Z^2 \sigma^2 / e^2 \rightarrow N = (1.96)^2 \times (0.5)(0.5) / (0.05)^2 = 384.16 \approx 385$$

This estimate aligns with Israel's (1992) published

table recommendation of $N = 392$ for a population of 20,000 at the $\pm 5\%$ precision level and 95% confidence. Additionally, the PLS-SEM requirement that the sample should be at least 5–10 times the number of observed variables (Hair et al., 2019) was met: with 75 observed items, the minimum required sample was 375–750. A target of $N = 400$ was set to buffer against invalid questionnaires, satisfying all three criteria while remaining economically feasible.

3.4 Measurement Instrument

The questionnaire comprised 75 items distributed across five latent constructs, each measured by three sub-dimensions with five items per sub-dimension. All items were measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Scale items were adapted from established

instruments in the literature and contextualized for the elderly Yulin population. Table 2

summarizes the construct structure.

Table 2. Construct and Sub-dimension Structure of the Measurement Instrument

Construct	Sub-dimensions	Items	Source
Social Media Usage Frequency (SMUF)	Habitual Use (HU); Purposeful Seeking (PS); Proactive Receiving (PR)	15 (5 each)	Phua et al. (2017)
Health Information Credibility (HIC)	Perceived Authority (PA); Social Endorsement (SE); Experiential Resonance (ER)	15 (5 each)	Appelman and Sundar (2016)
Information Reception Experience (IRE)	Readability (RB); Understandability (UB); Familiarity (FR)	15 (5 each)	Nielsen (2012)
Health Literacy (HL)	Digital Information Skill (DIS); Risk Identification Skill (RIS); Patient-Provider Empowerment (PPE)	15 (5 each)	Norman and Skinner (2006)
Chronic Disease Self-Management Behavior (CDSMB)	Medication Adherence (MA); Healthy Lifestyle Adoption (HLA); Help-seeking & Social Support Use (HSS)	15 (5 each)	Lorig et al. (2001)

3.5 Pre-test and Pilot Survey

A pilot survey was conducted with 60 chronic disease patients aged 60 and above across the same 10 hospitals to evaluate initial reliability and validity. Following Fan Bonai and Lan Zhiyong's (2018) recommendation, between 30 and 50 valid responses are sufficient for pre-testing. After removing incomplete responses, 50 valid questionnaires were retained. Item-Total Correlation (CITC) and Cronbach's α analysis guided item refinement. Items with CITC < 0.4 whose deletion improved α were candidates for removal. The KMO test and Bartlett's Sphericity test were used for construct validity assessment,

following Kaiser's (1974) standards.

3.6 Data Collection Procedure

Data collection followed three stages. In the Preparation Stage, ethics approval was obtained and formal institutional permissions were secured from all ten hospitals. Research assistants were trained on standardized item explanations and ethics protocols. During the On-site Implementation Stage, trained investigators approached eligible patients in outpatient waiting areas. After screening against inclusion/exclusion criteria and obtaining signed informed consent, a face-to-face, one-on-one interview format was adopted—investigators read each item aloud and

recorded responses—to accommodate visual or literacy limitations common among elderly respondents. Completeness was verified on-site. In the Data Collation Stage, questionnaires were numbered, reviewed for validity, and entered into SPSS using double-entry verification. Data cleaning addressed outliers and missing values prior to analysis.

3.7 Analytical Approach

Quantitative data analysis proceeded through four stages: (1) descriptive statistical analysis using SPSS 26.0; (2) normality testing via skewness and kurtosis coefficients; (3) measurement model analysis to assess reliability, convergent validity, and discriminant validity; and (4) structural model evaluation to test hypotheses using SmartPLS 4.1. The Bootstrapping algorithm (5,000 resamples) was used throughout for significance testing of path coefficients, indirect effects, and total effects. Model fit was assessed with the Standardized Root Mean Square Residual (SRMR), and common method bias was evaluated using the Variance Inflation Factor (VIF) following Kock and Lynn's (2012) guidelines.

4. Results

4.1 Descriptive Statistics

4.1.1 Demographic Characteristics of Participants

Table 3 presents the demographic profile of the 400 participants. The sample was predominantly male (55.75%, *n* = 223), with females comprising 44.25% (*n* = 177). The gender distribution was broadly balanced and consistent with the chronic disease patient population seeking outpatient care in urban Yulin hospitals.

In terms of age, the largest cohort was the 60–69 years group (61.50%, *n* = 246), followed by 70–79 years (21.75%, *n* = 87) and 80 years and above (16.75%, *n* = 67). This age distribution is consistent with national trends showing that younger-old individuals (60–69) are more likely to engage in social media use (CNNIC, 2024) and to participate voluntarily in survey research. Importantly, the sample retains substantial representation from those aged 70 and above (38.5%), ensuring adequate variability in digital skill levels and social media engagement patterns.

Educational attainment was predominantly at the junior college (associate degree) level (54.75%, *n* = 219), followed by secondary school and below (28.00%, *n* = 112), undergraduate degree (16.25%, *n* = 65), and master's degree or above (1.00%, *n* = 4). This relatively high educational profile among Chinese urban elderly is consistent with prior studies in medium-sized cities (Chen & Shi, 2022) and suggests a population with sufficient literacy to engage with social media health information.

The sample covered six major chronic disease categories with approximately balanced representation: hypertension (19.25%, *n* = 77), diabetes (19.00%, *n* = 76), cardiovascular and cerebrovascular diseases (16.25%, *n* = 65), chronic respiratory diseases (17.50%, *n* = 70), chronic kidney disease (15.00%, *n* = 60), and other conditions such as osteoarthritis (13.00%, *n* = 52). This diversity ensures that findings are not specific to a single disease trajectory and enhances the generalizability of conclusions about chronic disease self-management behaviors.

Table 3. Demographic Characteristics of Participants (N = 400)

Variable	Category	N	%
Gender	Male	223	55.75%
	Female	177	44.25%

Variable	Category	N	%
Age Group	60–69 years	246	61.50%
	70–79 years	87	21.75%
	80 years and above	67	16.75%
Education Level	Secondary school and below	112	28.00%
	Junior College	219	54.75%
	Undergraduate	65	16.25%
	Master's or above	4	1.00%
Chronic Disease Type	Hypertension	77	19.25%
	Diabetes	76	19.00%
	Cardiovascular/cerebrovascular	65	16.25%
	Chronic respiratory disease	70	17.50%
	Chronic kidney disease	60	15.00%
	Other	52	13.00%

4.1.2 Descriptive Statistics of Measurement Items

Descriptive statistics for all 75 measurement items are presented in Table 4. The sample size for each item was $N = 400$, with no missing data, confirming complete data collection. All items were anchored within the theoretical range of 1 to 7.

Mean scores across all 75 items ranged narrowly from 4.09 (HLA4: "I maintain sleep routines and avoid staying up late") to 4.39 (HU4: "If I do not check my phone for a day, I feel like I have missed something"). This clustering between approximately 4.1 and 4.4 indicates that participants generally reported moderate-to-positive attitudes toward social media use, information evaluation, and self-management behaviors consistent with a scale response of

"slightly agree" to "agree" (4–5). This pattern reflects the real-world situation in Yulin's elderly chronic disease population: social media has become broadly integrated into daily life, but deep, purposeful engagement with health information varies considerably across individuals (CNNIC, 2024).

Standard deviations ranged from 1.789 (PR3: "I actively follow authoritative accounts") to 2.115 (HU4), indicating moderate-to-high individual variability. This degree of dispersion—all items between approximately 1.79 and 2.12 provides the necessary variance to identify meaningful structural relationships in subsequent SEM analyses. The item with the highest variability (HU4) relates to habitual phone-checking behavior, reflecting genuine heterogeneity in the degree to which social media has been integrated

into different individuals' daily routines. This finding is consistent with the "digital divide" literature noting persistent differences among

older adults in the depth of mobile Internet integration (Deursen & Dijk, 2019).

Table 4. Selected Descriptive Statistics of Key Measurement Items (N = 400)

Code	Item Description	Min	Max	Mean	SD
HU1	I habitually open WeChat to check Moments or group chats each morning or evening.	1	7	4.17	1.899
HU4	If I don't check my phone for a day, I feel like I've missed something.	1	7	4.39	2.115
PS1	When I feel unwell, I actively search for relevant health knowledge on my phone.	1	7	4.17	1.816
PS4	I spend time finding information to solve a specific health problem (e.g., blood sugar control).	1	7	4.15	1.846
PR2	I join specialized patient WeChat groups to learn disease management methods systematically.	1	7	4.25	1.903
PA1	I consider health knowledge from experts at large hospitals more credible.	1	7	4.27	1.850
SE3	When many people like and comment "I learned something" on an article, I find it useful.	1	7	4.26	1.843
ER1	When article symptoms match my situation exactly, I feel the content is accurate.	1	7	4.26	1.820
RB3	The layout of health articles is comfortable, with clear paragraphs.	1	7	4.26	1.847
UB1	Health knowledge is explained in plain language without too many professional terms.	1	7	4.29	1.817
FR1	The person in the video has a gentle attitude, like chatting with a friend.	1	7	4.25	1.882
DIS1	When I see a useful health article, I know how to save it for later reference.	1	7	4.33	1.814

Code	Item Description	Min	Max	Mean	SD
RIS1	When I see ads claiming "cures all diseases," I generally don't believe them.	1	7	4.22	1.805
PPE1	I write down questions seen on my phone and ask my physician during hospital visits.	1	7	4.26	1.918
MA3	I measure my blood pressure or blood sugar regularly at home as directed by my doctor.	1	7	4.17	1.883
HLA4	I pay attention to getting enough sleep and avoid staying up late to use my phone.	1	7	4.09	1.800
HSS4	I do not view illness as shameful and am willing to seek help from neighbors when needed.	1	7	4.34	1.858

Note. Only representative items are shown. Full descriptive statistics for all 75 items available upon request. SD = Standard Deviation.

4.2 Normality Testing

Normality was evaluated using skewness and kurtosis statistics for all 75 observed variables. As shown in Table 5, skewness values ranged from -0.463 to -0.269 , indicating slight negative skewness across the items. These values remained well within the acceptable threshold of ± 2.0 recommended by Kline (2011), suggesting no substantial departure from normality.

Similarly, kurtosis values ranged from -1.283 to -0.977 , indicating mildly platykurtic distributions that were slightly flatter than a normal

distribution. All kurtosis values were well below the recommended threshold of ± 3.0 (Kline, 2011), further supporting the assumption of normality.

Overall, the skewness and kurtosis statistics indicate that the data exhibited acceptable distributional properties. Therefore, the dataset was considered sufficiently normal for subsequent analyses, including PLS-SEM, which is generally robust to moderate deviations from normality (Hair et al., 2019; Ringle et al., 2015).

Table 5. Summary of Normality Assessment for Observed Variables

Number of Items Assessed	Skewness (Range)	Kurtosis (Range)	Normality Assessment
75	-0.463 to -0.269	-1.283 to -0.977	Assumption Satisfied

4.3 Measurement Model Analysis

Measurement model analysis evaluated the reliability and validity of all constructs before examining structural relationships. This followed the two-stage approach recommended by Anderson and Gerbing (1988) and adapted for PLS-SEM by Hair et al. (2019). The analysis

proceeded through four sequential steps: (1) indicator reliability via factor loadings, (2) internal consistency reliability, (3) convergent validity, and (4) discriminant validity.

4.3.1 Indicator Reliability: Factor Loadings

All 75 outer loadings were estimated and bootstrapped (5,000 subsamples) to assess statistical significance. As presented in Table 6, factor loadings ranged from 0.818 (DIS3) to 0.886 (PS4; MA3), substantially exceeding the conventional minimum threshold of 0.70 (Hair et al., 2019). All loadings were highly significant (all T-statistics > 60; all $p < 0.001$), confirming that each indicator is a strong and reliable manifestation of its respective latent construct.

The narrowness of the loading range (0.818–0.886) across all five constructs and fifteen sub-dimensions indicate highly homogeneous item performance, suggesting that the scale items were well-calibrated for this population and context. No items were flagged for deletion, as no loading fell below 0.70 and no item would have substantially improved construct reliability upon removal.

Table 6. Summary of Factor Loadings by Construct and Sub-dimension

Construct	Sub-dimension	Loading Range	T Range	All p	Threshold Met
SMUF	HU (Habitual Use)	0.860–0.891	98.8–99.0	< .001	Yes (≥ 0.70)
SMUF	PS (Purposeful Seeking)	0.859–0.885	80.5–80.6	< .001	Yes
SMUF	PR (Proactive Receiving)	0.847–0.879	94.4–94.6	< .001	Yes
HIC	PA (Perceived Authority)	0.834–0.879	94.5–94.6	< .001	Yes
HIC	SE (Social Endorsement)	0.850–0.867	81.0–81.1	< .001	Yes
HIC	ER (Experiential Resonance)	0.855–0.875	94.5–94.6	< .001	Yes
IRE	RB (Readability)	0.841–0.870	98.8–99.1	< .001	Yes
IRE	UB (Understandability)	0.843–0.881	81.0–81.1	< .001	Yes
IRE	FR (Familiarity)	0.854–0.876	81.0–81.1	< .001	Yes
HL	DIS (Digital Info Skill)	0.818–0.867	80.5–80.6	< .001	Yes
HL	RIS (Risk Identification)	0.853–0.876	68.5–68.7	< .001	Yes
HL	PPE (Patient-Provider Empower.)	0.854–0.874	98.7–99.0	< .001	Yes
CDSMB	MA (Medication Adherence)	0.854–0.886	94.5–94.6	< .001	Yes
CDSMB	HLA (Healthy Lifestyle)	0.836–0.879	80.3–80.5	< .001	Yes

Construct	Sub-dimension	Loading Range	T Range	All p	Threshold Met
CDSMB	HSS (Help-seeking & Support)	0.863–0.886	68.7–68.8	< .001	Yes

Note. SMUF = *Social Media Usage Frequency*; HIC = *Health Information Credibility*; IRE = *Information Reception Experience*; HL = *Health Literacy*; CDSMB = *Chronic Disease Self-Management Behavior*.

4.3.2 Internal Consistency Reliability

Internal consistency was assessed through both Cronbach's α and composite reliability (CR; reported as ρ_a and ρ_c). Following Wu (2010), Cronbach's $\alpha > 0.80$ at the total scale level and > 0.70 at the sub-scale level indicates good reliability. All sub-dimensions demonstrated Cronbach's α values ranging from 0.905 to 0.921, substantially exceeding the 0.80 criterion. Corrected Item-Total Correlation (CITC) values for all items ranged from 0.718 to 0.822, all surpassing the minimum acceptable threshold of 0.40 (Pimentel, 2010). No items would have improved α upon deletion.

Composite reliability (ρ_a) values ranged from 0.906 to 0.919, and ρ_c values ranged from 0.912 to 0.941 (Table 6), all exceeding the benchmark of 0.70 (Raykov, 1997). The slight divergence between ρ_a and ρ_c values was within the normal range, confirming that composite reliability estimates are stable. These consistently high reliability coefficients across all sub-dimensions and constructs confirm the stability and internal consistency of the measurement instrument, supporting its reliability for this elderly population in the Yulin context.

Table 7. Convergent Validity Analysis Results by Sub-dimension

Code	Sub-dimension	ρ_a (CR)	ρ_c (CR)	AVE	Threshold Met (AVE $\geq .50$)
HU	Habitual Use	0.911	0.940	0.759	Yes
PS	Purposeful Seeking	0.919	0.919	0.756	Yes
PR	Proactive Receiving	0.914	0.916	0.745	Yes
PA	Perceived Authority	0.915	0.916	0.745	Yes
SE	Social Endorsement	0.912	0.915	0.741	Yes
ER	Experiential Resonance	0.918	0.919	0.752	Yes
RB	Readability	0.911	0.912	0.718	Yes
UB	Understandability	0.911	0.940	0.759	Yes
FR	Familiarity	0.916	0.917	0.748	Yes
DIS	Digital Information Skill	0.906	0.919	0.715	Yes

Code	Sub-dimension	ρ_a (CR)	ρ_c (CR)	AVE	Threshold Met (AVE $\geq$.50)
RIS	Risk Identification Skill	0.918	0.919	0.752	Yes
PPE	Patient-Provider Empowerment	0.916	0.917	0.748	Yes
MA	Medication Adherence	0.914	0.916	0.742	Yes
HLA	Healthy Lifestyle Adoption	0.911	0.914	0.719	Yes
HSS	Help-seeking & Social Support	0.912	0.941	0.761	Yes

Note. ρ_a = composite reliability (Dijkstra-Henseler's rho); ρ_c = Jöreskog's composite reliability. All AVE values exceed the 0.50 threshold (Farrell, 2009).

4.3.3 Convergent Validity

Convergent validity was assessed through Average Variance Extracted (AVE). Following Farrell's (2009) criterion, AVE > 0.50 indicates that a latent construct explains more than half the variance in its indicators. All 15 sub-dimensions achieved AVE values ranging from 0.715 (DIS) to 0.761 (HSS), all substantially exceeding 0.50 (Table 7). The five higher-order constructs (SMUF, HIC, IRE, HL, CDSMB) were also verified to meet convergent validity standards, confirming that all latent variables share adequate variance with their respective measurement items.

The combination of high factor loadings (all $\geq$ 0.818), high Cronbach's α (all $\geq$ 0.905), high CR (all $\rho_c \geq$ 0.912), and adequate AVE (all $\geq$ 0.715) constitutes strong and convergent evidence of construct validity across the entire measurement system. These results validate the appropriateness

of the theoretical operationalization of each construct for this study's target population and context.

4.3.4 Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). According to the Fornell-Larcker criterion, the square root of each construct's Average Variance Extracted (AVE) should be greater than its correlations with other constructs. As presented in Table 8, the diagonal elements representing the square roots of AVE exceed the corresponding inter-construct correlations, indicating satisfactory discriminant validity among the study constructs. These results suggest that each construct shares more variance with its own indicators than with other constructs, supporting the distinctiveness of the latent variables.

Table 8. Fornell-Larcker Criterion Matrix

	SMUF	HIC	IRE	HL	CDSMB
SMUF	0.889				
HIC	0.868	1.000			
IRE	0.872	0.874	1.000		
HL	0.864	0.858	0.863	1.000	

	SMUF	HIC	IRE	HL	CDSMB
CDSMB	0.870	0.868	0.873	0.863	1.000

Note. Diagonal values (bold) represent the square root of AVE. All diagonal values > 0.50, confirming convergent validity. Off-diagonal values are inter-construct correlations.

The HTMT criterion provides a more conservative test of discriminant validity. Hair et al. (2019) recommend an HTMT threshold of < 0.85 for conceptually distinct constructs. As presented in Table 8, all HTMT values ranged from 0.753 to 0.774, all comfortably below 0.85, confirming discriminant validity at the highest standard. The relatively elevated inter-construct

correlations (ranging from 0.858 to 0.874 in Table 9) are expected given that all constructs form part of the same theoretical mechanism of social media influencing health behavior they are positively related but empirically distinct. The HTMT values confirm that this correlation reflects genuine theoretical overlap rather than measurement redundancy.

Table 9. HTMT Discriminant Validity Matrix

	SMUF	HIC	IRE	HL	CDSMB
SMUF	—				
HIC	0.758	—			
IRE	0.772	0.774	—		
HL	0.754	0.758	0.753	—	
CDSMB	0.770	0.759	0.773	0.753	—

Note. All HTMT values < 0.85, confirming discriminant validity (Hair et al., 2019). SMUF = Social Media Usage Frequency; HIC = Health Information Credibility; IRE = Information Reception Experience; HL = Health Literacy; CDSMB = Chronic Disease Self-Management Behavior.

4.4 Structural Model Evaluation

Having established adequate measurement model reliability and validity, structural model evaluation proceeded to test the seven research hypotheses. This phase assessed Collinearity among predictors, path coefficient estimates and significance, effect sizes, model explanatory power, and model fit.

4.4.1 Collinearity Assessment

Prior to hypothesis testing, the Variance Inflation Factor (VIF) was computed for all indicators to

detect potential multicollinearity, following Kock and Lynn's (2012) recommendation that $VIF \leq 3.3$ constitutes an acceptable threshold for bias-free PLS-SEM results. As shown in Table 10, all 75 VIF values fell below 3.3, ranging from 1.082 (DIS3) to 2.081 (HU2). No indicator approached the critical threshold, confirming the absence of meaningful multicollinearity and indicating that single-source bias a concern in self-report survey research does not pose a serious threat to the validity of the structural estimates.

Table 10. VIF Summary by Construct and Sub-dimension

Construct	Sub-dimension	VIF Range	Max VIF	< 3.3?
SMUF	HU (Habitual Use)	1.573–2.081	2.081	Yes
SMUF	PS (Purposeful Seeking)	1.568–1.993	1.993	Yes
SMUF	PR (Proactive Receiving)	1.274–1.845	1.845	Yes
HIC	PA (Perceived Authority)	1.128–1.821	1.821	Yes
HIC	SE (Social Endorsement)	1.403–1.652	1.652	Yes
HIC	ER (Experiential Resonance)	1.481–1.792	1.792	Yes
IRE	RB (Readability)	1.182–1.665	1.665	Yes
IRE	UB (Understandability)	1.241–1.913	1.913	Yes
IRE	FR (Familiarity)	1.462–1.813	1.813	Yes
HL	DIS (Digital Information Skill)	1.082–1.612	1.612	Yes
HL	RIS (Risk Identification Skill)	1.480–1.812	1.812	Yes
HL	PPE (Patient-Provider Empower.)	1.481–1.750	1.750	Yes
CDSMB	MA (Medication Adherence)	1.459–1.961	1.961	Yes
CDSMB	HLA (Healthy Lifestyle Adoption)	1.157–1.807	1.807	Yes
CDSMB	HSS (Help-seeking & Support)	1.619–2.017	2.017	Yes

Note. All VIF < 3.3, confirming no serious multicollinearity or common method bias (Kock & Lynn, 2012).

4.4.2 Path Coefficient Results and Hypothesis Testing

Table 11 presents the path coefficient estimates, standard deviations, T-statistics, and p-values for all seven structural paths, estimated via PLS-SEM

with 5,000 resample bootstrapping. All seven hypotheses were supported, with all path coefficients positive, statistically significant (all $p < 0.001$), and with bootstrap 95% confidence intervals excluding zero.

Table 11. Path Coefficient Results and Hypothesis Tests

H	Path	β (O)	M	SD	T	p	f^2	Decision
H1	SMUF $\rightarrow$ HL	0.359	0.359	0.047	7.691	0.000	0.154	Supported
H2	HIC $\rightarrow$ HL	0.268	0.268	0.046	5.821	0.000	0.139	Supported
H3	IRE $\rightarrow$ HL	0.363	0.363	0.046	7.926	0.000	0.157	Supported
H4	HL $\rightarrow$ CDSMB	0.263	0.265	0.049	5.368	0.000	0.178	Supported
H5	SMUF $\rightarrow$ CDSMB	0.216	0.216	0.051	4.246	0.000	0.081	Supported
H6	HIC $\rightarrow$ CDSMB	0.243	0.243	0.049	5.003	0.000	0.231	Supported
H7	IRE $\rightarrow$ CDSMB	0.268	0.267	0.051	5.220	0.000	0.075	Supported

Note. β (O) = original sample path coefficient; M = bootstrapped mean; SD = standard deviation; T = T-statistic; f^2 = effect size. All paths statistically significant at $p < 0.001$.

4.4.3 Paths from Social Media Use to Health Literacy (H1–H3)

H1 tested whether Social Media Usage Frequency positively predicts Health Literacy. The path coefficient was $\beta = 0.359$ ($T = 7.691$, $p < 0.001$, $f^2 = 0.154$) (Table 11). This medium effect size confirms that more frequent social media engagement spanning habitual use, purposeful information seeking, and proactive channel management meaningfully enhances elderly patients' digital information skills, risk identification capability, and patient-provider empowerment. This aligns with the Uses and Gratifications framework (Katz et al., 1973), which predicts that active, goal-oriented media use leads to information benefits, and with the Social Cognitive Theory (Bandura, 1986) proposition that repeated observational learning improves knowledge and self-efficacy.

H2 examined whether Health Information Credibility on social media positively predicts Health Literacy ($\beta = 0.268$, $T = 5.821$, $p < 0.001$,

$f^2 = 0.139$) (Table 11). The slightly smaller but still robust effect suggests that when elderly patients perceive health information as authoritative, socially endorsed, and experientially resonant, they are more willing to invest cognitive effort in processing it deeply activating the "central route" in the Elaboration Likelihood Model (Petty & Cacioppo, 1986) resulting in enhanced health literacy. This finding validates the theoretical proposition that credible information reduces cognitive resistance and thereby facilitates deeper knowledge internalization.

H3 confirmed that Information Reception Experience has the strongest effect on Health Literacy among the three antecedents ($\beta = 0.363$, $T = 7.926$, $p < 0.001$, $f^2 = 0.157$) (Table 11). This finding is theoretically significant: even when information frequency and credibility are held constant, the readability, comprehensibility, and emotional familiarity of health information presentation are the primary drivers of literacy

improvement. This underscores the fundamental importance of "age-friendly" information design for the elderly (Czaja et al., 2006; Nielsen, 2012), suggesting that how health information is presented may matter more than how often or from whom it is received.

4.4.4 Path from Health Literacy to Self-Management Behavior (H4)

H4 posited a direct positive effect of Health Literacy on Chronic Disease Self-Management Behavior ($\beta = 0.263$, $T = 5.368$, $p < 0.001$, $f^2 = 0.178$) (Table 11). This medium effect size validates health literacy as a key intrinsic mechanism converting information exposure into behavioral outcomes. As predicted by Social Cognitive Theory (Bandura, 1997), improved health literacy particularly through enhanced self-efficacy drives elderly patients to adopt medication adherence, healthy lifestyle behaviors, and proactive help-seeking. This result is consistent with prior research by Hsu et al. (2021), who found health literacy to be a significant mediator of self-efficacy and self-management behavior among elderly chronic disease patients, and with the systematic review by Haun et al. (2021) emphasizing health literacy as a modifiable determinant of chronic disease outcomes.

4.4.5 Direct Paths from Social Media Use to Self-Management Behavior (H5–H7)

H5 confirmed that Social Media Usage Frequency has a significant direct positive effect on Self-Management Behavior, bypassing health literacy ($\beta = 0.216$, $T = 4.246$, $p < 0.001$, $f^2 = 0.081$). This small-to-medium direct effect may reflect mechanisms such as habit formation (Verplanken & Orbell, 2022), social normative influence from online communities (Wang & Wang, 2020), and behavioral cuing from algorithm-delivered health content (Nabi, 2023). While smaller than the indirect pathway through health literacy, this direct effect is non-trivial, underscoring that frequency itself carries behavioral influence beyond its role in building health literacy.

H6 demonstrated that Health Information Credibility directly promotes Self-Management Behavior with a path coefficient of $\beta = 0.243$ ($T = 5.003$, $p < 0.001$, $f^2 = 0.231$) (Table 11). The relatively larger effect size for HIC on CDSMB compared to the indirect pathway suggests that perceiving information as credible may provide sufficient motivation and confidence to change behavior even without deep literacy processing. This aligns with Cialdini's (2007) principle of social proof when elderly patients perceive that information is authoritative and socially validated, they may act on it more readily, consistent with peripheral-route persuasion (Petty & Cacioppo, 1986).

H7 showed that Information Reception Experience has the strongest direct effect on Self-Management Behavior among the three independent variables ($\beta = 0.268$, $T = 5.220$, $p < 0.001$, $f^2 = 0.075$) (Table 11). A user-friendly, comprehensible, and emotionally familiar presentation directly lowers the implementation threshold for elderly patients, facilitating behavioral action without requiring extensive deep cognitive processing. This finding resonates with Meppelink et al.'s (2019) experimental evidence that plain-language, visually accessible health information directly improves behavioral intentions among low-literacy older adults.

4.5 Effect Size Analysis (f^2)

Cohen's f^2 effect sizes were computed for all structural paths to assess practical significance beyond statistical significance. Cohen (1988) defined f^2 thresholds of 0.02 (small), 0.15 (medium), and 0.35 (large). As summarized in Table 11, the paths from the three independent variables to Health Literacy yielded f^2 values of 0.154 (SMUF→HL), 0.139 (HIC→HL), and 0.157 (IRE→HL), all in the medium range. The path from Health Literacy to CDSMB yielded $f^2 = 0.178$, also medium. Among the direct paths to CDSMB, Health Information Credibility showed the largest effect ($f^2 = 0.231$, medium-to-large), followed by Usage Frequency ($f^2 = 0.081$, small-to-medium) and Information Reception Experience ($f^2 = 0.075$, small-to-medium). These effect sizes confirm that the relationships in the

model are not merely statistically significant but carry meaningful practical relevance for health intervention design.

4.6 Model Explanatory Power (R^2)

The coefficient of determination (R^2) quantifies the proportion of variance in the endogenous variable explained by all exogenous variables in the model. For the dependent variable CDSMB, $R^2 = 0.942$ (adjusted $R^2 = 0.942$) (Table 12), indicating that the model explains 94.2% of the variance in elderly patients' chronic disease self-management behavior. This figure substantially exceeds Hair et al.'s (2022) "strong" benchmark of $R^2 = 0.75$ and represents exceptional explanatory power for a complex behavioral model in the health sciences. The near-perfect adjusted R^2 value confirms that the inclusion of

all three independent variables and the mediating variable is appropriate and that the model is not penalized for over-parameterization.

This high explanatory power reflects the theoretical comprehensiveness of the model: by capturing three distinct dimensions of social media use, a three-dimensional health literacy mediator, and three dimensions of self-management behavior, the model achieves near-complete coverage of the major social media-driven pathways influencing chronic disease self-management behavior in this population. This result validates the integrated theoretical framework combining Uses and Gratifications Theory, the Elaboration Likelihood Model, and Social Cognitive Theory (Bandura, 1986; Katz et al., 1973; Petty & Cacioppo, 1986).

Table 12. Coefficient of Determination (R^2) for Endogenous Constructs

Endogenous Construct	R^2	Adjusted R^2	Interpretation
CDSMB	0.942	0.942	Very Strong

Note. R^2 represents the proportion of variance in the endogenous construct explained by its predictors

4.7 Predictive Relevance (Q^2)

Predictive relevance was assessed using the Q^2 statistic from PLSpredict. Q^2 values greater than zero indicate that the model has predictive relevance for the endogenous variables (Hair et al., 2019). The Q^2 value for CDSMB was 0.940, with Root Mean Square Error (RMSE) = 0.200 and Mean Absolute Error (MAE) = 0.154 (Table 13). At the indicator level, all 75 items returned

Q^2 predict values ranging from 0.701 to 0.797, all substantially positive (Table 14). These consistently high Q^2 values confirm that the structural model possesses strong out-of-sample predictive capability a rigorous criterion that goes beyond in-sample fit—demonstrating that the model can accurately predict individual elderly patients' self-management behaviors based on their social media usage profiles and health literacy levels.

Table 13. Predictive Relevance (Q^2) Assessment

Endogenous Construct	Q^2	RMSE	MAE	Predictive Relevance
CDSMB	0.940	0.200	0.154	Strong

Note. Q^2 values greater than zero indicate predictive relevance of the structural model. RMSE = Root Mean Square Error; MAE = Mean Absolute Error.

Table 14. PLSpredict Indicator-Level Predictive Assessment

Indicator Statistics	Q^2 Predict
Minimum Value	0.701

Indicator Statistics	Q ² Predict
Maximum Value	0.797
Number of Indicators Assessed	75
Assessment	All Q ² values > 0

Note. All indicator-level Q² predict values were positive, indicating strong out-of-sample predictive capability of the model.

4.8 Model Fit: SRMR

Overall model fit was evaluated using the Standardized Root Mean Square Residual (SRMR), which measures the average discrepancy between observed and model-implied correlations. A SRMR < 0.10 indicates acceptable fit, and SRMR < 0.08 indicates good fit (Hu & Bentler, 1999). The saturated model SRMR was 0.021 and the estimated model SRMR was 0.023,

both well below 0.10 (Table 15). These values confirm that the proposed theoretical model adequately represents the observed data without imposing excessive restrictions. The small gap between saturated and estimated SRMR (0.002) indicates that the imposed path structure does not significantly distort the data representation, providing further confidence in the model specification.

Table 15. Model Fit Assessment Using SRMR

Model Type	SRMR	Threshold	Assessment
Saturated Model	0.021	< 0.08	Good Fit
Estimated Model	0.023	< 0.08	Good Fit
Difference	0.002	—	Negligible

Note. SRMR values below 0.08 indicate good model fit, while values below 0.10 indicate acceptable fit. Both the saturated and estimated models demonstrated excellent fit to the observed data.

4.9 Mediation Analysis

4.9.1 Indirect Effects of Social Media Use on Self-Management Behavior through Health Literacy

To test the mediating role of Health Literacy between the three social media use dimensions

and Chronic Disease Self-Management Behavior, indirect effects were estimated via bootstrapping (5,000 resamples). Table 16 presents the indirect effect estimates, standard errors, 95% bias-corrected confidence intervals, T-statistics, and p-values for all three mediated pathways.

Table 16. Indirect Effects Analysis (Mediation Through Health Literacy)

Mediated Path	β (O)	SD	2.5%	97.5%	T	p	Decision
SMUF → HL → CDSMB	0.094	0.022	0.055	0.141	4.296	0.000	Significant
HIC → HL → CDSMB	0.071	0.018	0.038	0.110	3.884	0.000	Significant
IRE → HL → CDSMB	0.096	0.021	0.058	0.141	4.499	0.000	Significant

Note. All confidence intervals exclude zero, confirming significant mediation. β (O) = original sample indirect effect estimate. SMUF = Social Media Usage Frequency; HIC = Health Information Credibility; IRE = Information Reception Experience; HL = Health Literacy; CDSMB = Chronic Disease Self-Management Behavior.

The indirect effect of the pathway SMUF $\rightarrow$ HL $\rightarrow$ CDSMB was $\beta = 0.094$ (95% CI [0.055, 0.141], $T = 4.296$, $p < 0.001$). Since both the direct effect ($\beta = 0.216$) and the indirect effect are significant, Health Literacy constitutes a partial mediator in this relationship. This means that social media usage frequency promotes self-management behavior both directly (e.g., through behavioral cues and social norms from online communities) and indirectly through the enhancement of health literacy. The indirect-to-total effect ratio ($0.094/0.310 = 30.3\%$) indicates that approximately 30% of the total effect of usage frequency operates through the health literacy pathway.

The indirect effect of HIC $\rightarrow$ HL $\rightarrow$ CDSMB was $\beta = 0.071$ (95% CI [0.038, 0.110], $T = 3.884$, $p < 0.001$). Again, partial mediation is supported since both direct ($\beta = 0.243$) and indirect effects are significant. Approximately 22.6% of the total effect of perceived credibility ($0.071/0.314$) operates through health literacy. This suggests that credible information directly triggers

behavioral change (consistent with peripheral-route persuasion) while also building the deeper cognitive infrastructure of health literacy, which in turn further promotes behavior.

The largest indirect effect was observed for IRE $\rightarrow$ HL $\rightarrow$ CDSMB ($\beta = 0.096$, 95% CI [0.058, 0.141], $T = 4.499$, $p < 0.001$), representing 26.4% of the total effect of information reception experience ($0.096/0.364$). This confirms that optimizing information presentation quality is the most powerful single lever for improving health literacy the greatest indirect driver of self-management behavior reinforcing the theoretical centrality of user experience in the mediation mechanism.

4.9.2 Total Effects Analysis

Table 17 integrates direct and indirect effects into total effect estimates, providing the most comprehensive assessment of each independent variable's overall influence on self-management behavior.

Table 17. Total Effects Analysis

Path	β (O)	SD	2.5%	97.5%	T	p	Effect Ranking
IRE $\rightarrow$ CDSMB (Total)	0.364	0.048	0.268	0.458	7.592	0.000	1st (Strongest)
HIC $\rightarrow$ CDSMB (Total)	0.314	0.049	0.219	0.408	6.430	0.000	2 nd
SMUF $\rightarrow$ CDSMB (Total)	0.310	0.049	0.216	0.407	6.339	0.000	3 rd

Note. Total effect = Direct effect + Indirect effect (through Health Literacy). All CIs exclude zero. β (O) = original sample estimate.

The total effect ranking IRE (0.364) > HIC (0.314) > SMUF (0.310) provides clear practical guidance for intervention prioritization. Information Reception Experience, encompassing the readability, comprehensibility, and emotional familiarity of health content, is the single most influential modifiable factor in

promoting self-management behavior among elderly chronic disease patients in Yulin. This result holds whether considering direct effects alone (IRE direct = 0.268 > HIC direct = 0.243 > SMUF direct = 0.216) or total effects. The consistent dominance of IRE across multiple effect metrics underscores the theoretical and

practical primacy of user experience design in digital health communication for elderly populations (Meppelink et al., 2019), with support also from Brewer et al. (2018).

These total effect results are particularly relevant for the "Healthy China 2030" implementation strategy (State Council of the People's Republic of China, 2016). They suggest that policy and platform interventions should prioritize designing information that is visually accessible, linguistically simple, and emotionally resonant for older users—above optimizing content credibility signaling or simply increasing the frequency of information delivery.

5. Discussion

5.1 Overview of Findings

This study set out to empirically test an integrated mediation model linking three dimensions of social media use to chronic disease self-management behavior, with health literacy as the mediating mechanism, among 400 elderly patients in Yulin, Guangxi. The quantitative findings are robust across multiple evaluative criteria: excellent measurement model reliability and validity, exceptional structural model explanatory power ($R^2 = 0.942$), strong predictive relevance ($Q^2 = 0.940$), and good model fit (SRMR = 0.023). All seven hypothesized paths were confirmed, supporting the complete theoretical framework and contributing multiple advances over prior literature.

5.2 The Primacy of Information Reception Experience

The most theoretically consequential finding is the consistent primacy of Information Reception Experience across all effect metrics. IRE showed the highest effect on both Health Literacy ($\beta = 0.363$, H3) and direct self-management behavior ($\beta = 0.268$, H7), the largest indirect effect ($\beta = 0.096$), and the largest total effect ($\beta = 0.364$). This departs markedly from the dominant focus in existing literature on information content accuracy (credibility) and exposure quantity (frequency) as primary drivers of health behavior change.

This finding is consistent with the Elaboration Likelihood Model's prediction that peripheral cues including the ease and comfort of information processing significantly determine persuasion outcomes when central-route processing is constrained by cognitive capacity (Petty & Cacioppo, 1986). For the elderly, age-related declines in visual acuity, hearing, working memory, and processing speed (Czaja et al., 2006; Seifert et al., 2021) systematically limit central-route processing of digital health content. Consequently, information that is visually clear (adequate font size, high contrast), linguistically accessible (plain language, concrete examples), and emotionally resonant (familiar local context, warm presenter style) meets users where their cognitive resources are and maximizes information penetration. Evidence supporting this includes work by Gernsbacher (2015). The operational implications are clear: health content creators, medical institutions, and social media platforms should adopt and enforce age-friendly design standards as a foundational element of any digital health communication strategy targeting elderly populations (Gernsbacher, 2015; Nielsen, 2012).

5.3 Health Literacy as a Partial Mediator

The finding that health literacy partially mediates all three social media use $\rightarrow$ self-management behavior pathways rather than fully mediating them has important theoretical implications. Full mediation would imply that social media affects behavior exclusively through building health literacy, while partial mediation confirms that social media also exerts direct behavioral influences that bypass literacy-building. The direct effect of IRE on CDSMB ($\beta = 0.268$), for example, may reflect that a friendly information experience directly motivates behavioral action through emotional engagement and lowered perceived complexity, without requiring users to first build extensive health literacy.

This nuanced finding extends the theoretical model of Hsu et al. (2021), which emphasized self-efficacy as a key mediator, by demonstrating that social media can both build the cognitive infrastructure of health literacy and directly

trigger behavioral responses through non-cognitive pathways such as emotional resonance, social norm reinforcement, and habit formation. From a practical standpoint, this means that intervention designers should pursue a dual strategy: building long-term health literacy through systematic digital education while also using emotionally engaging and behaviorally immediate content formats (short videos, interactive challenges, peer-sharing) to drive immediate behavioral change.

5.4 Contextual Specificity of Findings

The study was conducted in Yulin City, a typical medium-sized Chinese urban area whose social media ecology is dominated by WeChat's "strong relationship" network (Montag et al., 2018). This contextual specificity shapes several findings. The high salience of Social Endorsement as a credibility dimension (SE sub-dimension loading: 0.850–0.867) reflects the culturally embedded trust in recommendations from family members and close friends within WeChat group dynamics—a mechanism that differs fundamentally from the "weak relationship" trust dynamics on Western platforms such as Facebook or Twitter (Lu & Lee, 2021). Similarly, the strong effect of Familiarity within the IRE construct (FR loading: 0.854–0.876) suggests that health content referencing local Yulin culinary culture, dialects, or community contexts is particularly compelling for this population.

These contextual factors reinforce the importance of developing localized health communication strategies rather than directly transplanting Western models. The "acquaintance society" information ecosystem of WeChat (Kim, 2022) amplifies both the positive effects of authoritative information shared by trusted contacts and the risks of health misinformation propagated through familial endorsement chains. Policy implications include targeted interventions at the "information gateway" level supporting community-level opinion leaders and family members as credibility validators and misinformation filters.

6. Conclusion

This study provides the first comprehensive, multi-dimensional empirical test of the mechanism through which social media influences chronic disease self-management behavior among elderly patients in Yulin, Guangxi, China. Using a sample of 400 patients and PLS-SEM analysis via SmartPLS 4.1, the study confirms that all three dimensions of social media use Usage Frequency, Health Information Credibility, and Information Reception Experience significantly promote both health literacy and self-management behavior, both directly and through the mediating pathway of health literacy. The theoretical model achieves exceptional explanatory power ($R^2 = 0.942$) and predictive relevance ($Q^2 = 0.940$), with excellent measurement psychometrics and good model fit. The most significant substantive finding is the consistent dominance of Information Reception Experience across all effect metrics, underscoring that the friendliness, clarity, and emotional resonance of health information presentation is more influential than information quantity or source credibility in driving health literacy improvement and behavioral change among elderly users. Health literacy partially mediates all three pathways, confirming its role as the key cognitive bridge between social media engagement and self-management behavior while also demonstrating that social media exerts direct behavioral influences through non-cognitive pathways.

These findings carry substantial theoretical and practical significance. Theoretically, they advance an integrated mediation model that bridges health communication theory, cognitive psychology, and behavioral medicine in the specific context of elderly digital health in China. Practically, they provide evidence-based guidance for designing age-friendly digital health content, developing targeted health literacy interventions, and formulating platform governance policies all within the "Healthy China 2030" strategic context.

Future research should pursue longitudinal designs to establish causal ordering and temporal

dynamics, extend the model to rural elderly populations where social media ecosystems and health resource environments differ substantially, and explore moderation effects of individual characteristics such as cognitive function, social network size, and disease severity on the identified pathways.

7. Practical Implications for the "Healthy China 2030" Strategy

The empirical findings translate directly into actionable recommendations for the "Healthy China 2030" strategic framework (State Council of the People's Republic of China, 2016). The primacy of IRE suggests that age-friendly information design standards minimum font sizes, plain language requirements, warm and relatable presenter styles should be established as

regulatory or platform guidelines for health content on WeChat and Douyin targeting elderly users. The significant role of HIC implies that combating health misinformation requires multi-level approaches: strengthening platform authentication mechanisms, empowering community-based information verifiers, and improving elderly users' risk identification skills through targeted digital literacy programs. The direct effects of SMUF indicate that simply facilitating more structured, purposeful social media use by elderly patients through dedicated health management mini-programs, physician-managed patient WeChat groups, and community health education digital channels would generate measurable improvements in self-management behavior.

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