Risk Management and Healthcare Policy

Dovepress
Taylor & Francis Group

Open Access Full Text Article

ORIGINAL RESEARCH

Digital Literacy and Self-Rated Health in China: Dual Pathways Through Information Accessibility and Mental Health

Chunyun Tan[1], Jiangwei Hu[1], Hongxuan Tong[2], Jiale Zhang[2,3]

[1]School of Chinese Literature and Media, Hubei University of Arts and Science, Xiangyang, Hubei, People's Republic of China; [2]Institute of Basic Theory for Chinese Medicine, China Academy of Chinese Medical Sciences, Beijing, People's Republic of China; [3]China Science and Technology Development Center of Chinese Medicine, Beijing, People's Republic of China

Correspondence: Hongxuan Tong; Jiale Zhang, Email thongxuan1@163.com; zhang_tcm@163.com

Background: Digital literacy is increasingly recognized as a key determinant of health, yet the mechanisms linking it to self-rated health in transitional economies like China remain underexplored. This study examines how digital literacy influences self-rated health, directly and indirectly through mental health, while exploring heterogeneity across age and gender groups.

Methods: Using data from the 2023 Chinese General Social Survey (n=8,039 adults aged 18 and above), we constructed a multidimensional digital literacy index via entropy weighting and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), integrating dimensions of digital access, usage, and entertainment. Structural equation modeling (SEM) and multi-group analyses were employed to test relationships, controlling for gender, age, and education. Model fit was assessed using RMSEA, CFI, and other indices; robustness was verified through alternative specifications, sensitivity checks, and outlier trimming.

Results: Digital literacy had a significant positive effect on self-rated health (β=0.115, p<0.001), comprising a direct effect (β=0.076, p<0.001) and an indirect effect via mental health (β=0.039, p<0.001; mediation proportion=33.9%). Multi-group SEM revealed heterogeneity: effects were strongest in young and middle-aged females (β=0.141–0.143, p<0.001) and weaker in older adults (eg, β=0.050 for females >60, p<0.01). Mental health mediated more strongly in older groups (β=0.500, p<0.001). The model explained 38.5% of variance in self-rated health.

Conclusion: Digital literacy positively influences self-rated health by enhancing resource access and mental well-being, with pronounced benefits for younger and female populations. Policymakers should prioritize age-appropriate digital literacy initiatives with psychological support to reduce disparities, aligning with China's "Healthy China 2030" and "Digital China" strategies.

Keywords: digital literacy, self-rated health, dual pathways, information accessibility, mental health, Healthy China

Introduction

Digital literacy (DL) has been increasingly recognized as an essential determinant of health, influencing how individuals access, understand, and apply information in a digitalized environment.[1] In contrast, digital health literacy (DHL) refers more specifically to individuals' ability to seek, comprehend, and use online health information for disease prevention and health promotion, as defined by the World Health Organization.[2] While related, DL represents a broader skill set encompassing digital access, usage, and entertainment, whereas DHL is a subdomain focused on health-related contexts.[3] This study primarily focuses on digital literacy, which serves as the foundation for developing health-related digital competencies. Meanwhile, as the application of digital technologies expands, it offers new opportunities for healthcare delivery but may also deepen health inequalities.[4] Therefore, equity-oriented digital strategies remain crucial to ensure that innovation benefits all individuals without widening existing disparities.

Relationship between digital literacy and health is multifaceted. On one hand, it facilitates the acquisition and utilization of health information. Through the internet and mobile devices, individuals can more conveniently access medical information, schedule appointments, and participate in online health communities, thereby enhancing self-

Received: 30 August 2025
Accepted: 8 December 2025
Published: 12 December 2025

management capabilities and overall health levels.[5] On the other hand, insufficient digital literacy can lead to an information divide, making vulnerable groups less likely to benefit from digital health services.[6] For example, older adults, low-income populations, and those with lower educational attainment may encounter challenges such as inadequate digital skills, limited device availability, or restricted internet access, placing them at a disadvantage in the digital health era.[7]

Research has demonstrated associations between digital literacy and health behaviors, self-perceived health status, and healthcare utilization.[8] Improving digital literacy can promote enhancements in health-related quality of life. However, inadequate digital literacy also poses risks to patients, such as difficulties in discerning misinformation and potential privacy breaches.[9]

Mental health may serve as a mediator between digital literacy and self-rated health. Enhancing digital literacy can promote mental health, thereby indirectly improving self-rated health.[10] Related studies have found that through participation in online social activities, acquisition of mental health knowledge, and use of mental health applications, individuals can alleviate feelings of loneliness, anxiety, and depression, while strengthening social support and psychological resilience.[11] This mechanism is theoretically supported by the social support theory, which posits that social interaction and perceived support can buffer stress and enhance psychological well-being, and by psychological resilience frameworks, which emphasize individuals' adaptive capacity to cope with challenges through digital engagement and community connection. Together, these perspectives explain how digital literacy fosters emotional stability and mental well-being, thereby linking technological competence with health outcomes. Nevertheless, improper use of digital technologies may also exert negative associations on mental health.

In addition to age and socioeconomic differences, gender also plays a crucial role in shaping digital literacy and health outcomes. Studies have shown that women often engage in digital environments differently from men—prioritizing social communication and health information seeking—while men tend to emphasize instrumental and technical use. Cultural expectations and gender norms may further link digital participation, access to online health resources, and help-seeking behaviors, leading to gender-based disparities in both digital competence and health status. Recognizing these gendered patterns provides an essential foundation for examining heterogeneity in the associations of digital literacy across demographic groups.

In the context of China's rapid digital transformation and aging population, digital literacy has become a crucial factor influencing equitable access to healthcare resources and the overall effectiveness of national health strategies. Despite the country's progress under the "Healthy China 2030" and "Digital China" initiatives, disparities in digital competence across demographic groups continue to shape differences in health outcomes. Understanding how digital literacy affects self-rated health through both direct and mental health–mediated pathways is therefore essential for promoting inclusive health policies and addressing emerging digital inequalities.

Theoretical Framework and Research Gaps

Existing research confirms that digital literacy links health outcomes through pathways such as information acquisition and social participation, but it predominantly focuses on direct associations, with limited systematic validation of potential transmission paths like mental health.[12] It is essential to integrate structural equation modeling (SEM) with multi-group analysis to systematically deconstruct the dynamic link mechanisms of digital literacy on self-rated health. Digital health literacy may exert a mediating effect between digital literacy and mental health, whereby digital literacy could link individuals' digital health literacy and, in turn, affect their mental health. Furthermore, studies addressing the unique social context of China's transitional period remain scarce. There is a pressing need for more empirical research grounded in China's national conditions to elucidate the associations between digital literacy and health.

This study breaks through traditional paradigms by constructing a three-dimensional evaluation system encompassing digital access, usage intensity, and entertainment participation. Combined with structural equation modeling (SEM) and multi-group analysis, it systematically deconstructs the dynamic link mechanisms of digital literacy on self-rated health. The research hypotheses are as follows:

H1: Digital literacy is significantly positively correlated with self-rated health;

https://doi.org/10.2147/RMHP.S560744

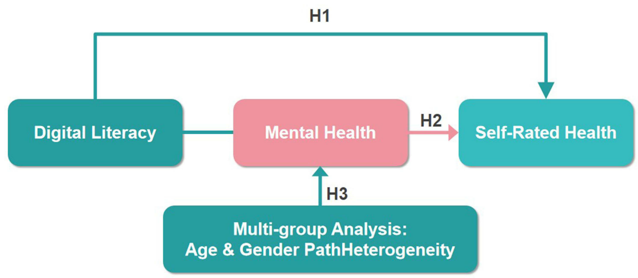

Figure 1 Conceptual Framework: Pathways Linking Digital Literacy, Mental Health, and Self-Rated Health with Heterogeneity Across Demographic Groups.

H2: Mental health plays a partial mediating role in the association between digital literacy and health;

H3: The health associations of digital literacy exhibit heterogeneity across age and gender.

Figure 1 presents the conceptual framework delineating the hypothesized pathways through which digital literacy links self-rated health, with mental health serving as a partial mediator.

Methods

Data

This study draws on data from the 2023 Chinese General Social Survey (CGSS 2023), recognized as the largest and most authoritative nationwide social survey in mainland China. Organized by Renmin University of China and implemented by the China Survey Data Center, CGSS systematically compiles extensive and continuous information on social structure, quality of life, and public opinion. Since its inception in 2003, it has conducted annual cross-sectional surveys using a multistage, stratified probability sampling strategy, reaching approximately 10,000 households across 31 provinces, autonomous regions, and municipalities. Over the past two decades, this dataset has served as an indispensable resource for empirical research and policy evaluation in the social sciences.

The data collection procedures adhered strictly to ethical standards aligned with the Declaration of Helsinki. All survey protocols were reviewed and approved by the Ethics Committee of Renmin University of China, and informed consent was obtained from participants during fieldwork. The CGSS 2023 dataset employed in this study is publicly accessible and fully anonymized, ensuring compliance with all ethical requirements. Accordingly, no additional ethical approval or informed consent was required for this secondary analysis.

This research included all respondents from the CGSS 2023 dataset, resulting in a total of 8,039 valid cases. These data provide a robust empirical foundation for examining the pathways linking digital literacy, Self-Rated Health, mental health, and socioeconomic outcomes in the Chinese population.

Measure

Independent Variable: Digital Literacy

Digital literacy is the core independent variable in this study. Building on the conceptualizations of Liu et al[13] and international frameworks on digital competence,[14,15] digital literacy is conceptualized as the ability to engage with digital tools and resources in everyday life to obtain information, communicate, learn, and participate in social and economic activities.

Although digital literacy may encompass operational, critical, and evaluative skills, the CGSS dataset primarily captures behavioral engagement with digital technologies. Therefore, the measurement adopted in this study reflects the behavioral application dimension of digital literacy rather than task-based skill proficiency. This aligns with population-level research in which digital literacy is operationalized through observable digital participation patterns when direct assessments of skill competence are unavailable.[16,17] Accordingly, the index reflects the intensity and breadth of digital engagement in everyday contexts, rather than the ability to perform specific technical operations.

Preprocessing and Normalization

Binary items (mobile phone ownership and recent Internet access) were recoded to 0 = No and 1 = Yes, while the two Likert-scale items (Internet use frequency and leisure web surfing, originally measured on a 1–5 scale) were normalized to the [0,1] interval using min–max scaling. The detailed formulas for entropy weighting, TOPSIS closeness coefficient computation, and the full step-by-step index construction workflow are provided in the Supplementary Material.

Entropy–TOPSIS Index Construction

Four behavioral indicators across three dimensions—digital access, usage frequency, and digital entertainment—were integrated into a composite index (Tables 1–3). Indicator weights were determined using the entropy weighting method, and the final index was computed using the TOPSIS procedure.[18]

This combined entropy-TOPSIS approach minimizes subjective weighting bias and enables an objective synthesis of multidimensional behavioral data. Higher index values indicate stronger levels of digital literacy.

Dependent Variable: Self-Rated Health

Self-Rated Health serves as the core dependent variable in this study. Idler and Benyamini[19] demonstrated that self-rated health is a widely accepted and reliable indicator of individuals' overall health status. Zhou[20] further highlighted that self-assessments of health among the general population show high levels of reliability and validity in capturing both physical and mental health dimensions.

Accordingly, the outcome variable is renamed as "Self-Rated Health (SRH)" rather than "Physical Health" to more accurately reflect the conceptual scope of the CGSS item used in this study. SRH was measured by the CGSS 2023 question: "Overall, how would you rate your health status (including both physical and mental health)?" Responses were coded as follows: "Very Poor" = 1, "Poor" = 2, "Moderate" = 3, "Good" = 4, "Very Good" = 5. Higher scores indicate better overall self-rated health, providing a robust dependent variable for analyzing population-level health outcomes.

Table 1 The Index System of Digital Literacy Measurement

Category	Dimension	Corresponding Item	Assignment Method	Attribute
Digital Literacy	Digital Access	A30a. Do you have a mobile phone for your personal use?	Yes = 5; No = 1	(+)
	Digital Usage	[5. Internet (including mobile internet)] A28. In the past year, how often did you use the following media?	Never = 1; Rarely = 2; Sometimes = 3; Often = 4; Very Often = 5	(+)
		A30b. In the past six months, have you accessed the Internet (including via computer, mobile phone, smart devices)?	Yes = 5; No = 1	(+)
	Digital Entertainment	[12. Internet surfing] A30. In the past year, how often did you engage in the following activities during leisure time?	Never = 1; Rarely = 2; Sometimes = 3; Often = 4; Very Often = 5	(+)

Table 2 Descriptive Statistics of Digital Literacy Indicators

Dimension	Corresponding Item	Mean	SD	Min	Max
Digital Access	A30a. Do you have a mobile phone for your personal use?	1.95	0.223	1	2
Digital Usage	[5. Internet (including mobile internet)] A28. In the past year, how often did you use the following media?	3.33	1.670	1	5
	A30b. In the past six months, have you accessed the Internet (including via computer, mobile phone, smart devices)?	1.70	0.459	1	2
Digital Entertainment	[12. Internet surfing] A30. In the past year, how often did you engage in the following activities during leisure time?	3.55	1.806	1	5

Table 3 Correlation Matrix of Digital Literacy Indicators (Spearman)

Indicator	1	2	3	4
1.Digital Access	1			
2.Digital Usage (Frequency)	0.272***	1		
3.Digital Usage (Internet Access)	0.320***	0.785***	1	
4.Digital Entertainment	0.281***	0.837***	0.839***	1

Notes: Spearman rank-order correlation coefficients reported. ***p < 0.001.

Although SRH encompasses both physical and psychological health dimensions, it is widely recognized in population health research as a valid and theoretically appropriate global health indicator. We acknowledge that this conceptual scope may introduce some proximity to the mediating variable of mental health; however, this overlap does not compromise the validity of the mediation analysis and is addressed transparently as a methodological limitation in the Discussion section.

Mediating Variable: Mental Health

Mental health is specified as the mediating variable in this study. It reflects respondents' subjective evaluation of their psychological well-being, particularly emotional states related to depression and low mood. Drawing on the framework proposed by Deng,[21] we measure mental health using survey items from the 2023 Chinese General Social Survey (CGSS).

In this study, mental health was assessed through the CGSS 2023 question: "How frequently do you feel depressed or in low spirits?" Responses were coded as follows: "Very Poor" =1, "Poor" =2, "Moderate" =3, "Good" =4, "Very Good" =5. Higher scores indicate better mental health status, enabling the analysis of its mediating role between digital literacy and physical health.

Although this measure is based on a single survey item, single-item indicators of depressive affect and emotional distress are widely used in national and international population health surveys (eg, World Values Survey, European Social Survey), particularly when multi-item psychological scales such as the CES-D are not included. Prior empirical studies have demonstrated that single-item mood and distress measures show acceptable convergent validity and predictive utility, especially when the construct of interest reflects global affective experience rather than clinical diagnostic categories.[22,23]

Moreover, while both mental health and self-rated health originate from the same survey source, the two variables represent conceptually distinct domains (emotional well-being vs perceived physical condition), reducing the risk of common-method inflation. Consistent with established practice in large-scale social surveys and given the absence of multi-item psychological scales in CGSS 2023, the use of this single-item indicator is theoretically justified, empirically supported, and contextually appropriate.

Control Variables

To control for individual background characteristics and enhance the robustness of the model estimation, this study incorporates three key demographic variables as controls. Gender is coded as 1 = female and 2 = male. For descriptive statistics we report Age in years, but in regression models we include Year of Birth (YOB) as a continuous predictor; under this coding, a higher YOB value indicates a younger respondent. Education level reflects individuals' human capital accumulation and is included as an ordinal variable ranging from 1 to 5, where 1=No Formal Education, 2=Basic Education, 3=Secondary Education, 4=Higher Education, and 5=Postgraduate and Above. These control variables are critical for minimizing bias and ensuring a more precise estimation of the relationships between digital literacy, mental health, and physical health.

 https://doi.org/10.2147/RMHP.S560744

Sample Inclusion and Missing Data Handling

The analytical sample comprised all adult respondents (aged 18 years and above) from the 2023 Chinese General Social Survey (CGSS) who provided valid responses for the key variables in this study—digital literacy indicators, mental health, self-rated health, and control variables.

The overall item-level missingness across all variables was below 5%. Cases with missing data on any of the key variables were addressed through listwise deletion, resulting in a final analytical sample of 8,039 valid observations. Given the minimal level of missingness and the absence of systematic patterns, this approach ensured data integrity without introducing substantial bias.

Statistical Analysis

This study adopted a comprehensive analytical strategy to systematically examine the relationship between digital literacy, mental health, and Self-Rated Health. Initially, descriptive statistics were computed to summarize the demographic characteristics of the sample and the distribution of key variables, with means and standard deviations reported for continuous variables and frequencies and percentages for categorical variables. Pearson correlation coefficients were then calculated to explore bivariate associations among digital literacy, mental health, and Self-Rated Health, providing a preliminary empirical basis for model specification.

Building on this foundation, stepwise multiple linear regression models were estimated to assess the direct associations of digital literacy with Self-Rated Health, progressively introducing control variables to evaluate changes in explanatory power and coefficient stability. To rigorously test the hypothesized mediation pathways, Structural Equation Modeling (SEM) was employed using the Maximum Likelihood estimation method. The significance of indirect associations was determined through the bias-corrected bootstrap method with 5,000 resamples and 95% confidence intervals, and model fit was assessed using standard indices such as the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

Robustness checks were conducted to validate the stability of the findings, including winsorizing outliers, alternative operationalizations of key variables, and re-estimation of models within subgroups. Continuous variables (digital literacy, mental health, self-rated health, and age) were winsorized at the 1st and 99th percentiles to mitigate the influence of extreme values while preserving the integrity of the dataset. This approach reduced the leverage of outliers without affecting the overall distributional structure, ensuring robustness of the statistical inferences.

The Chinese General Social Survey (CGSS) employs a multistage, stratified probability sampling strategy to ensure population representativeness. However, the publicly released CGSS dataset does not include identifiers for sampling strata or primary sampling units (PSUs) due to confidentiality restrictions, which makes full design-based variance estimation infeasible. In line with prior CGSS-based studies published in Population and Development and Frontiers in Public Health, this study conducted unweighted regression and SEM analyses with heteroscedasticity-consistent (HC) standard errors. The individual weight variable was applied in descriptive statistics to approximate population proportions, and robustness checks confirmed that incorporating weights did not materially alter the coefficients and significance levels. Therefore, the results are considered stable with respect to the survey design.

All data processing and statistical analyses were carried out using R software (version 4.3.0). Prior to model estimation, the distributional properties of key variables were examined; skewness and kurtosis indicated no severe departures from normality, and multicollinearity diagnostics showed all variance inflation factors (VIFs) below 2, suggesting that the assumptions for SEM estimation were satisfied. All analyses were conducted using fully scripted and version-controlled R code with fixed random seeds to ensure reproducibility. The complete variable recoding procedures and model syntax are available from the corresponding author upon reasonable request.

Results

Descriptive Statistics

Table 4 presents the descriptive statistics for all variables included in the analysis. The average score for digital literacy was 3.22 (SD = 1.51), ranging from 1.00 to 4.63, indicating a moderate level of digital engagement among the respondents. The mean mental health score was 3.94 (SD = 1.08), with 40.5% of participants rating their mental health

Table 4 Basic Variable Description Statistics

Variable	Samples	Mean/Percentage	Standard Deviation	Min	Max
Digital Literacy	8039	3.22	1.51	1	4.63
Mental Health	8039	3.94	1.08	1	5
Very Poor = 1 Poor = 2 Moderate = 3 Good = 4 Very Good = 5	2.50% 8.20% 22.30% 26.50% 40.50%				
Self-Rated Health	8039	3.71	1.05	1	5
Very Poor = 1 Poor = 2 Moderate = 3 Good = 4 Very Good = 5	2.50% 9.90% 16.40% 34.30% 37.00%				
Gender	8039	1.55	0.50	1	2
Female = 1 Male = 2	45.20% 54.80%				
Age	8039	55.55	17.54	22	103
Education Level	8039	2.50	0.97	1	5
No Formal Education = 1 Basic Education = 2 Secondary Education = 3 Higher Education = 4 Postgraduate and Above = 5	11.10% 49.90% 18.40% 19.20% 1.40%				

as "very good" and 26.5% as "good," whereas only 2.5% reported "very poor" mental health. Self-Rated Health had a mean score of 3.71 (SD = 1.05), with 37.0% of respondents rating their Self-Rated Health as "very good" and 34.3% as "good." By contrast, only 2.5% reported "very poor" Self-Rated Health.

Regarding demographic variables, females accounted for 45.2% of the sample, while males represented 54.8%. The average age of respondents was 55.55 years (SD = 17.54), with a range from 22 to 103 years. In terms of education level, 11.1% of participants reported having no formal education, 49.9% had attained basic education, 18.4% had completed secondary education, 19.2% had higher education, and only 1.4% held a postgraduate degree or above.

These results provide a clear overview of the sample characteristics and establish the empirical foundation for subsequent analyses. The range of the digital literacy index (1.00–4.63) results from the entropy–TOPSIS normalization procedure, rather than a raw Likert scale.

Correlation Analysis

Table 5 presents the Pearson correlation coefficients among the key variables. Digital literacy was positively and significantly associated with both mental health ($r=0.149$, $p<0.001$) and Self-Rated Health ($r=0.363$, $p<0.001$), indicating that individuals with higher levels of digital literacy tend to report better mental and Self-Rated Health. Mental health also demonstrated a strong positive correlation with Self-Rated Health ($r=0.507$, $p<0.001$).

Gender showed a negligible and statistically insignificant correlation with digital literacy ($r = -0.004$, ns), indicating no meaningful relationship between the two variables. A weak but significant negative correlation was observed between gender and education level ($r = -0.11$, $p < 0.001$), suggesting minor gender differences in educational attainment. Given

Table 5 Pearson's Correlations Among Relevant Study Variables

Variables	1	2	3	4	5	6
1. Digital Literacy	1	0.149***	0.363***	−0.004	−0.637***	0.520***
2. Mental Health		1	0.507***	−0.105***	−0.090***	0.148***
3. Self-Rated Health			1	−0.052***	−0.386***	0.308***
4. Gender				1	−0.033**	−0.105***
5. Age					1	−0.530***
6. Education Level						1

Notes: ** < 0.01; ***p < 0.001.

the coding of gender (female = 1, male = 2), the negative correlation between gender and Self-Rated Health ($r = -0.05$, $p < 0.001$) indicates slightly lower health ratings among males.

Age was negatively correlated with both digital literacy ($r = -0.64$, $p < 0.001$) and education level ($r = -0.53$, $p < 0.001$), reflecting generational differences in access to digital technologies and educational opportunities. Education level, in contrast, was positively correlated with both digital literacy ($r = 0.52$, $p < 0.001$) and mental health ($r = 0.15$, $p < 0.001$).

OLS Regression Results

Table 6 reports the results of stepwise Ordinary Least Squares (OLS) regression models examining the associations among demographic characteristics, digital literacy, mental health, and Self-Rated Health.

In Model 1, gender (β=−0.101, SE=0.0216, p<0.001), Year of Birth (β=−0.0188, SE=0.0007, p<0.001), and education level (β=0.1456, SE=0.0131, p<0.001) were significantly associated with Self-Rated Health, accounting for 16.6% of the variance (R^2=0.166). Given the coding (female=1, male=2), the negative coefficient on Gender indicates that males tended to report lower Self-Rated Health. Because Age entered the model as Year of Birth (higher values = younger), the negative coefficient implies that respondents from later birth cohorts (ie, younger) tended to report lower Self-Rated Health. In Model 2, digital literacy was introduced and found to be positively associated with Self-Rated Health (β=0.1148, SE=0.0094, p<0.001). After including digital literacy, the coefficients for gender (β=−0.103, SE=0.0215, p<0.001) and education level (β=0.1000, SE=0.0135, p<0.001) slightly attenuated, while Year of Birth (β=−0.0139, SE=0.0008, p<0.001) remained significant. The explanatory power of the model increased modestly (R^2=0.181).

Table 6 Stepwise OLS Regression Results Predicting Self-Rated Health

Variables	Model 1	Model 2	Model 3
Gender	−0.101*** (0.0216)	−0.103*** (0.0215)	−0.012 (0.0187)
Year of Birth	−0.0188*** (0.0007)	−0.0139*** (0.0008)	−0.0148*** (0.0007)
Education Level	0.1456*** (0.0131)	0.1000*** (0.0135)	0.0540*** (0.0117)
Digital Literacy		0.1148*** (0.0094)	0.0759*** (0.0082)
Mental Health			0.4439*** (0.0086)
Constant (b)	4.551***	4.0235***	2.4241***
Constant (t)	−59.23	−45.912	−29.538
N	8039	8039	8039
R^2	0.166	0.181	0.385

Notes: Gender coded 1 = Female, 2 = Male; Education Level ranges 1–5 (1 = No formal education, 5 = Postgraduate+); Year of Birth: higher values = younger; Age (years) is used in descriptive statistics only. ***p < 0.001.

 https://doi.org/10.2147/RMHP.S560744

In Model 3, mental health was added as a potential mediator. Mental health showed a strong positive association with Self-Rated Health (β=0.4439, SE=0.0086, p<0.001). The effect of digital literacy on Self-Rated Health decreased but remained significant (β=0.0759, SE=0.0082, p<0.001), suggesting partial mediation. The coefficient for Gender became non-significant (β=−0.012, SE=0.0187, ns), consistent with the notion that gender differences in SRH are largely explained by digital literacy and mental health in the full model. Model 3 explained 38.5% of the variance in Self-Rated Health (R^2=0.385), representing a substantial improvement over the previous models.

Robustness Check

Table 7 summarizes the results of robustness checks for the OLS regression models predicting Self-Rated Health. The baseline model showed that digital literacy (β=0.0759, SE=0.0082, p<0.001) and mental health (β=0.4439, SE=0.0086, p<0.001) were significant predictors of Self-Rated Health. Education level also demonstrated a positive association (β=0.0540, SE=0.0117, p<0.001), while gender remained non-significant (β=−0.012, SE=0.0187, ns).

To examine the robustness of the results, several alternative model specifications were estimated. In the robust standard error model, all coefficients remained virtually unchanged, indicating that heteroscedasticity had little influence on the estimates. The alternative measurement model employed a different operationalization of digital literacy, in which the four behavioral indicators were combined using equal weighting rather than the entropy–TOPSIS weighting scheme. The resulting coefficient for digital literacy (β=0.1437, SE=0.0219, p<0.001) was slightly larger due to differences in the scale of measurement, but the direction and significance remained consistent with the baseline model.

A log-transformed model was also tested to check whether mild skewness in continuous variables (digital literacy and Self-Rated Health) affected the results. The findings were nearly identical to those of the baseline model (β=0.0710, SE=0.0071, p<0.001). Finally, a trimmed model was estimated after excluding extreme values to ensure that outliers did not unduly affect the estimates. Because only a small number of observations were affected, the results remained unchanged from the baseline model.

Overall, model fit and coefficient patterns were stable across all specifications (R^2 ranging from 0.377 to 0.385). These robustness checks collectively confirm that the observed associations are not sensitive to alternative scaling, transformation, or outlier treatment procedures, thereby strengthening the reliability of the findings.

Path Analysis and Mediation (Observed-Variable Model)

Table 8 reports the standardized path coefficients from the observed-variable path model estimated within an SEM framework. Because all constructs are measured by single observed indicators, the model is just identified (df = 0). Therefore, global fit indices such as RMSEA and CFI are mathematically fixed and not informative for model evaluation. Consistent with methodological guidance for saturated models, our interpretation focuses on the magnitude and statistical significance of the estimated paths rather than on fit statistics. This approach ensures that the reported associations reflect the theoretical structure rather than fit artifacts.

Digital literacy had significant direct associations with mental health (β = 0.088, SE = 0.011, CR = 8.109, p < 0.001) and Self-Rated Health (β = 0.076, SE = 0.009, CR = 8.528, p < 0.001). Mental health showed a strong positive effect on

Table 7 Robustness Check Results for OLS Regression Models

Variables	Baseline Model	Robust SE Model	Alternative Measure Model	Log-Transformed Model	Trimmed Model
Digital Literacy	0.0759*** (0.0082)	0.0759*** (0.0091)	0.1437*** (0.0219)	0.0710*** (0.0071)	0.0759*** (0.0082)
Mental Health	0.4439*** (0.0086)	0.4439*** (0.0098)	0.4479*** (0.0086)	0.4683*** (0.0092)	0.4439*** (0.0086)
Education Level	0.0540*** (0.0117)	0.0540*** (0.0130)	0.0674*** (0.0116)	0.0146*** (0.0029)	0.0540*** (0.0117)
Gender	−0.012 (0.0187)	−0.012 (0.0186)	−0.0105 (0.0187)	−0.0026 (0.0047)	−0.012 (0.0187)
Year of Birth	−0.0148*** (0.0007)	−0.0148*** (0.0007)	−0.0168*** (0.0007)	−0.0033*** (0.0002)	−0.0148*** (0.0007)
R^2	0.385	0.385	0.381	0.377	0.385

Notes: ***p < 0.001.

Table 8 Structural Equation Modeling Results: Direct, Indirect, and Total Associations

Model Paths			S.E.	C.R.	P	Direct Effect	Indirect Effect	Total Effect
Mental Health	←	Digital Literacy	0.011	8.109	***	0.088	—	0.088
Mental Health	←	Gender	0.024	−8.591	***	−0.205	—	−0.205
Mental Health	←	Age	0.001	2.435	*	0.002	—	0.002
Mental Health	←	Education Level	0.015	7.068	***	0.104	—	0.104
Self-Rated Health	←	Mental Health	0.01	44.968	***	0.444	—	0.444
Self-Rated Health	←	Digital Literacy	0.009	8.528	***	0.076	—	0.076
Self-Rated Health	←	Gender	0.019	−0.662	ns	−0.012	—	−0.012
Self-Rated Health	←	Age	0.001	−21.064	***	−0.015	—	−0.015
Self-Rated Health	←	Education Level	0.011	4.902	***	0.054	—	0.054
Indirect (Digital Literacy→Mental Health→Self-Rated Health)			0.005	7.946	***	—	0.039	0.039
Total (Digital Literacy→Self-Rated Health)			0.01	11.24	***	0.076	0.039	0.115

Notes: *p < 0.05; ***p < 0.001. ← denotes the direction of the modeled path (from predictor to outcome).

Self-Rated Health (β = 0.444, SE = 0.010, CR = 44.968, $p < 0.001$). The indirect association of digital literacy with Self-Rated Health through mental health was also significant (β = 0.039, SE = 0.005, CR = 7.946, $p < 0.001$), yielding a total association of β = 0.115 ($p < 0.001$).

Control variables demonstrated expected patterns: education level was positively associated with both mental health (β = 0.104, $p < 0.001$) and Self-Rated Health (β = 0.054, $p < 0.001$); gender negatively predicted mental health (β = –0.205, $p < 0.001$) but had no significant association with Self-Rated Health; age was positively associated with mental health (β = 0.002, $p < 0.05$) and negatively with Self-Rated Health (β = –0.015, $p < 0.001$).

Table 9 presents the identification indices of the path model estimated within the SEM framework. Because all variables in the mediation structure are observed, the model is saturated (df = 0). In such models, the sample covariance matrix is perfectly reproduced ($\chi^2 = 0$), and global fit indices (eg, RMSEA, GFI, CFI) take fixed values that do not provide meaningful information about model adequacy.

Accordingly, the values reported in Table 9 (RMSEA = 0; GFI, AGFI, NFI, NNFI, IFI = 1.000) reflect the inherent mathematical properties of a saturated specification rather than empirical evidence of excellent model fit. These statistics therefore indicate model identification rather than comparative model quality.

Given this structure, the evaluation of model adequacy relies on the theoretical justification of the specified relationships and the statistical significance of the estimated paths, rather than on global fit indices. This practice aligns with methodological recommendations for mediation analyses based solely on observed variables.

Multi-Group SEM Analysis

Table 10 reports the results of the multi-group structural equation modeling (SEM), providing insights into potential heterogeneity across gender and age groups in the pathways linking digital literacy, mental health, and Self-Rated Health.

Table 9 Model Fit Indices for the Structural Equation Model

Index	χ^2/df	RMSEA	GFI	AGFI	NFI	NNFI	IFI
Acceptable values	< 3	<0.08	>0.90	>0.90	>0.90	>0.90	>0.90
Observed values	—	0	1	1	1	1	1

Table 10 Multi-Group SEM Results by Gender and Age Groups

Variables	Male <40	Male 40–60	Male >60	Female <40	Female 40–60	Female >60
Digital Literacy (A1)	0.1048* (0.0478)	0.1307*** (0.0222)	0.0888*** (0.0173)	0.1407*** (0.0354)	0.1429*** (0.0188)	0.0502** (0.0169)
Mental Health (B1)	0.3326*** (0.0216)	0.4762*** (0.0231)	0.4400*** (0.0217)	0.3179*** (0.0191)	0.4452*** (0.0187)	0.5001*** (0.0189)
Education Level (d3)	0.0321 (0.0220)	0.1242*** (0.0285)	0.0879* (0.0352)	−0.0137 (0.0201)	0.0626* (0.0259)	0.0847** (0.0328)
R^2	0.227	0.318	0.24	0.223	0.323	0.317

Notes: *p < 0.05; ** < 0.01; ***p < 0.001.

The analyses revealed that digital literacy consistently exerted a positive linked to Self-Rated Health across all subgroups, though the magnitude of these associations varied. Among males, the strength of association was most pronounced in the middle-aged group (β=0.1307, p<0.001), while attenuated slightly in the older cohort (β=0.0888, p<0.001). In contrast, females under 40 demonstrated the highest magnitude of association (β=0.1407, p<0.001), followed closely by those aged 40–60 (β=0.1429, p<0.001), whereas the effect in females over 60 was comparatively weaker (β=0.0502, p<0.01). These patterns suggest that younger and middle-aged individuals, particularly women, may benefit more from digital engagement in promoting Self-Rated Health, potentially reflecting generational differences in technology adoption and utilization.

Mental health emerged as a robust and consistent predictor of Self-Rated Health across all subgroups, with magnitude of associations ranging from β=0.3179 (p<0.001) among younger females to β=0.5001 (p<0.001) in older females. Notably, the stronger associations observed in older age groups underscore the heightened importance of psychological well-being in supporting Self-Rated Health among aging populations.

Relationship between education level and Self-Rated Health showed heterogeneity as well. While positive and significant in most subgroups, the association was not statistically significant among younger males (β=0.0321, ns) and younger females (β=−0.0137, ns), suggesting that educational attainment may play a less critical role in health outcomes for younger cohorts compared to older adults.

The explanatory power of the models, as reflected in R^2 values, ranged from 22.3% to 32.3% across the six subgroups, indicating substantial variance accounted for by the predictors. Collectively, these findings highlight the necessity of adopting age- and gender-sensitive approaches when designing interventions to enhance health outcomes through digital literacy and mental health pathways.

Discussion

Theoretical and Practical Implications of Core Findings

This study used a multidimensional digital literacy framework and structural equation modeling to explain how digital literacy relates to self-rated health among Chinese adults. It found both a direct association (β = 0.076, p < 0.001) and an indirect association through mental health (β = 0.039, p < 0.001), resulting in a total association of β = 0.115 (p < 0.001). These findings clarify the "digital–health" connection and highlight digital literacy as a form of resource empowerment. Individuals with stronger digital abilities tend to make better health-related decisions and maintain stronger social networks that support psychological resilience within the social determinants of health framework (SDH).[24] In practice, improving digital literacy may contribute to population health, but claims about national-level interventions should remain cautious until confirmed by longitudinal or policy-based evidence.[25]

Methodological Breakthrough in Multidimensional Indicator Construction

This research addressed prior methodological gaps by developing a multidimensional digital literacy index using entropy weighting and the TOPSIS method. The composite index explained health outcomes more effectively than single indicators such as device ownership (R^2 = 0.385). Incorporating the entertainment dimension (eg, leisure internet use) revealed that non-instrumental digital activities were also positively associated with mental health (β = 0.088, p < 0.001), a finding consistent with emerging evidence that moderate entertainment use can enhance social connectedness and emotional well-being.[26]

 https://doi.org/10.2147/RMHP.S560744

Social Structural Roots of Group Heterogeneity

Multi-group SEM analysis revealed distinct age- and gender-related variations. The association between digital literacy and health declined with age (β = 0.1407 for young females vs β = 0.0502 for older females), reflecting intergenerational digital inequality. Older adults often face learning barriers (r = –0.637, p < 0.001) and limited age-friendly design, a pattern consistent with the "digital aging paradox".[27] Gender patterns also differed: middle-aged women showed stronger associations (β = 0.1429), possibly because digital tools assist them in family health management. Among men, the association peaked in middle age (β = 0.1307) but was non-significant among younger men (β = 0.0321, ns). This may indicate a "ceiling effect" in health literacy rather than a confirmed saturation effect; future research should test this with larger samples and more refined behavioral indicators.

Mechanisms of Mental Health Mediation

This study is among the first in China to confirm mental health as a mediator, explaining 33.9% of the total association between digital literacy and self-rated health. Digital literacy was associated with fewer depressive symptoms by fostering social support (β = 0.088), which in turn improved self-rated health (β = 0.444). Individuals with higher digital literacy were more capable of accessing credible health information and avoiding risky behaviors, particularly among older adults (β = 0.5001). However, excessive digital engagement may lead to psychological fatigue; future research should examine this potential "digital burnout" phenomeno.[28] Importantly, reverse causality cannot be ruled out—better mental health may also encourage greater digital engagement.

Study Limitations and Future Directions

Several limitations should be acknowledged. First, the cross-sectional CGSS 2023 data cannot establish causality. The SEM paths reflect statistical associations, and reverse causation remains possible. Longitudinal or quasi-experimental designs are recommended to determine temporal order. Second, self-rated health captures overall perceptions and may partly overlap with psychological well-being; future studies could include objective measures (eg, chronic conditions or biomarkers) to improve construct separation. Third, mental health was measured with a single item—a common but limited practice. Subsequent research should adopt validated multi-item scales for greater reliability. Finally, the digital entertainment dimension focused on usage frequency; future work should differentiate between health-related and non-health-related content to enhance behavioral interpretation.

Conclusion

Using nationally representative data, this study constructed a multidimensional digital literacy framework to explore its association with self-rated health among Chinese adults. The analysis identified two key pathways—direct resource empowerment and indirect mediation through mental health—underscoring digital inclusion as a crucial social determinant of health. Rather than emphasizing numerical coefficients, the results collectively indicate that individuals with higher levels of digital literacy are more likely to report better self-perceived health, partly through enhanced psychological well-being and improved access to reliable health information. Beyond statistical significance, this finding implies that mental health serves as a lever in translating digital participation into tangible health benefits, suggesting that digital interventions should also incorporate psychological support mechanisms.

At the construct level, the three dimensions of digital literacy—access, usage, and entertainment—exert differentiated influences. Access provides fundamental opportunities for online health engagement, usage promotes informational efficiency and self-efficacy, and entertainment activities may relieve psychological stress and strengthen social connectedness. This multidimensional perspective deepens understanding of how diverse forms of digital participation contribute to overall well-being.

Subgroup analyses reveal distinct patterns: younger and middle-aged women gain the greatest health benefits from digital engagement, whereas older adults and low-education rural groups remain most vulnerable to digital exclusion. This contrast highlights the need for stratified policy design: developing age-friendly interfaces and digital training for older populations, while improving infrastructural and skill-based inclusion for disadvantaged rural users.

 https://doi.org/10.2147/RMHP.S560744

From a policy perspective, these results provide evidence-based insights rather than prescriptive solutions. Integrating digital literacy enhancement into national health initiatives (eg, Healthy China 2030) holds promise but requires cautious evaluation of large-scale programs such as "digital health counselors" through pilot and longitudinal studies. Future research should examine how digital-skill interventions can be embedded within community health systems to achieve equitable and sustainable outcomes. Finally, given the cross-sectional nature of the data and the single-item measure of mental health, causal interpretations should be made cautiously. Longitudinal validation and multi-dimensional psychological measures will be essential for future improvement. By coupling technological access with mental and social empowerment, digital technologies can evolve from instruments of privilege into foundations of health equity.

Highlights

Digital literacy positively influences links self-rated health via dual pathways: direct (β=0.076) and mental health-mediated (β=0.039), with a total effect of β=0.115.

A one-standard-deviation increase in digital literacy elevates self-rated health by 11.5%, underscoring its role as a social determinant of health.

Age and gender heterogeneity is evident, with stronger effects associations in young and middle-aged females; older adults face barriers due to digital exclusion.

Innovative entropy-TOPSIS index outperforms unidimensional measures, enhancing explanatory power (R^2=0.385) by capturing access, usage, and entertainment dimensions.

Findings advocate for targeted policies integrating digital skills training with mental health services to promote health equity in China.

Data Sharing Statement

The data that support the findings of this study are available from Chinese General Social Survey (CGSS, http://cgss.ruc.edu.cn/English/Home.htm). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the corresponding author.

Informed Consent Statement

The survey program of the Chinese General Social Survey (CGSS) was organized by Renmin University of China (RUC). The CGSS adhered to the ethical standards of the RUC Ethics Committee. Informed consent was obtained from all individual participants prior to their involvement in the original study. For the secondary analysis of de-identified data in the current study, all procedures were reviewed and exempted from further ethical review by the Institutional Review Board (IRB) of Hubei University of Arts and Science, in accordance with national guidelines for secondary data analysis. This exemption was granted because the study utilized anonymized data previously collected under the CGSS framework, and no direct interaction with participants was required. The study protocol conformed to the principles of the 1964 Helsinki Declaration and its subsequent amendments, as well as comparable ethical standards.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

The authors report no conflicts of interest in this work.

References

1. López A, Ong BA, Borrat Frigola X, et al. Digital literacy as a new determinant of health: a scoping review. *PLOS Digital Health*. 2023;2(10): e0000279. doi:10.1371/journal.pdig.0000279

2. Patel S, Sreelal BS, Kalyani S, et al. Digital health literacy among the ageing population: a comparative cross-sectional study between rural and urban Telangana, India. *Med J Armed Forces India*. 2024;80(3):313–319. doi:10.1016/j.mjafi.2023.09.006
3. Sambah F, Quansah F, Srem-Sai M, et al. Assessing secondary school students' digital health literacy, information searching behaviours, and satisfaction with online COVID-19 information in Northern Ghana. *Heliyon*. 2023;9(7):e17936. doi:10.1016/j.heliyon.2023.e17936
4. Gallifant J, Celi LA, Pierce RL. Digital determinants of health: opportunities and risks amidst health inequities. *Nat Rev Nephrol*. 2023;19 (12):749–750. doi:10.1038/s41581-023-00763-4
5. Wu P, Zhang R, Zhu X, Liu M. Factors Influencing Continued Usage Behavior on Mobile Health Applications. *Healthcare*. 2022;10(2):208. doi:10.3390/healthcare10020208
6. Spanakis P, Peckham E, Mathers A, Shiers D, Gilbody S. The digital divide: amplifying health inequalities for people with severe mental illness in the time of COVID-19. *Br J Psychiatry*. 2021;219(4):529–531. doi:10.1192/bjp.2021.56
7. Liu S, Lu Y, Wang D, et al. Impact of digital health literacy on health-related quality of life in Chinese community-dwelling older adults: the mediating effect of health-promoting lifestyle. *Front Public Health*. 2023;11:1200722. doi:10.3389/fpubh.2023.1200722
8. Bíró É, Vincze F, Nagy-Pénzes G, Ádány R. Investigation of the relationship of general and digital health literacy with various health-related outcomes. *Front Public Health*. 2023;11:1229734. doi:10.3389/fpubh.2023.1229734
9. Kozelka EE, Acquilano SC, Al-Abdulmunem M, et al. Documenting the digital divide: identifying barriers to digital mental health access among people with serious mental illness in community settings. *SSM - Mental Health*. 2023;4:100241. doi:10.1016/j.ssmmh.2023.100241
10. Yang J, Li Y, Gao R, Chen H, Yang Z. Relationship between mental health literacy and professional psychological help-seeking attitudes in China: a chain mediation model. *BMC Psychiatry*. 2023;23(1):956. doi:10.1186/s12888-023-05458-5
11. Chen T, Ou J, Li G, Luo H. Promoting mental health in children and adolescents through digital technology: a systematic review and meta-analysis. *Front Psychol*. 2024;15:1356554. doi:10.3389/fpsyg.2024.1356554
12. Zhao X, Stadnick NA, Ceballos-Corro E, et al. Facilitators of and Barriers to Integrating Digital Mental Health Into County Mental Health Services: qualitative Interview Analyses. *JMIR Form Res*. 2023;7:e45718. doi:10.2196/45718
13. Liu D, Yang K, Sun S. Digital literacy and life satisfaction among rural households: an empirical analysis based on CGSS data. *J Shandong Agric Univ*. 2025;27(01):42–45.
14. Eshet-Alkali Y, Amichai-Hamburger Y. Experiments in digital literacy. *Cyberpsychol Behav*. 2004;7(4):421–429. doi:10.1089/cpb.2004.7.421
15. Dong Q, Liu T, Liu R, Yang H, Liu C. Effectiveness of Digital Health Literacy Interventions in Older Adults: single-Arm Meta-Analysis. *J Med Internet Res*. 2023;25:e48166. doi:10.2196/48166
16. Rajkhowa P, Qaim M. Mobile phones, off-farm employment and household income in rural India. *J Agric Econ*. 2022;73(3):789–805. doi:10.1111/1477-9552.12480
17. Ma S, Hu Z. Does Digital Finance Affect Labor Mobility? Based on the Micro Perspective of China's Floating Population. *China Economic Quarterly*. 2022;22(01):303–322. doi:10.13821/j.cnki.ceq.2022.01.15
18. Zhao M, Yang N, Zhou J, Liu B. The impact of digital literacy on the family migration of rural migrant workers: an empirical analysis based on CFPS data. *Agricultural Economy*. 2023;2023(9):88–90.
19. Idler EL, Benyamini Y. Self-rated health and mortality: a review of twenty-seven community studies. *J Health Soc Behav*. 1997;38(1):21–37. doi:10.2307/2955359
20. Zhou G. Self-assessed functional ability among older adults in China: differences and development. *Southern Population*. 2008;2018(01):51–58.
21. Deng M. Social relationships, mental health levels and subjective well-being improvement among older adults-An empirical analysis based on CGSS2015 data. *Population Development*. 2019;25(03):85–93.
22. Cheung F, Lucas RE. Assessing the validity of single-item life satisfaction measures: results from three large samples. *Qual Life Res*. 2014;23 (10):2809–2818. doi:10.1007/s11136-014-0726-4
23. Kessler RC, Andrews G, Colpe LJ, et al. Short screening scales to monitor population prevalences and trends in non-specific psychological distress. *Psychol Med*. 2002;32(6):959–976. doi:10.1017/s0033291702006074
24. Li H, Yang Z. The impact of digital literacy on personal health: evidence from the China family panel study. *Int J Health Plann Manage*. 2024;39 (5):1411–1433. doi:10.1002/hpm.3816
25. Kok Wah JN. Empowering minds: how self-efficacy, self-esteem, and social support drive digital mental health engagement. *Front Public Health*. 2025;13:1565327. doi:10.3389/fpubh.2025.1565327
26. Heo J, Chun S, Lee S, Lee KH, Kim J. Internet use and well-being in older adults. *Cyberpsychol Behav Soc Netw*. 2015;18(5):268–272. doi:10.1089/cyber.2014.0549
27. Xiang J, Xing H. The promotion mechanism of physical and mental health of the elderly in China: the impact of the digital divide and social capital. *BMC Public Health*. 2025;25(1):2457. doi:10.1186/s12889-025-23411-x
28. Cotten SR, Anderson WA, McCullough BM. Impact of internet use on loneliness and contact with others among older adults: cross-sectional analysis. *J Med Internet Res*. 2013;15(2):e39. doi:10.2196/jmir.2306