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Article

Digital Health Communication and Health Behavior Change: Mediation, Network, and Predictive Evidence

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Abstract: Digital health communication has become an important component of contemporary health promotion, although the processes linking health-related social media use to health behavior change remain insufficiently understood. Existing research has predominantly examined construct-level explanatory relationships, with limited consideration of the psychological pathways involved, the item-level organization of these relationships, and their predictive relevance. Guided by the Knowledge, Attitude and Practice framework, the present study integrated parallel mediation analysis, item-level association network analysis, and topology-enhanced predictive modeling. Cross-sectional survey data were obtained from 204 social media users in China. Health information acquisition ability, health information beliefs, and health self-efficacy were examined as parallel mediators between health-related social media use and self-reported health behavior change. Network analysis was subsequently used to characterize associations and centrality among 29 questionnaire items, while repeated cross-validation assessed whether topology-derived features contributed predictive information beyond the original item responses. The direct association between health-related social media use and health behavior change was not significant after the mediators were included, whereas the three indirect associations were statistically significant. Health self-efficacy exhibited the largest indirect effect of 0.295, with a 95% confidence interval of [0.184, 0.401], and accounted for 50.77% of the total indirect effect. Consistent with the mediation results, items measuring health self-efficacy and health behavior change occupied central positions in the association network and formed dense cross-construct connections. The addition of topology-derived features produced a modest improvement in random forest prediction. These findings indicate that health self-efficacy represents the most prominent statistical pathway linking digital health communication to health behavior change. The results also show that item-level network analysis can reveal relational patterns that are not captured by construct-level mediation models, while network topology may provide limited and model-dependent predictive information.

Keywords: digital health communication; health behavior change; health self-efficacy; item-level network analysis; topology-enhanced predictive modeling

1. Introduction

Health has become an important indicator of social development and human well-being as global public health challenges continue to intensify [1]. The World Health Organization defines health as a state of complete physical, mental, and social well-being rather than merely the absence of disease [2]. In recent years, chronic

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diseases, population aging, and recurrent public health events have made health governance and behavior intervention central issues in public health and social development [3]. In this context, health information dissemination plays an important role in improving health awareness, shaping health attitudes, and guiding behavior change [4]. Improving access to health information and enhancing health literacy have also become important pathways for promoting health equity and universal health coverage, especially in developing countries [5]. In China, the Healthy China 2030 strategy has elevated health to a national development priority and emphasized the cultivation of self-directed and disciplined healthy lifestyles [6].

With the rapid development of digital technologies, social media has become a major channel through which residents obtain health information [7]. Traditional health information channels, such as science journals, public health bulletin boards, and medical institution-based education, are authoritative and professional, but they are often limited by slow updates, restricted reach, and insufficient interactivity. By contrast, social media provides timely, personalized, and interactive access to health information. In 2024, approximately 5.17 billion people worldwide used at least one form of social media [8], and China accounted for the largest share of global social media usage within health-information contexts (SMU) [9]. In China, approximately 1.06 billion people used social media in 2024, accounting for 74.2% of the national population [10]. Through immediacy, personalized recommendation, community interaction, and user-generated content, social media has transformed health communication from one-way information transmission into multidirectional participation and interaction [11]. This transformation also reflects a broader shift in the spatial context of health behavior formation, as digital environments increasingly function as health-relevant spaces embedded in individuals' daily lives [12]. Particularly in the post-pandemic era, social media has played an important role in disseminating health crisis information, shaping public risk perception, and guiding health-related behaviors [13].

Existing studies suggest that social media usage in health-information contexts can influence health information acquisition and health behavior adoption through multiple psychological and cognitive mechanisms. The Health Belief Model, the theory of planned behavior, and social cognitive theory (SCT) have been widely used to explain how media content affects health-related cognition, attitudes, intentions, and behaviors. For example, studies based on the Health Belief Model show that health information on social media can improve risk perception, outcome expectations, and perceived benefits, thereby influencing vaccination intentions [14]. Research based on the Theory of Planned Behavior suggests that social media usage in health-information contexts can affect attitudes, subjective norms, and perceived behavioral control, which in turn influence intentions toward health behaviors such as exercise and sleep [15]. Studies based on SCT further emphasize that social comparison, reinforcement feedback, observational learning, and self-efficacy are important mechanisms through which social media affects health behavior change [16]. These theories provide complementary explanations for health behavior change. Empirical studies have also shown that the quality, presentation style, and emotional framing of health content influence users' information acceptance and willingness to act [17], while source credibility and community membership can strengthen positive health attitudes and behavioral norms [18]. Social media interventions also led to significant improvements in health behaviors such as physical activity, sleep, and smoking cessation [19]. Therefore, this study develops an extended Knowledge-Attitude-Practice (KAP) framework by incorporating psychological mechanisms from SCT and health cognition perspectives. Specifically, health information acquisition ability (HIAA) represents the knowledge acquisition process, while health information beliefs (HIB) capture the cognitive evaluation and acceptance of health information. Health self-efficacy (HSE), derived from SCT, is conceptualized as a behavioral capability that facilitates the translation of health cognition into behavioral practice. Resident health behavior change (RHBC) represents the behavioral outcome corresponding to the practice dimension.

Although existing studies have provided valuable evidence regarding the association between health-related social media use and health behavior change, the mechanisms through which digital health communication is translated into behavioral practice remain insufficiently understood. To address this limitation, this study conceptualizes digital health communication as a cognitive and behavioral capability formation process, as shown in Figure 1. Based on the extended KAP framework, the study examines three theoretically distinct mechanisms, including HIAA, HIB, and HSE, and evaluates their relative contributions within a unified analytical framework. Second, construct-level analysis may conceal differences in the roles of individual questionnaire items. The present study introduces item-level association network analysis to identify central items, strong associations, and connections across constructs. This analysis provides relational evidence that complements the mediation results and clarifies the structural position of key constructs within the questionnaire system. Third, existing research has focused mainly on explanatory relationships and has given limited attention to predictive assessment under the same analytical framework. This study incorporates topology-informed features to examine their incremental predictive value. The present study derives topology-informed features from the predictor network and

incorporates them into models of health behavior change. This design evaluates the incremental predictive contribution of network topology beyond the original questionnaire responses. Together, these analyses connect construct-level mediation, item-level relational structure, and out-of-sample prediction. The integrated framework extends digital health communication research from pathway estimation to structural analysis and predictive assessment, providing a more detailed account of the association between health-related social media use and health behavior change in China.

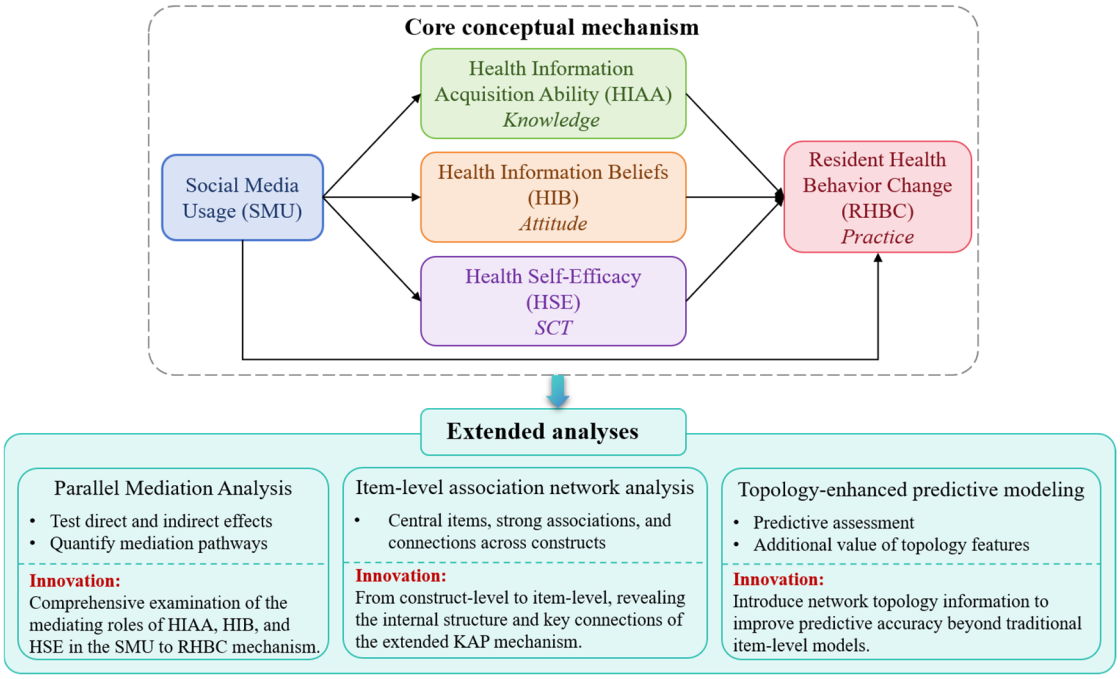

Figure 1. Integrated analytical framework.

2. Theory and Hypotheses Development

2.1. Knowledge, Attitude, Practice

Knowledge, attitude, and practice are the three main components of the KAP hypothesis. It is one of the most developed and extensively used theories in behavioral science and health education. While attitudes and beliefs work as catalysts that convert ideas into tangible acts, health knowledge provides the cognitive basis for behavioral change. Higher levels of disease-related information are associated with increased risk perception and preventive beliefs, which increase adherence to protective actions like mask wearing and social distancing, according to research on COVID-19 prevention [20]. Empirical research on dengue fever prevention shows that proactive preventative attitudes are fostered by residents' comprehension of disease transmission mechanisms. As a result, they are more inclined to take part in environmental sanitation and mosquito control initiatives, which encourages behavioral changes in the community to stop outbreaks in endemic areas [21]. Based on relevant research in the field of health communication on social media, the more health-related content people access through short videos about oral health on TikTok, the greater their health knowledge and the more they prioritize their health, which in turn increases their willingness to adopt health-protective behaviors [22]. When taken as a whole, these findings support the KAP model's ability to explain health behavior.

Users come across a plethora of diverse health information in today's media environment, especially on social media [23]. Before this knowledge may affect attitudes or actions, it must be screened, assessed, and integrated. The extended KAP offers a theoretical framework for examining the associations between SMU and RHBC across phases of information acquisition and awareness, belief construction, and behavioral practice. In order to analyze the mediating roles that these three factors play in changing residents' health behaviors during SMU, this study integrates HIAA, HIB, and HSE into the theoretical framework, as shown in Figure 2. These three mediating factors, often referred to as health information literacy, cover the whole process from information exposure and processing to application, providing the essential psychological basis for promoting changes in health-related behaviors. Information identification ability, information understanding capacity, credibility assessment ability, and practical application ability are its fundamental constituents. HIB are equivalent to attitude, representing a person's assessment of the reliability and behavioral significance of health information. This has a significant

impact on their behavioral drive and willingness to accept the knowledge [24]. Grounded in SCT, HSE is conceptualized as a behavioral competency that enables the effective translation of health-related cognitions into corresponding practical actions.

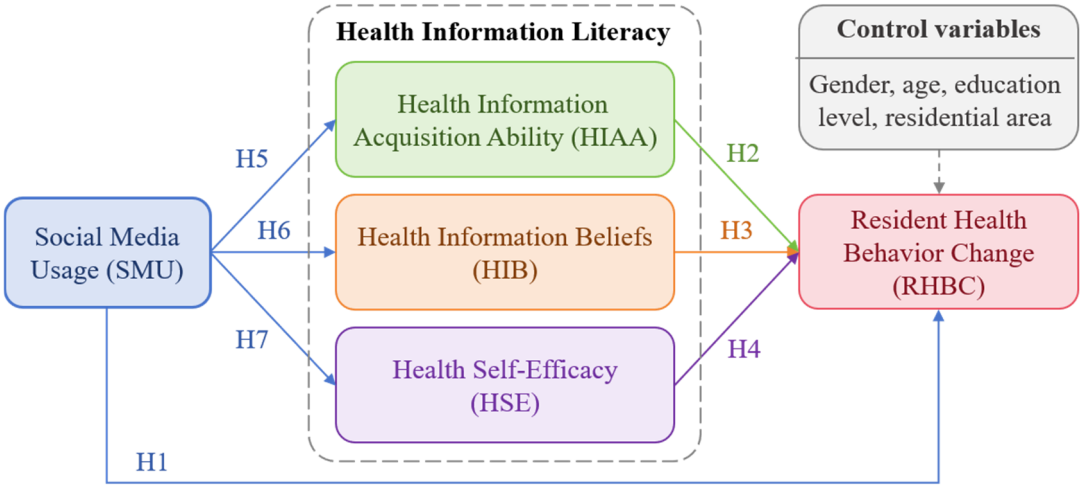

Figure 2. Theoretical Model.

2.2. Social Media Usage and Resident Health Behavior Change

As a digital platform that combines social interaction and information sharing, social media offers people a rich social context in which to see, assess, and engage in health-related behaviors [25]. Because of its visual character and openness, health behaviors in social networks are easier to observe and replicate. Social media's interactive structure and content presentation offer important social cues for observational learning. When users regularly see behavioral examples of psychological adjustment, scientifically supported exercise, or healthy eating, they form cognitive beliefs about the efficacy of these behaviors and are willing to participate in them through social comparison and outcome evaluation. Exercise intentions, for example, are favorably predicted by utilizing fitness-related social media, although this association is moderated by attitudes [26]. The social normative influence of health habits is further reinforced by social media algorithms and feedback mechanisms, which increase users' drive to practice and the beliefs of their viability.

Therefore, social media functions as a social cognitive environment that encourages behavioral imitation, upholds normative standards, and propels the internalization of health behaviors in addition to being a conduit for the dissemination of health information. This view is consistent with the broader understanding of smart society, in which digital platforms, algorithmic infrastructures, and information networks do not merely transmit information but reshape social interaction, value formation, and behavioral environments [27]. Recent research has also shown that health behaviors are shaped by the interaction between individual cognition and broader spatial and environmental contexts, including socially and digitally constructed environments [28]. When taken as a whole, these mechanisms show that SMU can directly and favorably affect residents' changes in health-related behaviors.

H1. *Social media usage in health-information contexts is positively associated with resident health behavior change.*

2.3. Health Information Acquisition Ability and Resident Health Behavior Change

Positive health-related behavioral changes are greatly aided by the availability and distribution of health information, and social media has emerged as a new avenue for knowledge exchange and acquisition [29]. Health information literacy has emerged as one of the major determinants of people's ability to successfully adopt health-promoting behaviors in the setting of digital health communication. According to existing studies, eHealth literacy was positively associated with disease prevention and management behaviors, likely because individuals with higher literacy better locate, understand, and apply health information for informed decisions [30]. Research has found that individuals with higher levels of eHealth literacy are more likely to use social media to search for health information and healthcare providers, and are less susceptible to the influence of digital influencers [31]. Access to health information is even more important in social media settings. Users must rely on their health information literacy to filter and analyze information due to the complexity of social media material, information asymmetry, and changing quality. Strong information processing abilities boost people's confidence in making health-related decisions, encourage behavioral change, and allow them to discern between scientific and pseudoscientific health

content. On the other hand, those with lower e-health literacy may believe false information on the internet, thus affecting the doctor-patient interactions process, which can lower the precision and durability of their behavioral [32].

According to SCT, information acquisition is a prerequisite for changing behavior, and the construction of healthy behaviors depends on the interaction of cognition, behavior, and environment. People's outcome expectations and perceived behavioral efficacy are reinforced when they can access high-quality, comprehensible, and practical health information from social media, which raises the possibility of behavior adoption. Exercise attainment rates, dietary improvements, and chronic illness management are all better in populations with more information literacy, according to research [33]. Based on these results, the study suggests that the ability to acquire health information in social media contexts is a crucial cognitive mechanism that propels the shift from information acquisition to behavioral transformation rather than just a result of information exposure. As a result, the following theory is put forth:

H2. *Health information acquisition ability is positively correlated with residents' health behavior change.*

2.4. Health Information Beliefs and Resident Health Behavior Change

Information belief is considered a crucial cognitive feature in health communication research that connects knowledge processing to behavioral adoption. It assesses people's willingness to take in information, assimilate it, and put it into practice. According to the Health Belief Model, people are more likely to adopt healthy behaviors when they believe that specific health information is highly reliable and may successfully help them avoid hazards or improve their health status [34]. This procedure entails a thorough evaluation of the information's perceived advantages, considered risks, and dependability. According to research, patients are more likely to make healthy lifestyle changes if they believe their doctor and follow the health advice themselves, by reducing their sedentary behavior and increasing their physical activity [35]. The significance of health information perceptions is further enhanced in social media environments. Users frequently rely on their belief systems to filter and assess the enormous amount of health content they come across because social media sites are accessible and the quality of information varies. Users are more likely to incorporate social media health information into their own health management strategies when they believe it to be trustworthy and supported by evidence [36]. People's expectations for health results increase when they believe that health information is scientific, practical, and successful. This boosts their confidence and persistence in engaging in these behaviors [37]. Thus, HIB influences not only behavioral intentions but also the long-term sustainability of behaviors. This leads to the following hypothesis:

H3. *Health information beliefs are positively correlated with changes in residents' health behaviors.*

2.5 Health Self-Efficacy and Resident Health Behavior Change

One fundamental psychological factor that affects people's choice, implementation, and persistence of healthy behaviors is self-efficacy [38]. The execution and durability of a person's health habits are strongly impacted by their HSE. The theory of self-efficacy suggests that if participants feel a sense of achievement and control over their personal health outcomes, they might sustain the desired health habit even after reward cessation, according to research [39]. Social media platforms give people access to a wealth of health-related knowledge and behavioral models, which helps them intuitively assess the viability of healthy practices and improve their self-efficacy. Social media platforms' interactive elements, such as likes and comments, give users instant feedback and social support, boosting their self-efficacy and encouraging the adoption and maintenance of healthy habits. In light of this, the following hypothesis is put forth:

H4. *Health self-efficacy is positively correlated with residents' health behavior change.*

2.6. Social Media Usage and Health Information Acquisition Ability

Social media has emerged as a crucial public health information channel in the context of digital health communication, providing people with easy and instant access to health-related content [40]. In addition to coming across a variety of health-related content on social media, users actively look for tailored health information using search, follow, and recommendation tools. People have limited cognitive resources because they are information processors, and social media's interactive features and presentation styles may affect users' ability to comprehend health information. Higher health literacy and information retrieval skills enable people to filter reliable and useful health information from social media, thereby improving their capacity to make health-related decisions. Li et al.'s

research shows that sources of health information, such as neighbors, newspapers, media, and medical professionals, have a big impact on people's health literacy [41]. In light of this, social media platforms not only enhance conventional information routes but also, via their accessibility and engagement, provide users with a distinctive information-access environment. According to Samy M and Abdelmalak R, social media became an essential resource for the public to obtain knowledge on preventing epidemics during the COVID-19 pandemic. Through these platforms, users gained health knowledge, evaluated the reliability of information, and modified their behavior accordingly [42]. Social media's interactive features and multimedia content forms, like text, photos, and videos, also help users comprehend difficult health ideas, improving their ability to digest and apply information. Therefore, this study proposes the following hypothesis:

H5. *Social media usage in health-information contexts is positively correlated with health information acquisition ability.*

2.7. Social Media Usage and Health Information Beliefs

In the context of social media, people's personal health views probably have a significant impact on how they interpret the wealth of information available, influencing whether or not they will accept it and adopt health-related activities. Through the dissemination of copious amounts of health content, user interactions, and the development of community support networks, social media platforms reinforce people's opinions about health knowledge. According to research, appealing social media content might boost people's propensity to adopt health-related information even in the absence of empirical proof when they view the sources as reliable and expect favorable results [43]. People are using social media's community engagement and information-sharing features more and more to connect with others, exchange experiences, and look for health-related information. Additionally, this influences users' views and behaviors regarding health information by encouraging them to rely on assessments and comments from people in their social circles when determining the reliability of health information [44]. In light of this, the following hypothesis is proposed:

H6. *Social media usage in health-information contexts is positively correlated with health information beliefs.*

2.8. Health Self-Efficacy and Social Media Usage

A person's confidence in their capacity to adopt and sustain healthy practices is known as HSE. Self-efficacy is a major factor in behavioral change since it not only affects a person's willingness to start a healthy activity but also how persistent they are in carrying it out in the face of obstacles [45]. The development of self-efficacy in social media contexts demonstrates novel social cognitive traits. Social media gives consumers vicarious experiences by presenting a wealth of observable examples of healthy practices, such as activity diaries, food management, and health challenge activities. Observing others' successful behavioral examples greatly increases self-efficacy, according to SCT [37]. According to research, people who regularly peruse health-related social media content are more likely to grow confident in their capacity to adopt such practices [46]. The interactive features of social media offer social support that fosters an increase in self-efficacy. This is especially noticeable in online health groups, where users get encouraging comments and emotional support from professionals and peers. This reinforcement increases willingness and persistence in carrying out healthy habits by strengthening perceptions of behavioral feasibility [47]. Disseminating health information, educational videos, and sharing diet and exercise regimens on social media all lessen the cognitive burden associated with implementing new behaviors. They increase users' confidence in their competence by making it simpler for them to comprehend and repeat healthy behaviors. Such knowledge's visual presentation and streamlined processes serve as important avenues to improve self-efficacy by lowering obstacles to action. On the other hand, excessive use of social media might worsen social media fatigue, which raises anxiety and lowers HSE [48]. Based on this, the study proposes the following hypothesis:

H7. *Social media usage in health-information contexts is positively correlated with health self-efficacy.*

2.9. Mediating Role of Health Information Literacy

As social media becomes a primary channel for residents to access health information, scholars generally concur that SMU does not directly drive individual RHBC, but rather exerts an indirect influence through a number of cognitive variables [49]. In order to better understand the relationship between SMU and RHBC, this study looks at the mediating roles of HIAA, HIB, and HSE.

2.9.1. Health Information Acquisition Ability

The study shows that eHealth literacy not only directly promotes health-promoting behaviors but also indirectly influences health-promoting behaviors through a chain of mediating pathways, including social media health information use, online health information seeking, and self-care ability [49]. Community elders' e-health literacy, especially among older persons, both directly predicts their health-promoting actions and indirectly influences them through pathways involving self-efficacy and self-care capacities [50]. This suggests that the ability to acquire and analyze information is a crucial link between digital health resources and everyday health habits.

Social media, a crucial source of health information, in turn influences people's ability to obtain health information. By using social media frequently to find and share health-related content, individuals can improve their search, filter, and evaluation skills via repeated practice. Furthermore, through health education programs, social media's varied content may directly raise public health literacy. SMU has a significant positive impact on health literacy, according to a cross-sectional study by Fathi et al. using a sample of people visiting Iranian healthcare facilities. This suggests that social media can be a key tool for improving residents' capacity to acquire health information [51]. In conclusion, SMU gives residents access to a wealth of easily accessible health information. It improves their access to health information through repeated information exposure and filtering techniques. Residents are encouraged to adopt healthy habits as a result of this enhanced potential. Therefore, this study posits:

H8a. *Health information acquisition ability mediates the relationship between social media usage in health-information contexts and changes in residents' health behaviors.*

2.9.2. Health Information Beliefs

The perception and confidence in online health information are a crucial expression of HIB in digital health contexts. In order to investigate the association between online health information seeking and healthcare service utilization, Li et al. built a joint model utilizing data from the Chinese General Social Survey and included views of online health information as a mediating variable. The findings support the mediating role of HIB between information behavior and health service utilization by showing that seeking out health information online significantly increases the frequency of outpatient visits by improving people's positive perceptions of online health information [52]. In a sample of Chinese nursing undergraduates, Sun et al. discovered that e-health literacy affects online health communication behaviors through pathways involving social media self-efficacy and health communication intentions, essentially reflecting the belief in the usefulness of social media health information [53]. Some studies have constructed a chain pathway of online health information seeking, health beliefs, eHealth literacy, and doctor-patient interaction to examine the public's online health information seeking behavior. These studies suggest that health beliefs are the key psychological mechanism linking information behaviors with health interaction behaviors [32].

Through elements including content quality and interactive experiences, SMU affects people's subjective assessments of the reliability and utility of health information in addition to changing the frequency and extent of their exposure to it. Whether or not health behaviors change is ultimately a result of these differences in health information views. Thus, this research suggests:

H8b. *Health information beliefs mediate the relationship between social media usage in health-information contexts and changes in residents' health behaviors.*

2.9.3. Health Self-Efficacy

By offering social support, professional advice, and other people's success stories, appropriate SMU boosts users' self-confidence in their ability to manage their health. Niu et al. discovered that among Chinese social media users, health literacy and health-related social media use affect people's intentions to seek health information by increasing health information self-efficacy, with self-efficacy acting as a partial mediating factor [54]. Wang et al.'s chain mediation model suggests that e-health literacy considerably enhances health-promoting behaviors among older individuals by boosting their HSE and self-care capacities [50]. In a similar vein, Yu et al.'s moderated mediation model study on Chinese older adults living in both urban and rural areas discovered that media use indirectly encourages improvements in health literacy by increasing self-efficacy [55]. Therefore, this study proposes:

H8c. *Health self-efficacy mediates the relationship between social media usage in health-information contexts and changes in residents' health behaviors.*

2.10. Control Variables

The associative pathways between sociodemographic characteristics, e-health literacy, online health information seeking, and perceived information quality are revealed by Liu's research, along with how these factors all work together to affect health outcomes [56]. This study includes age, gender, residential region, current status, and health condition as control variables since individual-level differences may influence social media-related behaviors and results. Since young adults made up the bulk of the study's respondents, educational attainment was also included as a control variable.

3. Research Methodology

3.1. Questionnaire Design

Following the completion of the first draft of the questionnaire, a small-scale pretest was carried out to assess the structural validity and item wording clarity, which resulted in scale adjustments and optimizations. The formal questionnaire, which covered five variables: SMU, HIAA, HIB, HSE, and RHBC, was created using the existing Likert scale structure. To make sure respondents understood the survey's goal, research application, and conceptual definition of social media, the questionnaire began with a study explanation. "Your average daily SMU time" was added as a screening item to weed out respondents who didn't fit the sample requirements, improving data quality and authenticity. Basic demographic data from respondents is gathered in the following parts (Table 1). The scale design for the five variables, which consists of 29 items, is included in the core part (Table 2). To further assess the measurement properties, the study conducted confirmatory factor analysis and common method bias analysis, with detailed results reported in Appendix A.

Table 1. Basic Information Items.

Dimension	Item
Gender	Male/Female
Age	Under 18/18–25/26–35/36–50/51 and above
Education Level	Junior high school or below/High school/Vocational school/College/Bachelor's degree/Master's degree or above
Residence Area	Urban/Suburban/Suburban-Rural Transition Zone/Rural Area
Current Status	Student/Healthcare Professional/Office worker/Freelancer/Self-Employed/Retired/Other
Do you work in a health-related field (e.g., medical, nursing, fitness, etc.)	Yes/No
Self-rated health status	Very poor/Poor/Fair/Good/Very good
Do you have any chronic conditions or long-term health issues	Yes/No/Unsure
How would you rate your health knowledge level	Almost none/Some understanding/Average/Fairly knowledgeable/Very knowledgeable
How much time do you spend on social media daily on average	None/Less than 1 h/1–3 h/3–5 h/More than 5 h

Table 2. Core Scale Items.

Variable Name	Measurement Item
SMU1	Social media is my most frequently used channel for obtaining information in daily life
SMU2	I habitually share and repost information that interests me on social media
SMU3	I frequently follow social media accounts or bloggers specializing in specific fields (e.g., health, medicine, wellness)
SMU4	I frequently like, save, or share health-related content
SMU5	I have participated in health-themed social media topics or activities (e.g., polls, live-stream interactions)
HIAA1	I frequently encounter health-related information on social media
HIAA2	I actively search for health knowledge on social platforms (e.g., disease prevention, dietary advice, exercise and fitness)

Table 2. *Cont.*

Variable Name	Measurement Item
HIAA3	I can understand the core content of most health information on social media
HIAA4	Health information on social media often contains technical jargon that confuses me
HIAA5	I proactively compare health information from different sources and assess its credibility
HIAA6	I prefer browsing health information presented with images, graphics, or videos
HIAA7	I have used health information from social media as a starting point to consult authoritative sources (e.g., Baidu Health, DXY)
HIB1	Health information on social media is important for managing my own health
HIB2	I believe online health knowledge is highly credible and can influence my behavioral decisions
HIB3	I am willing to try recommended health behaviors even if short-term effects are not immediately apparent
HIB4	Seeing others' health improvement stories strengthens my motivation to change
HIB5	Faced with overwhelming health information, I often feel overwhelmed and unable to make decisions
HIB6	I never doubt the authenticity of health information on social media
HSE1	I can discern the authenticity of health information on social media
HSE2	I can apply health information from social media to my daily life
HSE3	When encountering difficulties in implementing health behaviors, I can usually find solutions
HSE4	I can consistently adhere to health plans recommended on social media over the long term
HSE5	Using social media has improved my health management skills
RHBC1	My dietary structure has become more balanced
RHBC2	My exercise routine has become more frequent and scientifically structured
RHBC3	My daily routine has become healthier and more consistent
RHBC4	I have adjusted certain lifestyle habits based on health information shared on social media
RHBC5	I proactively purchase or try health products recommended on social media (e.g., health foods, exercise equipment, etc.)
RHBC6	My health awareness has increased

3.2. Data Collection

This study used an anonymous self-administered questionnaire method for data collection in order to guarantee the impartiality, authenticity, and representativeness of the survey results. WeChat groups and the online platform So Jump were used to distribute questionnaires to potential respondents in a variety of residential areas, age categories, and educational levels during the study procedure. A total of 208 surveys were gathered.

After the questionnaires were collected, their validity was strictly verified. Questionnaires were screened based on response time, removing those with an average time of less than 10 s per question to exclude random responses. Logical consistency checks were also performed, removing questionnaires with contradictory items, such as selecting not using social media while also choosing to frequently share health content. After the screening process, a total of 204 valid questionnaires were retained, resulting in an effective response rate of 98.08%.

As shown in Figure 3, the sample has a higher proportion of females, accounting for 63.2%. In terms of age structure, 58.3% are between 18 and 25 years old. The overall educational level of the survey population is relatively high, with a large proportion holding a bachelor's degree or higher. Regarding residential areas, 61.3% of participants live in urban areas. The demographic characteristics indicate that the sample contains a relatively high proportion of younger, urban, and highly educated participants. This distribution reflects the characteristics of active digital health information users recruited through online channels. In terms of occupation, the highest proportion is students, accounting for 51%, followed by regular office workers at 30.9%. Health-related characteristics show that only 51 participants work in health-related industries, accounting for 25%, while most participants are not involved in this field. In terms of self-assessed health status, 14.2% consider themselves very healthy, 39.7% consider their health status good, 39.7% consider it average, 5.9% consider their health status poor, and only 0.5% consider themselves very unhealthy. Furthermore, 80.4% of participants have no chronic diseases or related issues. In terms of health knowledge level, the majority have a basic understanding or general knowledge, with 34.3% and 32.8%, respectively. Regarding daily social media usage time, 31.9% use it for 1 to 3 h, 32.8% for 3 to 5 h, and 30.9% for more than 5 h. In general, social media was used extensively and for comparatively long periods of time.

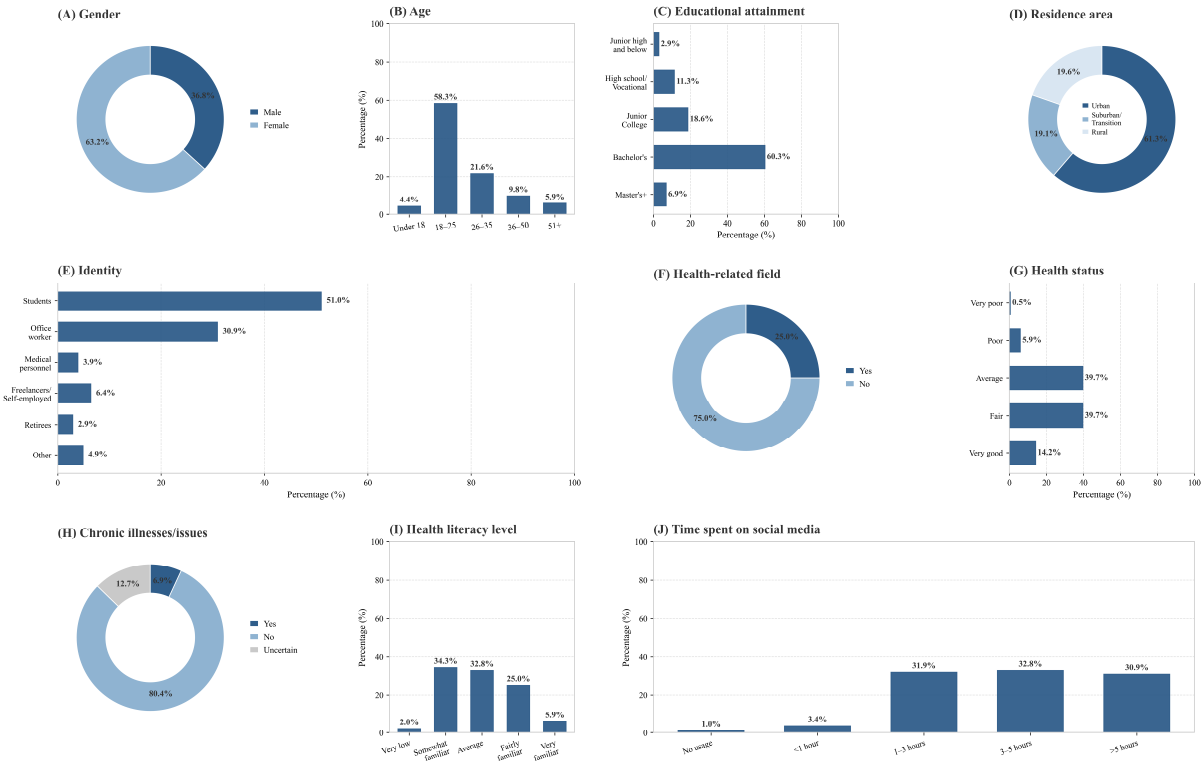

Figure 3. Sample characteristics of respondents (N = 204).

3.3. Mediation Model Specification

To examine the psychological and cognitive mechanisms linking social media use in health information contexts to resident health behavior change, this study specified a parallel mediation model. The proposed pathways among SMU, HIAA, HIB, HSE, and RHBC were grounded in the Knowledge, Attitude, and Practice framework and SCT. The cross-sectional data were used to assess the statistical consistency of these theoretically specified pathways. Accordingly, the estimated indirect effects are interpreted as statistical mediation and do not establish causal relationships. SMU was treated as the independent variable, RHBC was treated as the dependent variable, and HIAA, HIB, and HSE were treated as parallel mediators. The model was estimated using Model 4 in the SPSS PROCESS macro. Bootstrap confidence intervals were used to test the significance of indirect effects. Specifically, the study examined whether SMU affected RHBC indirectly through the three mediating pathways of SMU → HIAA → RHBC, SMU → HIB → RHBC, and SMU → HSE → RHBC.

3.4. Item-Level Association Network Construction

To further examine the structural relationships among questionnaire items, this study constructed an item-level association network based on the 29 core scale items. Each questionnaire item was treated as a network node, and the association between two items was treated as a weighted edge. Because the questionnaire items were measured using a five-point Likert scale, Spearman's rank correlation coefficient was used to measure item-level associations.

For two questionnaire items X_j and X_l, Spearman's rank correlation coefficient was calculated as:

$$\rho_j l = 1 - \frac{[6\Sigma_{i=1}^{n} d_i j l^2]}{[n(n^2-1)]} \quad (1)$$

where $d_i jl$ denotes the difference between the ranks of respondent *i* on item *j* and item *l*, and *n* denotes the number of valid respondents.

The adjacency matrix of the item-level association network was defined as:

$$A_j l = |\rho_j l|, if |\rho_j l| \geq \tau \; and \; p_j l < 0.05; \; A_j l = 0, otherwise \quad (2)$$

where $A_j l$ is the edge weight between item *j* and item *l*, $\rho_j l$ is the Spearman correlation coefficient, $p_j l$ is the significance level, and τ is the threshold for retaining item-level associations. In this study, a threshold of ($\tau = 0.40$) was used in the primary analysis to retain moderate-to-strong item-level associations while avoiding an excessively dense network. To examine whether the network findings depended on this cutoff, a sensitivity analysis was

conducted using thresholds ranging from 0.30 to 0.50. Changes in network density, connectivity, weighted-degree rankings, and the composition of the most central items were evaluated. The complete sensitivity analysis is reported in Appendix B.

The item-level association network was therefore represented as:

$$G = (V, E, W) \tag{3}$$

where *V* denotes the set of questionnaire items, *E* denotes the set of retained item-level associations, and *W* denotes the corresponding edge weights. Nodes were colored according to their theoretical constructs, including SMU, HIAA, HIB, HSE, and RHBC. Edge thickness represented the strength of item-level association.

To identify structurally important items, several centrality indicators were calculated. The weighted degree of item *j* was calculated as:

$$WD_j = \Sigma_{l \neq j} A_j l \tag{4}$$

where WD_j reflects both the number and strength of associations connected to item *j*. A larger weighted degree indicates that the item occupies a more central position in the association network. Degree centrality was calculated as:

$$DC_j = \frac{k_j}{(|V| - 1)} \tag{5}$$

where k_j is the number of edges connected to item *j*, and $|V|$ is the total number of nodes in the network. In this study, weighted degree was used as the primary indicator of item centrality because it captures both connection quantity and association strength. This analysis examined whether theoretically relevant mediating constructs, particularly HSE, also occupied central positions in the item-level network, thereby providing structural evidence complementary to the mediation analysis.

3.5. Topology-Enhanced Predictive Modeling

To assess whether item-level network information could provide additional predictive value, this study further conducted topology-enhanced predictive modeling. RHBC was treated as the prediction target. To avoid outcome leakage, RHBC items were excluded from the predictor set. Three feature strategies were compared. The first strategy used construct-level mean scores of SMU, HIAA, HIB, and HSE. The second strategy used the original item-level predictors from SMU, HIAA, HIB, and HSE. The third strategy used topology-enhanced features by adding weighted-degree-based topology scores to the original item-level predictors.

For each construct g, the construct-level mean score was calculated as:

$$S_i g = \left(\frac{1}{m_g}\right) \Sigma_{j \in g} x_i j \tag{6}$$

where $S_i g$ denotes the mean score of respondents *i* on construct *g*, m_g is the number of items belonging to construct *g*, and $x_i j$ denotes the score of respondent *i* on item *j*.

The topology score of construct *g* for respondent *i* was calculated by weighting item responses according to their weighted degree centrality in the predictor-only item association network:

$$TS_i g = \frac{\left[\Sigma_{j \in g} WD_j x_i j\right]}{\left[\Sigma_{j \in g} WD_j\right]} \tag{7}$$

where $TS_i g$ denotes the topology-enhanced score of construct *g*, WD_j denotes the weighted degree of item *j*, and $x_i j$ denotes respondent *i*'s score on item *j*. This formulation assigns greater weight to items that occupy more central positions in the predictor network.

In addition, an overall predictor topology score was calculated as:

$$TS_i^o verall = \frac{\left[\Sigma_{j \in P} WD_j x_i j\right]}{\left[\Sigma_{j \in P} WD_j\right]} \tag{8}$$

where *P* denotes the set of predictor items from SMU, HIAA, HIB, and HSE. This score captures the overall topology-weighted predictor profile of each respondent.

To examine whether topology-derived features provide additional predictive information, the item-level and topology-enhanced feature strategies were compared using identical predictive models and repeated cross-validation procedures. Repeated five-fold cross-validation with three repetitions was adopted, producing 15 paired test-fold results for each model.

To prevent information leakage, the predictor-only association network and its weighted-degree values were estimated independently within each training fold. The topology weights derived from the training data were then applied to both the corresponding training and test sets. Therefore, observations in the test fold did not contribute to network construction or topology-feature estimation.

For each model and evaluation metric, the incremental performance of the topology-enhanced strategy was calculated relative to the original item-level strategy. For R^2, the improvement was defined as:

$$\Delta R^2 = R^2_{\text{topology}} - R^2_{\text{item}} \tag{9}$$

For RMSE and MAE, the improvements were defined as:

$$\Delta\text{RMSE} = \text{RMSE}_{\text{item}} - \text{RMSE}_{\text{topology}} \tag{10}$$

$$\Delta\text{MAE} = \text{MAE}_{\text{item}} - \text{MAE}_{\text{topology}} \tag{11}$$

Under these definitions, positive values consistently indicate better performance after the addition of topology-derived features.

Model performance was evaluated using R^2, root mean square error, and mean absolute error. Mean paired improvements and their 95% bootstrap confidence intervals were calculated across the repeated test folds. Statistical differences were assessed using the Wilcoxon signed-rank test and the corrected repeated k-fold cross-validation test. The corrected test was treated as the more conservative inferential procedure because it accounts for dependence among repeated cross-validation estimates. Relative improvement percentages and the proportion of test folds in which the topology-enhanced model outperformed the item-level model were also reported to evaluate practical relevance.

Linear regression, random forest, and gradient boosting were retained as the main predictive models. Multilayer perceptron results were treated as supplementary because the limited sample size produced unstable out-of-sample performance.

An additional comparison between item-level weighted-degree centrality and out-of-sample permutation importance was conducted to examine the complementarity between the structural and predictive analyses. The complete procedure and results are reported in Appendix C.

4. Results Analysis

This study tested the validity and reliability of the questionnaire scales, as indicated in Appendix D. The findings show that all key variables have satisfactory Cronbach's α coefficients, indicating strong stability and consistency. With extracted common factors explaining more than 60% of cumulative variation, exploratory factor analysis validates the data's appropriateness for factor analysis. Structural validity is sound, supporting subsequent correlation analysis and mediation effect testing.

4.1. Correlation Analysis

The findings of the Pearson correlation analysis between the key variables are shown in Figure 4. Strong interrelationships are indicated by the considerable positive correlations found across all variables. Specifically, there is a significant positive association ($r = 0.694$, $p < 0.01$) between SMU and the capacity to obtain health information. This implies that people who use social media more often are better able to receive, understand, and process health information. This result is consistent with the study's theoretical hypothesis, which states that social media as an information environment greatly improves people's capacity to acquire health information (H5). Additionally, there is a substantial association ($r = 0.665$, $p < 0.01$) between HIB and HIAA. This suggests that people's opinions regarding health information on social media grow more favorable when they are able to comprehend and assess it more thoroughly, confirming the crucial role that health information processing plays. Additionally, HSE had the strongest association with improving health behavior ($r = 0.792$, $p < 0.01$) and substantial positive associations with all other factors. This result emphasizes that a fundamental psychological process influencing the adoption and maintenance of healthy habits is HSE. Lastly, there were strong positive associations ($r = 0.712$, $p < 0.01$; $r = 0.792$, $p < 0.01$) between HIB, HSE, and RHBC. This suggests that optimized health behaviors are encouraged by both positive attitudes and increased self-efficacy, which supports the H3 and H4 hypotheses.

Overall, the results of the correlation study show how HIAA, HIB, and HSE are mutually reinforcing, all of which point to better health behaviors. For later regression analysis and mediation effect testing, these results provide an essential statistical basis.

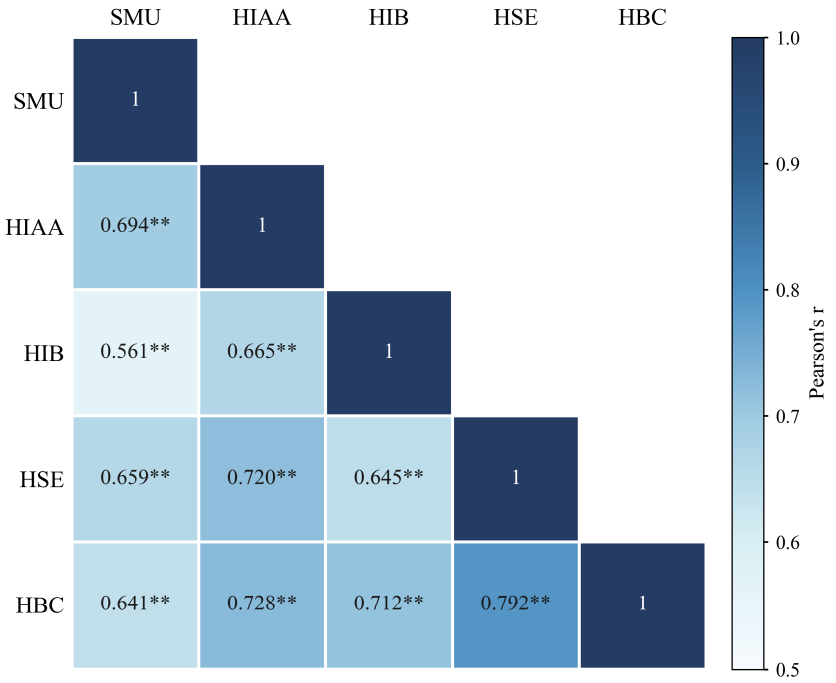

Figure 4. Correlation Analysis Results (Note: ** $p < 0.01$).

4.2. Regression Analysis

Table 3 indicates that the regression coefficients for HIAA, HIB, and HSE are significant at the 0.05 level, while social media usage in health-information contexts shows no significant effect in the regression equation. The R^2 value is 0.718, and the adjusted R^2 is 0.712, indicating that the regression equation explains 71.2% to 71.8% of the total variance, demonstrating good model fit.

HSE ($\beta = 0.438$) exerted the strongest influence on the dependent variable, followed by HIB ($\beta = 0.263$) and HIAA ($\beta = 0.183$). SMU had the smallest effect ($\beta = 0.078$). It can be seen that SMU does not directly affect the dependent variable, while all other variables exert significant influence on it, albeit to varying degrees.

Table 3. Regression Analysis Results.

Variable Name	*B*	*β*	*t*	*p*
Constant	−0.068		−0.361	0.719
SMU	0.074	0.078	1.406	0.161
HIAA	0.228	0.183	2.909	0.004
HIB	0.316	0.263	4.925	0.000
HSE	0.455	0.438	7.348	0.000
Adjusted R-squared			0.712	
F-value			126.587	

4.3. Mediating Effect Analysis

Table 4 reports the path coefficients of the parallel mediation model. SMU had significant positive effects on all three mediators. Specifically, SMU significantly predicted HIAA ($B = 0.7110$, $\beta = 0.6617$, $p < 0.001$), HIB ($B = 0.5157$, $\beta = 0.5399$, $p < 0.001$), and HSE ($B = 0.5604$, $\beta = 0.6088$, $p < 0.001$). These results indicate that individuals with higher levels of social media usage in health-information contexts tend to report stronger health information acquisition ability, more positive health information beliefs, and higher health self-efficacy.

After the three mediators were included in the model, HIAA, HIB, and HSE all showed significant positive effects on RHBC. HIAA significantly predicted RHBC ($B = 0.1981$, $\beta = 0.1856$, $p = 0.0036$), HIB also had a significant positive effect on RHBC ($B = 0.2822$, $\beta = 0.2350$, $p = 0.0001$), and HSE exerted the strongest effect on RHBC ($B = 0.5268$, $\beta = 0.4228$, $p < 0.001$). In contrast, the direct effect of SMU on RHBC was not significant after controlling for the mediators ($B = 0.1012$, $\beta = 0.0882$, $p = 0.1183$, 95% CI [−0.0260, 0.2284]). However, the total effect of SMU on RHBC was significant ($B = 0.6827$, $\beta = 0.5953$, $p < 0.001$, 95% CI [0.5640, 0.8014]). This pattern suggests that the effect of SMU on RHBC is mainly transmitted through psychological-cognitive mediating mechanisms rather than through a direct pathway.

Table 4. Path Coefficients of the Parallel Mediation Model.

Path	*B*	*β*	SE	*t*	*p*	LLCI	ULCI
SMU → HIAA	0.7110	0.6617	0.0552	12.8845	<0.001	0.6021	0.8198
SMU → HIB	0.5157	0.5399	0.0534	9.6588	<0.001	0.4104	0.6210
SMU → HSE	0.5604	0.6088	0.0488	11.4808	<0.001	0.4641	0.6566
SMU → RHBC	0.1012	0.0882	0.0645	1.5689	0.1183	−0.0260	0.2284
HIAA → RHBC	0.1981	0.1856	0.0672	2.9457	0.0036	0.0654	0.3307
HIB → RHBC	0.2822	0.2350	0.0687	4.1056	0.0001	0.1466	0.4178
HSE → RHBC	0.5268	0.4228	0.0751	7.0129	<0.001	0.3786	0.6749
Total effect of SMU → RHBC	0.6827	0.5953	0.0602	11.3398	<0.001	0.5640	0.8014

Table 5 presents the bootstrapping results for the mediating effects. The total indirect effect was 0.5815, with a 95% confidence interval of [0.4067, 0.7427], excluding zero. This indicates that the overall mediating effect of HIAA, HIB, and HSE was statistically significant. The total indirect effect accounted for 85.18% of the total effect, whereas the direct effect accounted for only 14.82% and was not statistically significant.

Table 5. Bootstrapping Test Results for Mediating Effects.

Model Effect	Effect Size	SE	LLCI	ULCI	Effect Proportion
Total Effect	0.6827	0.0602	0.5640	0.8014	100%
Direct Effect	0.1012	0.0645	−0.0260	0.22884	14.82% of total effect
Total Indirect Effect	0.5815	0.0867	0.4067	0.7427	85.18% of total effect
SMU → HIB → RHBC	0.1408	0.0641	0.0241	0.2722	24.21% of total indirect effect
SMU → HIAA → RHBC	0.1455	0.0398	0.0736	0.2296	25.02% of total indirect effect
SMU → HSE → RHBC	0.2952	0.0565	0.1844	0.4005	50.77% of total indirect effect

Among the three specific indirect pathways, all mediation effects were significant because their 95% confidence intervals did not include zero. The indirect effect through HIAA was 0.1455, with a 95% confidence interval of [0.0736, 0.2296]. The indirect effect through HIB was 0.1408, with a 95% confidence interval of [0.0241, 0.2722]. The indirect effect through HSE was 0.2952, with a 95% confidence interval of [0.1844, 0.4005]. Among the total indirect effects, the HSE pathway accounted for the largest proportion, 50.77%, followed by HIAA at 25.02% and HIB at 24.21%.

These findings demonstrate that SMU was not significantly associated with RHBC after accounting for the mediating variables. Instead, its influence is mainly realized through the enhancement of health information acquisition ability, the formation of positive health information beliefs, and especially the improvement of health self-efficacy. The strongest mediating role of HSE indicates that digital health communication becomes behaviorally effective only when users develop confidence and perceived capability to apply health information in daily health management.

4.4. Item-Level Association Network Analysis

As shown in Figure 5a, the item-level Spearman correlation matrix presents a generally positive association pattern among the five constructs. The correlations were particularly dense within RHBC items and between HSE and RHBC items, indicating that health self-efficacy is closely related to multiple dimensions of health behavior change. In contrast, several items related to information confusion or information overload showed relatively weaker associations with other items, suggesting that not all dimensions of digital health information processing contribute equally to behavioral transformation.

Figure 5b further visualizes the item-level association network. Each questionnaire item was treated as a node, and significant item-level associations were represented as weighted edges. The network shows that RHBC and HSE items are located close to the center of the network and form dense cross-construct connections. This indicates that health self-efficacy is not only a theoretically important mediator but also a structurally important bridge linking digital health communication and health behavior change at the item level. In particular, HSE-related items are closely connected with RHBC-related items, suggesting that users' perceived ability to apply health information, manage health behaviors, and persist in health plans is strongly associated with actual behavioral changes.

The strongest item-level associations are presented in Figure 5c. The largest association was observed between HIAA4 and HIB5, with a Spearman's rho of 0.733, indicating a strong relationship between health

information processing difficulty and information-related belief or overload. In addition, several of the strongest associations involved HSE5 and RHBC items, including HSE5–RHBC2, HSE5–RHBC6, HSE5–RHBC1, HSE5–RHBC4, and HSE5–RHBC3. These results suggest that the item reflecting improved health management ability through social media is strongly linked to multiple behavioral outcomes, such as dietary adjustment, exercise improvement, lifestyle change, and increased health awareness. This finding provides item-level structural evidence that health self-efficacy is a key pathway through which digital health communication is translated into health behavior change.

Figure 5d reports the top 15 central items in the association network based on weighted degree. RHBC1 showed the highest weighted degree, followed by HSE5, RHBC4, HSE2, RHBC2, and RHBC6. The centrality ranking indicates that RHBC and HSE items occupy dominant positions in the network. Among the top 15 central items, RHBC and HSE items accounted for the majority, while HIAA, HIB, and SMU items appeared less frequently. This pattern suggests that health behavior change and health self-efficacy constitute the core structure of the item-level network, whereas social media usage in health-information contexts and health information acquisition are more likely to function as upstream conditions.



Figure 5. Item-level association network analysis of digital health communication constructs.

These network findings are consistent with the mediation analysis. The mediation results showed that the direct effect of social media usage in health-information contexts on resident health behavior change was not significant, whereas the total indirect effect was significant. Among the three mediating pathways, the SMU → HSE → RHBC pathway had the largest effect, accounting for the highest proportion of the total indirect effect. The item-level network analysis provides additional structural support for this conclusion: HSE items were highly central and strongly connected with RHBC items, indicating that health self-efficacy is both a statistical mediator and a structural bridge in the digital health behavior change process.

4.5. Incremental Predictive Value of Topology-Enhanced Features

As shown in Table 6, the clearest improvement was observed for random forest among the evaluated models. The mean R^2 increased from 0.64 for the original item-level model to 0.66 after the topology-derived features were added. The absolute increase was 0.022, corresponding to a relative improvement of 3.37%. RMSE decreased from 0.40 to 0.39, with an absolute reduction of 0.014 and a relative reduction of 3.61%. MAE decreased from 0.28 to 0.27, with an absolute reduction of 0.013 and a relative reduction of 4.71%.

The topology-enhanced random forest produced better R^2 and RMSE values in 73.33% of the repeated test folds and a lower MAE in 86.67% of the folds. The 95% bootstrap confidence interval for the improvement in R^2 was [0.003, 0.041]. The corresponding intervals were [0.001, 0.028] for the RMSE reduction and [0.005, 0.021] for the MAE reduction. These intervals indicate that the observed improvements were consistently positive across the resampled paired comparisons.

The Wilcoxon signed-rank tests showed differences between the item-level and topology-enhanced random forest models for R^2 (p = 0.041), RMSE (p = 0.030), and MAE (p = 0.007). However, the more conservative corrected repeated cross-validation tests did not reach the conventional significance level for R^2 (p = 0.381), RMSE (p = 0.304), or MAE (p = 0.179). The observed gain should therefore be interpreted as modest and suggestive rather than as conclusive evidence of a statistically robust performance advantage.

From a practical perspective, the most notable improvement was observed for MAE. The topology-enhanced random forest reduced average absolute prediction error by 4.71% and outperformed the original item-level model in 86.67% of the test folds. This indicates that the topology-derived features improved prediction consistency for most cross-validation partitions, although the absolute magnitude of the improvement remained limited.

No incremental improvement was observed for linear regression. This result is expected because the topology scores are weighted linear combinations of the original item-level predictors and therefore do not expand the predictor space of an ordinary linear model. Gradient boosting also showed no consistent performance improvement after the topology-derived features were added. These results indicate that the contribution of topology-enhanced features is model-dependent rather than universal. Their predictive value was most apparent when used with random forest, which can exploit nonlinear associations and interactions between original item responses and topology-weighted summary features.

Figure 6 presents the paired performance improvements and their 95% bootstrap confidence intervals. Positive values indicate better performance for the topology-enhanced strategy. The random forest results show consistently positive improvements across all three-evaluation metrics, whereas the improvements for the other models were limited or inconsistent. Overall, the topology-enhanced strategy provided supplementary predictive information for random forest, particularly by reducing average absolute prediction error.

Table 6. Direct paired comparison between the item-level and topology-enhanced random forest models.

Metric	Item-Level Model	Topology-Enhanced Model	Absolute Improvement	Relative Improvement	95% Bootstrap CI	Topology Win Rate	Wilcoxon *p*	Corrected CV *p*
R^2	0.64	0.66	0.022	3.37%	[0.003, 0.041]	73.33%	0.041	0.381
RMSE	0.40	0.39	0.014	3.61%	[0.001, 0.028]	73.33%	0.030	0.304
MAE	0.28	0.27	0.013	4.71%	[0.005, 0.021]	86.67%	0.007	0.179

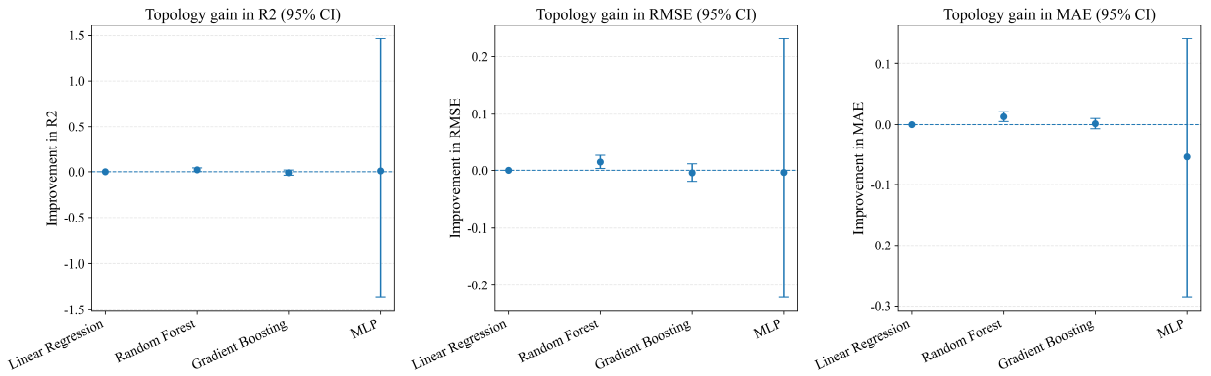

Figure 6. Paired predictive improvements obtained by adding topology-derived features.

Figure 7 presents the permutation importance results of the best topology-enhanced model, namely the random forest model. The overall predictor topology score was the most important predictor, indicating that the global structural position of questionnaire items in the predictor network contributed substantially to RHBC

prediction. Among the construct-specific topology features, HSE_topology_score ranked highest, followed by HIB_topology_score and HIAA_topology_score. Several HSE-related items, especially HSE4 and HSE5, also appeared among the top predictors. This result shows that health self-efficacy remains important even when the analysis shifts from theory-driven mediation to data-driven prediction.

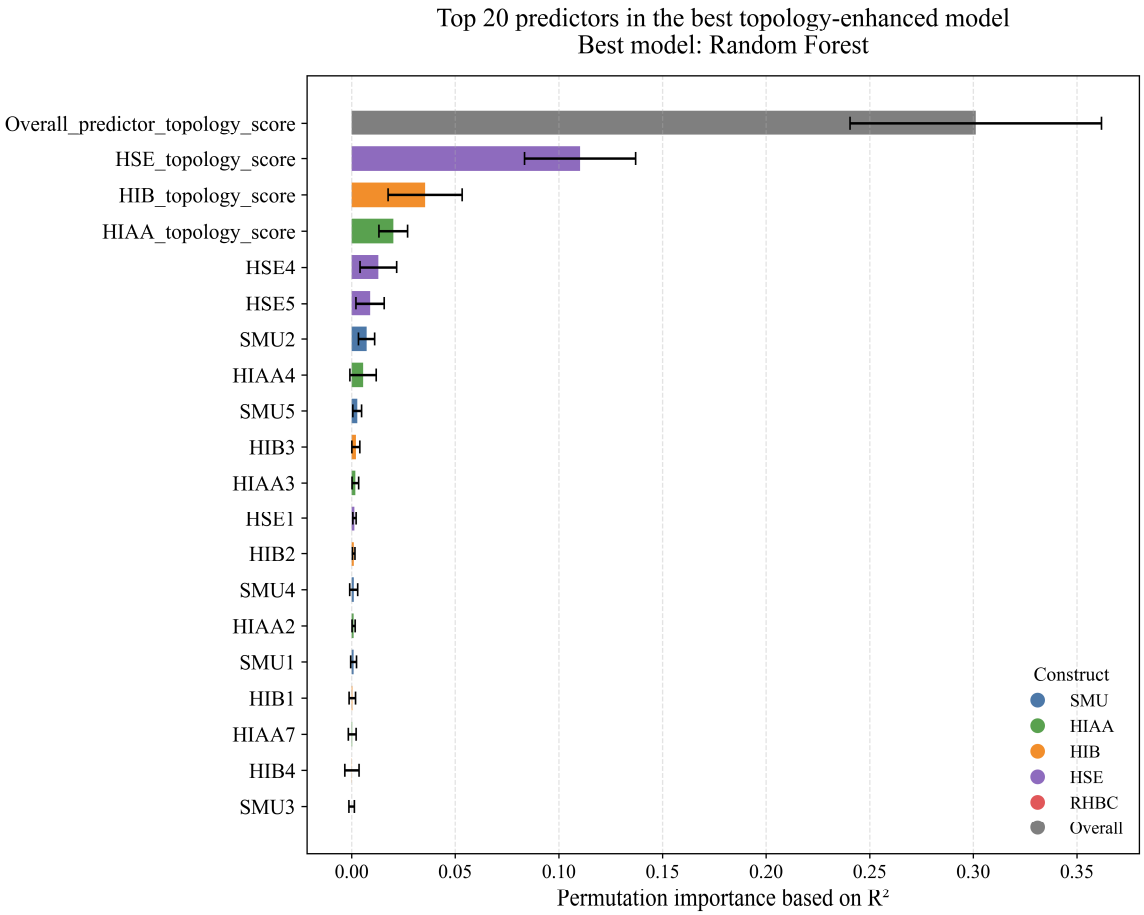

Figure 7. Top 20 predictors in the best topology-enhanced model.

A supplementary comparison between network centrality and predictive importance showed limited correspondence at the individual-item level, with a Spearman correlation of $\rho = 0.057$ ($p = 0.795$). However, a clearer convergence was observed at the construct level: HSE had the highest average network centrality and predictive importance, while HSE5 ranked first under both measures. These results indicate that the network and predictive analyses provide complementary rather than interchangeable evidence. Full results are reported in Appendix D.

Taken together, the topology-enhanced predictive analysis provides complementary support for the mediation findings. The mediation analysis showed that social media usage in health-information contexts did not directly influence RHBC, but exerted its effect mainly through HIAA, HIB, and especially HSE. The topology-enhanced analysis further shows that network-derived features have predictive value and that HSE-related topology features are among the most important predictors of RHBC. Therefore, the role of health self-efficacy can be understood at three levels: it is the strongest mediating pathway in the statistical mediation model, a structurally central construct in the item-level network, and an important predictor in the topology-enhanced model.

5. Discussion

5.1. Indirect Mechanism of Social Media Usage on Health Behavior Change

This study examined the associations between social media usage in health-information contexts and resident health behavior change through HIAA, HIB, and HSE. The results showed that the direct effect of SMU on RHBC was not statistically significant after the mediators were included. This indicates that health behavior change cannot be simply attributed to social media usage in health-information contexts itself. In fragmented and content-competitive digital media environments, users may be frequently exposed to health information, but exposure

alone does not necessarily lead to behavioral adjustment. The prevalence of misleading health content, excessive information exposure, and commercially oriented health messages may interfere with users' evaluation of health information and weaken the development of stable health information beliefs. Therefore, health information must first be accessed, understood, evaluated, trusted, and converted into actionable confidence before it can influence behavior [57,58]. This finding is consistent with the view that digital health communication affects behavior through internal psychological and cognitive processes rather than through simple information exposure [7]. However, some studies have shown that interactive social media interventions can directly improve health-related behaviors [59,60]. The difference may be related to the distinction between general social media usage in health-information contexts and structured intervention-based social media programs. General social media usage in health-information contexts is often heterogeneous and fragmented, while intervention programs usually provide targeted content, repeated feedback, professional guidance, and behavioral support. Therefore, the behavioral effect of social media depends not only on use frequency, but also on whether the platform environment activates information processing, belief formation, and self-efficacy enhancement.

The theoretical contribution of this finding lies in refining the conventional assumption that digital health communication directly facilitates behavioral improvement. The results indicate that information exposure represents only the initial condition of behavioral change, whereas the conversion of information into action requires the development of individual capabilities and psychological readiness. Specifically, HIAA provides the cognitive foundation for processing digital health information, HIB determine whether such information is accepted as meaningful and reliable, and HSE facilitates the transition from intention to behavioral implementation.

5.2. Central Role of Health Self-Efficacy

The results confirmed that HIAA, HIB, and HSE all significantly predicted RHBC. HIAA represents users' ability to access, understand, compare, and evaluate health information. Individuals with stronger health information acquisition ability are more capable of identifying useful and reliable health content, which increases the likelihood of behavior change. This is consistent with research showing that eHealth literacy and health information processing capacity are positively associated with health-related behaviors [61]. HIB also significantly influenced RHBC, suggesting that health behavior change depends on whether users believe health information is credible, useful, and actionable. This result is consistent with the Health Belief Model, which emphasizes that perceived credibility and benefits are important conditions for behavioral adoption [62].

Among the three mediators, HSE showed the strongest statistical association with RHBC and accounted for the largest proportion of the total indirect effect. This finding supports SCT, which emphasizes the central role of self-efficacy in behavioral initiation and maintenance. Users may acquire health information and form positive beliefs, but actual behavioral change is more likely to occur when they believe they can apply health knowledge, solve difficulties during implementation, and persist in health plans. This finding is also consistent with studies showing that health-related social media use and health literacy influence health information seeking and health-promoting behaviors through self-efficacy [50]. Similar evidence has been reported in research on media use, health literacy, and self-efficacy among older adults [55], as well as studies showing that eHealth literacy promotes health-promoting behaviors through multiple mediating mechanisms [49]. The prominent role of health self-efficacy has direct implications for social media platform design. Health content should provide clear behavioral guidance, attainable goals, and practical support for common implementation barriers. Progress tracking, personalized feedback, credible peer examples, and professionally moderated communities may strengthen users' confidence and support sustained behavior change. Recommendation systems should also reduce information overload, unrealistic success stories, and excessive social comparison by prioritizing credible, actionable, and appropriately challenging health information. Platform effectiveness should therefore be assessed through changes in health self-efficacy and sustained health behavior, together with conventional engagement indicators.

5.3. Methodological Contribution and Applications of Topology Enhanced Prediction

The topology enhanced analysis extends conventional questionnaire-based prediction by incorporating information about the relational organization of predictor items. Models based only on original item responses treat each response as an independent predictor and rely on the learning algorithm to identify relevant relationships. The topology features summarize the structural prominence of each item within the predictor network. Responses to items with stronger and more numerous associations therefore receive greater weight in the topology scores. This representation retains the original response information and adds a compact measure of the position of each response within the broader questionnaire system.

The predictive contribution of the topology features was most evident in the random forest model. Random forest can use nonlinear thresholds and interactions between original item responses and topology weighted summaries. The topology scores may help the model distinguish respondents with similar raw scores but different response configurations across structurally central items. This property provides a plausible explanation for the reductions in prediction error observed after the topology features were added. Linear regression showed no comparable improvement because the topology scores are weighted linear combinations of the original predictors and do not introduce a distinct linear dimension. The results therefore indicate that the contribution of topology features depends on the capacity of the predictive model to use relational summaries together with the original item responses.

This finding also clarifies the methodological contribution of the proposed analytical framework. Network centrality and predictive importance represent different properties of questionnaire items. Centrality describes an item's embeddedness in the item association network, whereas permutation importance estimates its contribution to out of sample prediction. Their weak correspondence at the item level indicates that structural prominence does not directly imply predictive importance. Their convergence at the construct level, particularly for health self-efficacy, shows that relational and predictive analyses can provide complementary evidence about theoretically relevant constructs. The topology enhanced approach consequently links item level network organization with predictive assessment without treating network centrality as a substitute for predictive importance.

This approach has several potential applications in digital health communication research. Topology informed features can support the identification of users whose response profiles indicate limited information acquisition ability, unstable health information beliefs, or low health self-efficacy. These profiles can inform differentiated communication strategies, including information verification support, simplified behavioral guidance, personalized feedback, and self-management assistance. The same framework can also be applied to evaluate digital health campaigns by examining changes in the centrality and predictive relevance of questionnaire items before and after an intervention. In longitudinal studies, changes in topology informed profiles may provide additional indicators of shifts in health cognition and behavioral readiness.

The observed predictive improvement was modest and was not statistically robust under the corrected repeated cross validation tests. The current results therefore establish the feasibility of incorporating item network information into predictive analysis rather than a general performance advantage. Larger samples, external validation, and longitudinal data are required to assess the stability, transferability, and intervention value of topology informed features across populations and digital health contexts.

6. Conclusions, Recommendations, and Limitations

6.1. Conclusions

This study refines the application of the KAP framework in digital health communication contexts by incorporating psychological capability as an intermediate mechanism between health cognition and behavioral practice. This study examined how social media usage in health-information contexts influences resident health behavior change through health information acquisition ability, health information beliefs, and health self-efficacy. By combining parallel mediation analysis, item-level network analysis, and topology-enhanced predictive modeling, the study provides an integrated explanation of digital health behavior change in China's social media context.

The findings show that social media usage within health-information contexts does not directly lead to resident health behavior change after the mediating variables are included. Instead, its influence is mainly transmitted through HIAA, HIB, and HSE. Among these pathways, HSE played the strongest mediating role, indicating that health behavior change depends not only on information exposure or belief formation, but also on users' confidence in applying health information and maintaining health-related actions. The item-level network and topology-enhanced predictive analyses further confirmed the central role of HSE from structural and predictive perspectives. Overall, the effect of social media usage in health-information contexts on health behavior change is indirect, structured, and self-efficacy-centered.

The principal contribution of this study lies in revealing the capability formation mechanism through which digital health communication is associated with health behavior change. The findings refine existing research by demonstrating that the relationship between health information exposure and behavioral improvement involves intermediate mechanisms. By integrating mediation analysis, item-level network analysis, and topology-enhanced prediction, this study provides complementary evidence regarding the pathways, structural organization, and predictive relevance of digital health behavior formation. The findings suggest that strengthening individual capability and psychological readiness is a critical condition for translating digital health communication into sustained behavioral practice.

6.2. Recommendations

Based on the findings, social media-based health communication should move beyond simple information exposure and place greater emphasis on the psychological and cognitive conditions through which health information is transformed into behavior. Specifically, intervention strategies should focus on improving users' health information acquisition ability, strengthening health information beliefs, and enhancing health self-efficacy.

First, social media health communication should improve users' ability to acquire, understand, and evaluate health information. Platforms and public health institutions should present health knowledge in accessible formats, such as short videos, infographics, text-image explanations, and question-oriented summaries. Health content can also be organized by themes, series, and tags to improve search efficiency and reduce information overload. In addition to providing health information, communication strategies should guide users to compare information sources, verify evidence, and distinguish reliable information from misleading content. This is important because users' ability to acquire and process health information is a necessary condition for transforming online health information into behavior-related knowledge.

Second, the credibility and transparency of health information should be strengthened. Social media platforms should encourage the participation of medical professionals, public health institutions, and credible science communicators in health information dissemination. Health content should clearly indicate its evidence base, including data sources, research references, expert review, or institutional endorsement. Platform governance should also reduce exaggerated, misleading, or commercially biased health content. A more transparent information environment can help users develop stable and rational beliefs about health information, which is important for promoting health behavior change.

Third, digital health communication should give priority to enhancing health self-efficacy. Health information should not only tell users what is healthy, but also help them understand how to act. Platforms and health communicators can provide step-by-step behavioral guidance, feasible health plans, progress tracking, and timely feedback to increase users' confidence in implementing health behaviors. Peer support, community interaction, successful role models, and experience sharing may also help users perceive health behavior change as achievable and sustainable. For users who encounter difficulties or setbacks, reminders, emotional support, and counseling resources can be provided to support long-term behavior maintenance.

Fourth, health communication strategies may incorporate more refined assessment and support mechanisms. Since this study suggests that item-level structural information can provide supplementary evidence for understanding and predicting health behavior change, future platform-based health communication can consider using questionnaire-based or behavior-based assessment tools to identify users who may have weak information acquisition ability, unstable health information beliefs, or low health self-efficacy. On this basis, differentiated support can be provided, such as basic health knowledge guidance for users with limited information acquisition ability, credibility verification tools for users with unstable information beliefs, and behavioral planning or feedback support for users with low self-efficacy.

6.3. Limitations

This study has several limitations. First, the sample was relatively concentrated among young, highly educated, and urban participants, which may limit the generalizability of the findings. Future studies should use stratified or targeted sampling to include more rural residents, older adults, and groups with lower educational levels.

Second, the cross-sectional design limits the ability to establish temporal relationships and causal inferences among the studied variables. Although the mediation analysis identifies statistically significant indirect associations, it cannot determine whether social media use precedes changes in health cognition or behavior. Reverse relationships may exist, such as individuals with stronger health behavior intentions being more likely to seek health information through social media. Future studies should employ longitudinal designs, panel surveys, or natural experiments to further examine the temporal dynamics underlying digital health communication and behavior change.

Third, the study focused on the core variables of SMU, HIAA, HIB, HSE, and RHBC, while other factors such as platform type, information overload, misinformation exposure, health anxiety, and active versus passive social media use were not fully examined.

Fourth, the predictive findings require further validation. Although the topology enhanced random forest showed modest performance gains, these improvements were not statistically significant under corrected repeated cross validation. The limited sample size, cross sectional self-reported data, and absence of external validation constrain model stability and generalizability. Future studies should use larger samples, independent datasets, and longitudinal or objective behavioral outcomes.

Finally, this study primarily examined the beneficial pathways through which digital health communication is associated with health behavior change, while potential negative aspects of online health environments were not directly measured. Factors such as misinformation exposure, information overload, privacy concerns, and commercialized health content may influence users' engagement with digital health information. Future research should incorporate these contextual factors to provide a more comprehensive understanding of digital health communication outcomes.

Author Contributions

H.H.: Conceptualization, Methodology, Data curation, Writing—original draft, Writing—review & editing, Funding acquisition; R.L.: Conceptualization, Writing—review & editing; Q.W.: Writing—review & editing; X.D.: Methodology; T.Z.: Data processing. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study was conducted in accordance with the ICMJE guidelines on the Protection of Research Participants, The Belmont Report, and the Declaration of Helsinki. Informed consent was obtained from all participants prior to their participation in the survey. The data collected from participants were anonymized to ensure confidentiality. This study did not require formal approval from an ethics committee, as the survey was anonymous and did not involve any sensitive personal information.

Informed Consent Statement

Informed consent was obtained from all participants for the publication of the data. Participants were informed at the start of the survey that their data would be anonymized and used only for research purposes.

Data Availability Statement

Data will be made available on request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used AI to assist with Chinese-to-English translation. After using this tool, the authors carefully reviewed, edited, and verified the content as needed and take full responsibility for the content of the published article.

Appendix A

This appendix reports the confirmatory factor analysis results for the five-factor measurement model, including factor loadings, composite reliability (CR), average variance extracted (AVE), discriminant validity, and model fit indices. The analysis was conducted using the full sample of 204 respondents. Table A1 presents the factor loadings for all items; Table A2 reports the CR and AVE values; Table A3 summarizes the model fit indices.

Table A1. Factor Load Coefficient Table.

Factor	Item	Unstandardized Loading	Standardized Loading	z	SE	*p*
SMU	SMU1	1	0.515	-	-	-
	SMU2	1.384	0.536	5.793	0.239	0.000 ***
	SMU3	1.766	0.7	6.771	0.261	0.000 ***
	SMU4	2.01	0.769	7.088	0.284	0.000 ***
	SMU5	2.192	0.759	7.046	0.311	0.000 ***
HIAA	HIAA1	1	0.686	-	-	-
	HIAA2	1.072	0.652	8.553	0.125	0.000 ***
	HIAA3	1.006	0.686	8.961	0.112	0.000 ***

Table A1. *Cont.*

Factor	Item	Unstandardized Loading	Standardized Loading	z	SE	*p*
HIAA	HIAA4	−0.075	−0.035	−0.472	0.159	0.637
	HIAA5	1.116	0.742	9.627	0.116	0.000 ***
	HIAA6	0.955	0.651	8.541	0.112	0.000 ***
	HIAA7	1.222	0.691	9.023	0.135	0.000 ***
HIB	HIB1	1	0.755	-	-	-
	HIB2	0.905	0.632	8.77	0.103	0.000 ***
	HIB3	0.828	0.65	9.035	0.092	0.000 ***
	HIB4	0.816	0.64	8.889	0.092	0.000 ***
	HIB5	0.266	0.139	1.869	0.143	0.062 *
	HIB6	0.756	0.43	5.859	0.129	0.000 ***
HSE	HSE1	1	0.746	-	-	-
	HSE2	0.999	0.76	10.93	0.091	0.000 ***
	HSE3	0.953	0.685	9.762	0.098	0.000 ***
	HSE4	1.171	0.716	10.244	0.114	0.000 ***
	HSE5	1.184	0.824	11.935	0.099	0.000 ***
RHBC	RHBC1	1	0.823	-	-	-
	RHBC2	1.008	0.792	13.124	0.077	0.000 ***
	RHBC3	1.081	0.763	12.449	0.087	0.000 ***
	RHBC4	0.954	0.793	13.15	0.073	0.000 ***
	RHBC5	0.836	0.644	9.955	0.084	0.000 ***
	RHBC6	0.894	0.759	12.356	0.072	0.000 ***

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table A2. Composite reliability and average variance extracted for each construct.

Factor	Average Variance Extracted	Composite Reliability
SMU	0.465	0.803
HIAA	0.356	0.763
HIB	0.276	0.676
HSE	0.557	0.862
RHBC	0.581	0.892

Table A3. Model Fit Indices.

Index	χ^2	df	*p*	χ^2/df	GFI	RMSEA	RMR	CFI	NFI	NNFI
Recommended criterion	-	-	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9
Value	1078.32	367	0	2.938	0.717	0.098	0.08	0.791	0.717	0.769

Because all constructs were measured using self-reported questionnaire data collected from the same respondents, a common method bias assessment was conducted. Following the Harman's single-factor test procedure, all measurement items were entered into an exploratory factor analysis without rotation. The results showed that the first unrotated factor accounted for 41.943% of the total variance, which was below the commonly used threshold of 50%. This result suggests that common method bias was unlikely to substantially influence the observed relationships among the constructs.

Table A4. Harman's single-factor test for common method bias.

Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
1	12.164	41.943	41.943
2	2.468	8.510	50.453
3	1.369	4.723	55.176
4	1.209	4.170	59.346
5	1.171	4.038	63.384

Appendix B

The item-level association network in the main analysis was constructed using statistically significant Spearman correlations with an absolute correlation threshold of ($\tau = 0.40$). Because the topology of a thresholded

correlation network may vary according to the selected cutoff, a sensitivity analysis was conducted to determine whether the main structural findings depended on this specific threshold

The item-level network was reconstructed using five increasingly stringent correlation thresholds ($\tau = 0.30, 0.35, 0.40, 0.45, 0.50$).

For each threshold, an undirected weighted network was constructed. Each questionnaire item was represented as a node, and an edge was retained when the absolute Spearman correlation coefficient between two items was equal to or greater than the specified threshold and the corresponding association was statistically significant at ($p < 0.05$). The absolute Spearman correlation coefficient was used as the edge weight.

The sensitivity analysis evaluated changes in the overall network structure using the following indicators: the number of retained edges, network density, mean degree, mean weighted degree, number of connected components, proportion of nodes included in the largest connected component, average clustering coefficient, and average path length within the largest connected component.

The stability of item centrality was further assessed using weighted degree. For each alternative threshold, the weighted-degree ranking of the 29 questionnaire items was compared with the ranking obtained under the primary threshold of 0.40 using Spearman rank correlation. The overlap between the top 15 central items under each alternative threshold and those identified at the threshold of 0.40 was evaluated using the Jaccard coefficient:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{A1}$$

where A represents the set of the top 15 central items under an alternative threshold and (B) represents the corresponding set under the primary threshold of 0.40. A higher Jaccard coefficient indicates greater consistency in the identification of structurally central items.

As shown in Table A5, increasing the correlation threshold progressively reduced the number of retained edges and network density. The number of edges decreased from 299 at ($\tau = 0.30$) to 68 at ($\tau = 0.50$), while network density decreased from 0.74 to 0.17. This pattern indicates that increasingly stringent thresholds removed weaker item-level associations and produced progressively sparser networks.

The network remained fully connected at the threshold of 0.30. At the thresholds of 0.35, 0.40, and 0.45, the largest connected component consistently contained 93.00% of all questionnaire items. At the most stringent threshold of 0.50, this proportion decreased to 79.00%, and the number of connected components increased to five. These findings indicate that the threshold of 0.50 removed a substantial number of associations and began to fragment the item-level network.

Despite these changes in network sparsity, the weighted-degree centrality rankings remained highly consistent across the examined thresholds. Relative to the primary threshold of 0.40, the rank correlations were 0.98 at ($\tau = 0.30$), 0.96 at ($\tau = 0.35$), 0.97 at ($\tau = 0.45$), and 0.92 at ($\tau = 0.50$). All rank correlations exceeded 0.90, indicating that the relative structural importance of the questionnaire items was largely preserved across the alternative network specifications.

The consistency of the most central items was also supported by the Jaccard coefficients. The overlap between the top 15 central items identified at ($\tau = 0.40$) and those identified at ($\tau = 0.30$) and ($\tau = 0.35$) was 0.88. The top 15 central items were identical at the thresholds of 0.40 and 0.45, resulting in a Jaccard coefficient of 1.00. Even at the more stringent threshold of 0.50, the coefficient remained 0.76. These results indicate that the centrality conclusions were not attributable to the use of a single threshold.

Table A5. Sensitivity of item-level network characteristics to alternative Spearman correlation thresholds.

Threshold	Nodes	Edges	Density	Mean Degree	Mean Weighted Degree	Connected Components	Largest Component Size	Largest Component Proportion	Average Clustering Coefficient	Average Path Length of LCC	Weighted Degree Rank Correlation with 0.40	Top 15 Jaccard Similarity with 0.40
0.30	29	299	0.74	20.62	9.13	1	29	1.00	0.51	3.08	0.98	0.88
0.35	29	260	0.64	17.93	8.24	2	27	0.93	0.50	2.78	0.96	0.88
0.40	29	196	0.48	13.52	6.57	2	27	0.93	0.43	3.08	1.00	1.00
0.45	29	134	0.33	9.24	4.75	2	27	0.93	0.37	3.67	0.97	1.00
0.50	29	68	0.17	4.69	2.61	5	23	0.79	0.36	3.86	0.92	0.76

Note: The centrality rank correlation is the Spearman correlation between the weighted-degree ranking at each threshold and the ranking obtained at the primary threshold of ($\tau = 0.40$). The Top-15 Jaccard coefficient measures the overlap between the 15 most central items at each threshold and those identified at ($\tau = 0.40$).

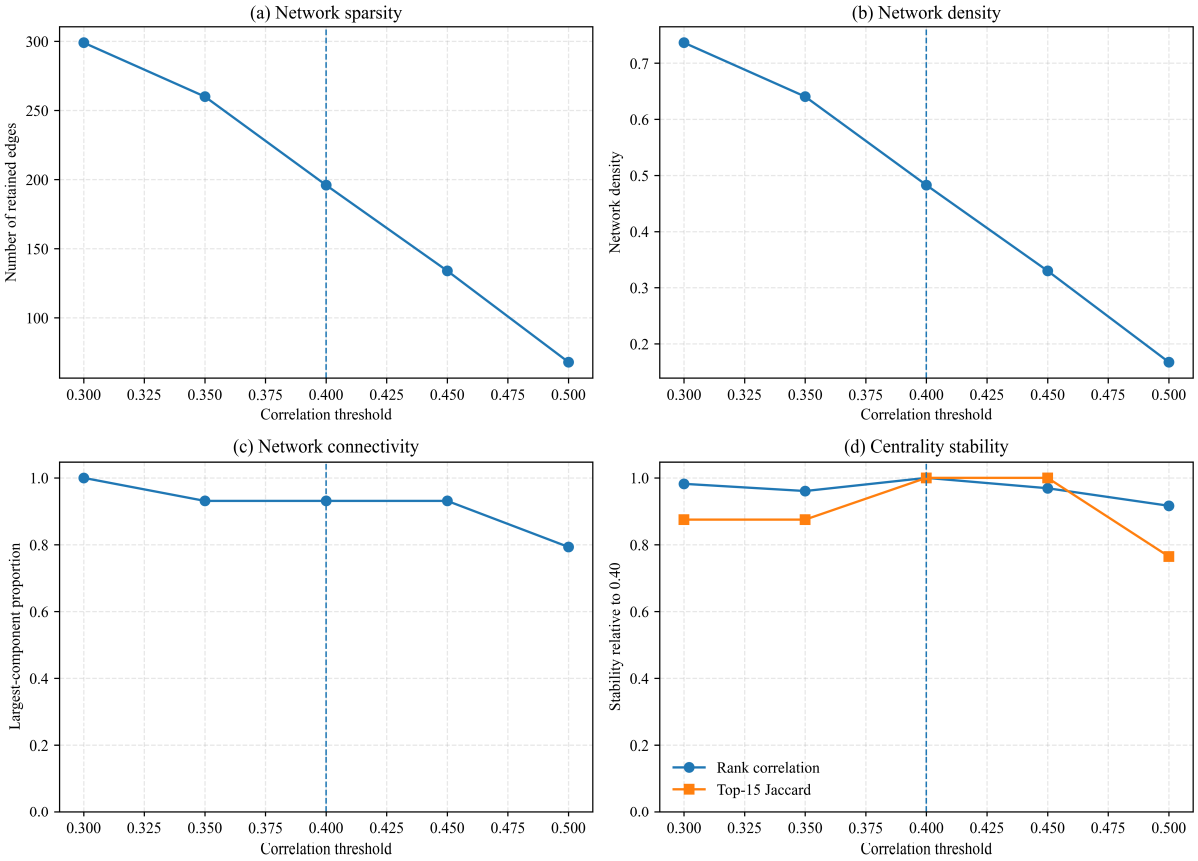

Figure A1. Sensitivity of the item-level association network to alternative Spearman correlation thresholds.

Figure A1 visually confirms the progressive reduction in network complexity as the threshold increased. The number of retained edges and network density declined monotonically across the examined thresholds. However, the proportion of nodes in the largest connected component remained unchanged at 93.10% between the thresholds of 0.35 and 0.45. The weighted-degree ranking correlations also remained above 0.90 across all alternative thresholds.

Taken together, the sensitivity analysis demonstrates that the primary network findings were robust to reasonable changes in the correlation threshold. The threshold of ($\tau = 0.40$) was retained for the main analysis because it provided a balance between structural information retention and network interpretability. Compared with the thresholds of 0.30 and 0.35, it substantially reduced network density and limited the influence of weaker associations. Compared with the thresholds of 0.45 and 0.50, it retained a larger number of potentially meaningful item-level relationships and avoided excessive network fragmentation. Therefore, ($\tau = 0.40$) represents a methodologically reasonable primary specification rather than an outcome-dependent cutoff.

Appendix C

To examine how the structural and predictive analyses complemented each other, an additional comparison was conducted between item-level network centrality and predictor importance in the topology-enhanced random forest model.

For each of the 15 repeated cross-validation test folds, weighted-degree centrality was estimated from the predictor-only association network using the corresponding training data. Permutation importance was then calculated for the topology-enhanced random forest model using the independent test fold. This procedure ensured that the test observations did not contribute to network construction or topology-feature estimation.

The weighted-degree and permutation-importance values of each predictor item were averaged across the repeated folds. At the item level, the association between mean weighted degree and mean permutation importance was evaluated using Spearman's rank correlation. The overlap between the 10 most central items and the 10 most important predictors was further assessed using the Jaccard coefficient. At the construct level, mean weighted degree and mean permutation importance were calculated separately for SMU, HIAA, HIB, and HSE.

Table A6. Comparison of network centrality and predictive importance for selected predictor items.

Item	Construct	Mean Weighted Degree	Centrality Rank	Mean Permutation Importance	Importance Rank
HSE5	HSE	7.75	1	0.006	1
HIAA1	HIAA	7.09	2	0.001	7
HSE2	HSE	7.05	3	0.000	20
HIB1	HIB	6.38	4	0.002	6
HSE4	HSE	5.15	9	0.003	3
SMU2	SMU	1.87	20	0.005	2
HIAA4	HIAA	0.73	22	0.003	4

At the item level, the overall association between network centrality and predictive importance was weak and statistically nonsignificant. The Spearman rank correlation between mean weighted degree and mean permutation importance was ρ = 0.057, with p = 0.795. The 10 most central items and the 10 most important predictors shared four items: HIAA1, HIB1, HSE4, and HSE5. The corresponding Jaccard coefficient was 0.25.

These results indicate that the two rankings showed only limited overlap and should not be treated as equivalent measures. Nevertheless, several theoretically important items were prominent in both analyses. HSE5 had the highest mean weighted degree, 7.75, and the highest mean permutation importance, 0.006, ranking first under both criteria. HSE4 ranked ninth in weighted degree and third in permutation importance. HIAA1 and HIB1 also appeared among the top 10 under both measures.

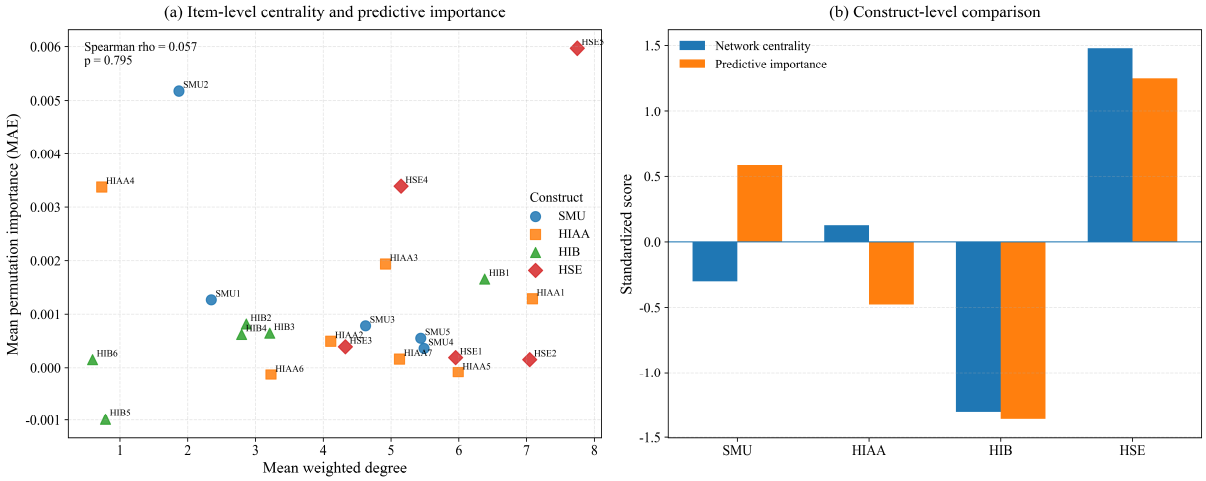

Figure A2. Comparison between network centrality and predictive importance.

Figure A2a presents the relationship between mean weighted degree and mean permutation importance for predictor items. The Spearman correlation was ρ = 0.057, with p = 0.795. Figure A2b compares standardized construct-level network centrality and predictive importance. Positive standardized scores indicate values above the construct-level mean.

At the construct level, a clearer convergence was observed. HSE had the highest mean weighted degree, 6.04, and the highest mean permutation importance, 0.002. After standardization, HSE also obtained the highest values for both network centrality and predictive importance, with standardized scores of 1.48 and 1.25, respectively.

The remaining constructs showed less consistent patterns. HIAA had a slightly above-average standardized centrality score of 0.13 but a below-average predictive-importance score of −0.48. SMU had a below-average centrality score of −0.30 but an above-average predictive-importance score of 0.59. HIB had the lowest standardized scores for both network centrality and predictive importance, with values of −1.31 and −1.36, respectively.

The weak item-level correlation is methodologically interpretable. Weighted degree measures how extensively and strongly an item is connected with the remaining predictor system. Permutation importance measures the change in out-of-sample prediction performance after the information carried by an item is disrupted. A highly central item may therefore have limited permutation importance when its information overlaps substantially with other strongly connected items. Conversely, a less central item may show high predictive importance when it contains distinctive information associated with RHBC.

For example, SMU2 had relatively low network centrality but ranked second in predictive importance. In contrast, HSE2 was among the most central items but had comparatively low permutation importance. These differences show that structural embeddedness and predictive contribution represent related but non-equivalent properties.

Taken together, the two analyses provide complementary evidence. Network centrality identifies the items that organize the internal association structure among SMU, HIAA, HIB, and HSE, whereas permutation importance identifies the variables that contribute to out-of-sample RHBC prediction. Their convergence at the HSE construct level, especially for HSE4 and HSE5, supports the central role of health self-efficacy. Their divergence at the individual-item level further demonstrates that structural centrality and predictive importance capture distinct dimensions of the digital health communication process.

Appendix D

Reliability refers to the consistency and stability of a measurement tool when repeated under identical conditions, reflecting the degree to which test results are free from random error. Reliability analysis validates the dependability of questionnaire data. Cronbach's alpha is commonly used as an assessment metric, with different alpha values indicating varying levels of reliability. This study included five variables (SMU, HIAA, HIB, HSE, and RHBC). The reliability analysis results for the measurement scales are presented in the table below. Both the overall scale and individual variable reliability coefficients demonstrated satisfactory values, meeting the reliability testing requirements.

Table A7. Survey Reliability Analysis Results.

Variable	Number of Items	Cronbach's Alpha Value
SMU	5	0.785
HIAA	7	0.728
HIB	6	0.675
HSE	5	0.863
RHBC	6	0.891
Overall Reliability	29	0.939

Table A8 shows that the overall KMO value of the questionnaire is 0.926, exceeding the threshold of 0.8 and meeting the standard. The significance level of the Bartlett's sphericity test is less than 0.01, indicating that the sample data possesses good validity and is suitable for subsequent analysis.

Table A8. KMO and Bartlett's Test.

KMO Measure of Sampling Adequacy		**0.926**
Bartlett's Sphericity Test	Approximate Chi-Square	3597.342
	Degrees of Freedom	406
	Significance	0

This study conducted exploratory factor analysis on the scale. The extracted factors and their total variance explained are detailed in Table A9 of this appendix. The analysis results indicate six common factors can be extracted, with a cumulative variance contribution rate of 67.086%. This exceeds the recommended standard of 60%, demonstrating that the measurement structure possesses good representativeness and explanatory power.

Table A9. Total Variance Explained.

Component	Initial Eigenvalue			Extracted Loadings		
	Total	Percentage of Variance Explained	Cumulative %	Total	Percentage of Variance	Cumulative %
1	12.164	41.943	41.943	12.164	41.943	41.943
2	2.468	8.510	50.453	2.468	8.510	50.453
3	1.370	4.723	55.176	1.370	4.723	55.176
4	1.209	4.170	59.346	1.209	4.170	59.346
5	1.171	4.038	63.384	1.171	4.038	63.384
6	1.073	3.702	67.086	1.073	3.702	67.086
7	0.833	2.873	69.959			
8	0.755	2.603	72.562			
9	0.729	2.513	75.074			
10	0.634	2.185	77.260			

Table A9. *Cont.*

Component	Initial Eigenvalue			Extracted Loadings		
	Total	Percentage of Variance Explained	Cumulative %	Total	Percentage of Variance	Cumulative %
11	0.594	2.047	79.306			
12	0.546	1.884	81.191			
13	0.537	1.850	83.041			
14	0.502	1.729	84.771			
15	0.465	1.605	86.376			
16	0.425	1.464	87.840			
17	0.389	1.341	89.181			
18	0.364	1.254	90.435			
19	0.350	1.208	91.643			
20	0.329	1.133	92.776			
21	0.321	1.105	93.882			
22	0.291	1.005	94.886			
23	0.275	0.948	95.834			
24	0.261	0.899	96.734			
25	0.249	0.859	97.593			
26	0.205	0.706	98.299			
27	0.185	0.637	98.936			
28	0.158	0.545	99.481			
29	0.151	0.519	100.000			

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