A model for predicting factors affecting health information avoidance on WeChat

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Abstract

Objective: WeChat serves as a crucial source of health information, distinguished by its highly personalized nature. Avoidance of such personalized health information has a direct impact on individuals' health decision-making. This study aims to identify the factors influencing personalized health information avoidance on WeChat and to construct a hierarchical framework illustrating the relationships among these factors.

Methods: A hybrid method was utilized. Semi-structured interviews and grounded theory were used to identify the influencing factors. The interpretive structural modeling (ISM) method was adopted to develop a hierarchical model of the identified factors, followed by matrice d'impacts croises-multiplication appliqué a un classemen (MICMAC) to analyze the dependence and driving power of each factor.

Results: The 20 predictors of personalized health information avoidance were broadly categorized into three groups: personal, informational, and social factors. These factors collectively form a three-tier explanatory framework, consisting of the top, middle and bottom layers. At the root layer, health characteristics and cognition exerted a strong driving force, while negative emotions and affective factors at the top layer showed a high degree of dependence. In contrast, the decision-making cognition, informational factors, and social factors in the middle layer exhibited relatively weaker driving force and dependence power.

Conclusion: This study bridged the research gap of information avoidance by providing new insights targeting the factors influencing personalized health information avoidance behavior on WeChat. It also contributed to enhancing personal health information management and the health information services provided on WeChat.

Keywords

WeChat, health information avoidance, health behavior, grounded theory, ISM model

Introduction

Recently, social media has substantially facilitated the dissemination of health information,[1] with an increasing number of people relying on social media as essential health information sources.[1,2] In the United States, nearly 90% of adults turn to social media such as Facebook and Twitter, for a wide array of health-related content,[3] including information on personal health conditions, disease symptoms, treatment experiences, medication recommendations, and wellness tips.[4] The shift toward social media for seeking health information has empowered the general health consumers through informed decision-making and has contributed to greater health literacy.[5–7]

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In China, social media apps such as WeChat and Douyin have similarly become pivotal tools for health information access. According to recent surveys, WeChat is now a primary health information source for 98.35% of the Chinese population, according to recent surveys.[8] Since its launch in 2011, WeChat has evolved from an instant messaging tool into a comprehensive information ecosystem that is deeply integrated with individuals' health.[9,10] Specifically, individuals are able to receive updates on health topics of personal interest through official accounts.[11] In addition, WeChat mini programs are embedded within WeChat in the form of apps,[12] providing users with personal health check-up reports through health monitoring, appointment scheduling, remote consultations, and online diagnosis, while also offering health analysis reports through health tracking and disease prediction.[13,14] Furthermore, WeChat groups and moments provide a space for individuals to share their health status with family and friends. It is evident that the above tailored and customized health information on WeChat[15] is directly related to individual health and serves as the primary basis for health decision-making.[16]

Despite the accessibility and richness of health information on WeChat, studies have shown that individuals may actively avoid health information.[17,18] This behavior, known as health information avoidance, is increasingly prevalent and is a concerning trend.[19,20] When individuals avoid health information, they may miss crucial guidance for preventive care, risk management, and timely interventions, which has an impact not only on personal health outcomes, but also on public health on a larger scale. Moreover, the proactive avoidance of general health information may primarily enhance the "filter bubble" and "echo chamber" effects, narrowing users' perspectives and limiting the breadth of their information access. The avoidance of highly tailored and personalized health information, especially, has a direct impact on individual health decisions and outcomes.

Additionally, from the perspective of cognitive dissonance theory, individuals are more likely to avoid information with a high degree of personal relevance, as they anticipate that such information may challenge or alter their self-concept.[21] If individuals perceive personally relevant information as indicating poor health,[22] or as amplifying their awareness and fear of health risks,[23] they may discontinue their search for information[24] and disengage from information sources,[25] thereby avoiding health information they consider personally relevant. Thus, the personal relevance of health information, which is typically determined by the extent to which a particular topic or issue affects an individual, plays a crucial role in influencing when and why individuals decide to avoid related information.[26]

Due to its implications for both public and individual health, health information avoidance has garnered increasing attention from scholars.[27] Existing research primarily focuses on the avoidance of information related to specific diseases such as the COVID-19 pandemic,[28,29] breast cancer,[30] colorectal cancer,[20,31] and diabetes.[32] In addition, some studies concentrate on analyzing the behavioral characteristics of individuals' avoidance of unverified,[33,34] negative,[17] and erroneous health information,[35] while some research primarily examines health information avoidance behaviors in specific groups, such as Generation Z[36] and the elderly.[37] However, few studies examine how the source and personalized nature of health information influence avoidance behaviors, despite the likelihood that the reasons for avoiding personalized health information differ significantly from those associated with general and average information. Furthermore, most studies assess information avoidance in controlled or experimental settings, where the focus on isolated factors may limit insights into the complex strategies, multidimensional influences, and hierarchical relationships inherent in real-world avoidance behaviors.[26,38]

Considering WeChat's prominent role in health information engagement in China,[39] this study aimed to explore the behavior and underlying factors of personalized health information avoidance on WeChat to better understand the phenomenon among Chinese social media users. In light of this, the current study explored WeChat to investigate the following research questions:

Q1. What internal and external factors influence the avoidance of personalized health information on WeChat?
Q2. What are the interrelationships among these influencing factors?
Q3. What are the driving forces and dependence powers of these factors?

The objective of this study was to comprehensively identify the factors influencing personalized health information avoidance on WeChat and their interrelationships. To achieve this, first, in-depth interviews with WeChat users were conducted in real-life contexts, then a grounded theory approach was employed to extract and categorize the relevant factors. Second, the ISM method was applied to analyze the interrelationships among these factors. Third, a MICMAC analysis was performed to evaluate the driving forces and dependence powers of the factors identified.

Literature review

Information avoidance, defined as any behavior aimed at preventing or delaying the acquisition of available but potentially unwanted information, is driven by individuals' desire to protect cognitive resources and reduce uncertainty.[21,23,26,40] Under this concept, the content of the information being avoided must be unknown and the avoidance should not include ignoring information due to a lack of interest, time, or energy.[26] While both information

avoidance and information seeking are strategies for sense-making and coping with uncertainty, they are fundamentally distinct.[26,36] Information seeking involves individuals recognizing information needs and actively striving to satisfy these needs, which is often characterized by effortful behavior with a high expectation of rewards,[41] whereas information avoidance aims to avoid information that threatens how individuals wish to think, feel, or behave.[42] Furthermore, several concepts are related to, albeit distinct from, information avoidance, including information non-seeking, information ignoring, and selective exposure. Specifically, information non-seeking refers to the absence of proactive information-seeking behavior, whereas information avoidance involves a deliberate effort to avoid attending to or engaging with certain information,[21,43] and it occurs less frequently than information non-seeking.[41,44] Unlike information ignoring, which is an unconscious behavior of disregarding information, information avoidance is an intentional choice.[45–47] Additionally, the distinction between information avoidance and selective exposure lies in the nature of the information encounter, that is, information avoidance typically occurs when individuals actively choose to avoid information due to uncertainty or lack of knowledge about its content, while selective exposure involves the intentionally selecting information that aligns with existing beliefs or attitudes and intentionally avoiding contradictory information.[21,48–50]

Information avoidance can be categorized into active and passive forms.[51] Active information avoidance refers to deliberate actions taken by individuals to actively prevent exposure to certain information, such as uninstalling software. In contrast, passive information avoidance involves ignoring received information or failing to take further actions to address it, such as neglecting to review a health check-up report.[26,52] Moreover, information avoidance typically manifests as behaviors such as selectively obtaining information from certain sources and channels,[53] diverting attention,[54] interpreting information in a biased manner, and engaging in selective forgetting.[55] On many occasions, researchers have observed people's tendency to avoid information. For example, individuals may avoid putting social information in their goal-pursuit journal to circumvent potentially negative comparisons,[56] consumers may avoid digital ads due to perceived goal impediments and prior negative experiences,[57] and researchers may avoid academic information under time pressure.[58] Despite the prevalence of the general phenomenon of information avoidance, it seems to be more prominent in healthcare than in other contexts. For instance, a survey conducted with a nationally representative sample in the United States revealed that 31.1% of adults preferred not to know the likelihood of their developing cancer.[59] Similarly, research by McCloud et al.[60] indicated that about one in three cancer survivors intentionally avoided seeking information on cancer.

The phenomenon of health information avoidance draws much research interest because it seemingly contradicts with some of the traditional assumptions of the information-seeking literature, as Kuhlthau (1993) noted that people are inclined to seek information to alleviate uncertainty.[61] However, a recent meta-analysis[62] revealed that the average observed association between illness uncertainty and health information seeking is nonsignificant, while the correlation between illness uncertainty and health information avoidance is more statistically significant. For example, studies have revealed that cancer patients' fears contribute to their avoidance of cancer-related information, which manifests as avoidance of cancer discussions and a refusal to seek out relevant information.

In addition to illness, the information overload caused by the explosive growth of health information on social media,[52] the proliferation of low-quality health content,[63] and the heightened perception of health risks[36] can lead to stress and discomfort. Moreover, public health crises confront individuals with significant uncertainty, and thus, uncertainty-related information avoidance is especially apparent in such risk contexts. During the COVID-19 pandemic, researchers spontaneously reported that people worldwide deliberately avoided health misinformation.[52,64] Public health crises seem to create a dilemma in which people possess a dual inclination: they aspire to access more valuable health information to mitigate risk, yet they lack the necessary resources to cope with numerous challenges such as information overload, anxiety, and fears.[65] Consequently, they are confused about whether to seek or avoid certain health information.

However, uncertainty is not the sole predictor of health information avoidance. Previous research indicates that feelings of discomfort triggered by health information are key factors driving consumers to steer clear of it. Studies suggested that individuals tend to avoid health information that might challenge their established beliefs, preferences, and habits, to reduce negative reactions and conflicts in health-related decisions makings.[66,67] For example, McCloud et al. discovered that smokers intentionally avoid health warnings on cigarette packaging to alleviate their perception of health risks, especially prevalent among individuals with lower socioeconomic status.[68] Some other motives can be found in the literature as well, such as cognitive fatigue stemming from the proliferation of false health information, mitigation of anxiety caused by information overload,[69,70] and negative emotions like the fear and disappointment associated with confronting undesirable health-related contents.[71,72] Moreover, significant differences in health information avoidance behavior are evident among individuals, depending on their age, gender, education,[73,74] health literacy,[75] and their ability and willingness to access information.[17,76]

Despite the recent proliferation of health information research, studies on health information avoidance remain relatively sparse, especially in comparison to studies on
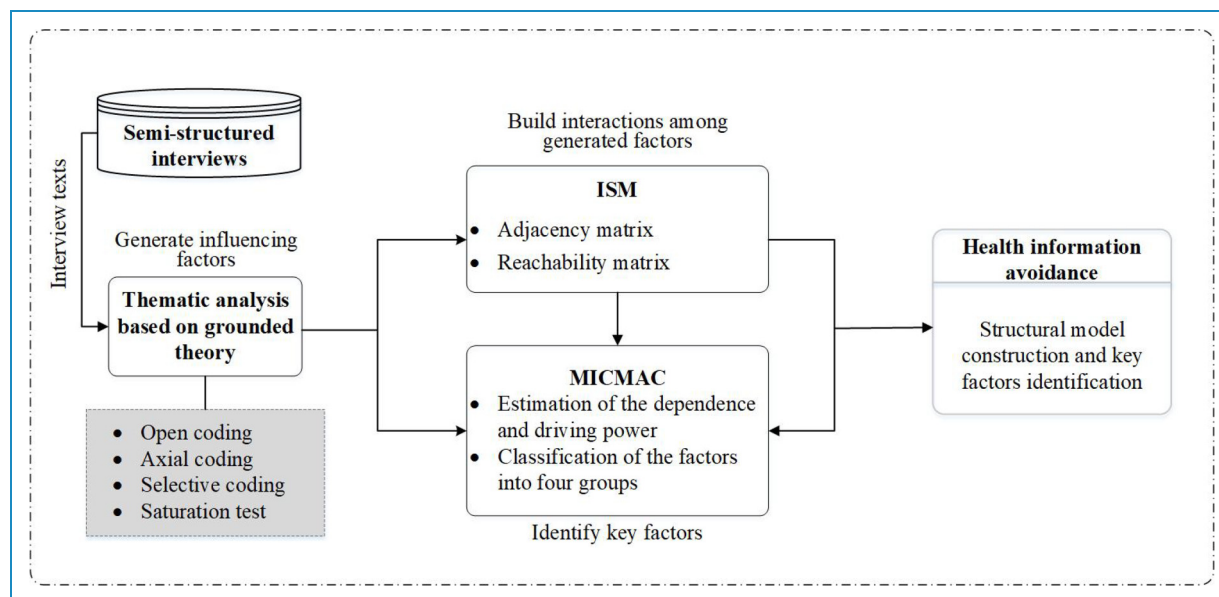
Figure 1. Research framework.

health information seeking, and significant gaps in the literature still exist. First, the prior studies were mostly conducted in disease- or risk-specific contexts and paid little to people's everyday life information practices. We argue that these two areas are inherently different. In day-to-day life settings (e.g., surfing social media), the external stimuli that trigger personalized health information avoidance may not be as apparent as those in disease- or risk-specific contexts. Therefore, we became interested in what motivates people to avoid personalized health information on social media, taking WeChat as an example. Second, it is seemingly clear that health information avoidance involves complex dynamics that stem from various factors, however, it remains relatively unclear how these factors are related to and influence each other, and thus, a further, finer-grained investigation is needed to uncover the structural relationships among the predictors. Motivated by these gaps, this study employed semi-structured interviews, the grounded theory, and ISM and MICMAC approach to examine health information avoidance behavior on a typical social media app WeChat and aimed to explore the influencing factors and underlying mechanisms of health information avoidance among the general population.

Research design

Research methods

This study applied a hybrid approach that integrated semi-structured interviews, grounded theory, ISM, and MICMAC to comprehensively identify the determinants of health information avoidance behavior on WeChat and to elucidate their

hierarchical structural relationships. Figure 1 shows the roles of the four methods in the steps of the procedure, which were: (1) identifying the factors that contribute to health information avoidance behavior on WeChat through semi-structured interviews and grounded theory (2) constructing a hierarchical model based on ISM, and (3) analyzing key factors using the MICMAC approach.

Grounded theory is a widely adopted qualitative research method designed to generate theories closely rooted in phenomena, events, or issues through the continuous interplay between data collection and analysis.[77] Based on different philosophical assumptions, grounded theory has been categorized into three main strands: classic Glaserian grounded theory,[78] straussian grounded theory,[79] and constructivist grounded theory.[80] These strands differ in their approaches to induction, deduction, and verification.[81] Among them, straussian grounded theory that is seen by scholars to have more reach and influence.[77,82] Building on the foundation of classic grounded theory, straussian grounded theory introduces a systematic and procedural approach, defining the coding process into three distinct steps: open coding, axial coding, and selective coding.[77] Straussian grounded theory is particularly well suited for developing more refined and structured theories directly from data, without relying on prior assumptions.[83] Therefore, we utilized straussian grounded theory to explore the multiple factors influencing personalized health information avoidance behavior on WeChat, examine the intricate interrelationships among these factors, and address the limitations of prior research in terms of analytical depth. Despite its approachable and flexible nature, grounded theory adheres to a structured sequence of well-defined methods for formulating a theory, model, or detailed description.

Thus, this study focused on the phenomenon of health information avoidance on WeChat, with the goal of developing a theoretical framework for personalized health information avoidance on the app by arriving at comprehensive explanations through the systematic application of sort encoding, analysis, comparison, and reanalysis.

ISM was employed to unravel the complex interrelationships among the factors that impacted the behavior. This approach, proposed by Warfield, enables the researcher to construct a multilevel hierarchical structural model, which facilitates the transition from a qualitative to a quantitative assessment of these relationships and of any mitigating subjective influences.[84] Additionally, to enhance objectivity and precision in characterizing the interrelations among these factors, we complemented ISM with the MICMAC method, which assisted with the hierarchical categorization and clarified the degrees of interdependency and influence among the factors.[85] The hybrid method has been widely adopted in various fields, including eHealth,[86] technology application,[87] and mobile wallet.[88] We also applied this mixed ISM-MICMAC method to establish the relationships and the degrees of association among the factors influencing personalized health information avoidance behavior.[89]

Data collection

Considering the intricate nature of the psychological states involved in avoidance behavior,[53,72] we conducted semi-structured interviews to gather qualitative data for the grounded theory analysis. Semi-structured interviews allow for dynamic interactions between interviewers and participants, such that interviewers can extemporize follow-up questions guided by participants' responses and emotional states. This approach provides participants with the space to articulate their perspectives during the interview process.[90] The flexibility inherent in semi-structured interviews, as emphasized by Barriball and While,[91] proved invaluable for the comprehensive exploration of WeChat health information avoidance.

This study set out to explore the avoidance of personalized health information on WeChat in everyday contexts, targeting interviewees who considered WeChat as a source of health information, had experiences of avoiding personalized health information, and possessed a level of perceptions and understanding of these avoidance behaviors. This selection criterion ensured that the data collected were aligned with the study's research objectives. Purposive sampling and snowball sampling were employed to select the interviewees, which ensured the suitability and sufficiency of the sample. The interviews were organized iteratively, with a pre-test of the initial outline involving three participants (two aged 20–35 and one aged 45–60), which was conducted before the formal start of the interviewing to ensure content validity and practicality. We gathered feedback from the participants to assess the

Table 1. Sample characteristics.

Demographic characteristics	Feature type	Total number	Proportion
Gender	Male	14	35%
	Female	26	65%
Age	18–30	15	37.5%
	31–45	9	22.5%
	46–60	10	25%
	Above 60	6	15%
Educational background	Below undergraduate	14	35%
	Undergraduate	14	35%
	Postgraduate and above	12	30%
Frequency of WeChat use	Very frequently	18	45%
	Frequently	16	40%
	Occasionally	6	15%
WeChat proficiency	Skilled	20	50%
	Less- skilled	14	35%
	Rusty	6	15%

interview's effectiveness and refine the outline. The main interview questions were formulated based on the research objectives, relevant literature, and participant feedback. A detailed outline of the interview questions is provided in Appendix 1. The formal data collection involved conducting in-depth qualitative interviews with a total of 34 participants. To ensure data saturation, an additional 6 interviews were conducted, bringing the total number to 40, each identified by "I + sequence number," for example, "1–40." The interviews were conducted in participants' homes, community activity rooms, and community parks. For those unable to meet face-to-face, supplementary online methods, such as WeChat videos or voice calls, were employed. Each interview lasted between 30 and 50 minutes, with an average duration of 35 minutes, resulting in a total interview time of 1411 minutes.

The interview sample consisted of 40 WeChat users, aged 18–70, from diverse regions, including Guangdong, Sichuan, Jiangxi, Jiangsu, Yunnan, Chongqing and Guangxi. Notably, the group comprised 14 males and 26 females, as detailed in

Table 1. The interview sample was well-balanced, encompassing various age groups and educational backgrounds. Moreover, participants exhibited varied patterns of WeChat usage: 6 used it occasionally, 16 frequently, and 18 daily. Most interviewees displayed a high level of familiarity with WeChat. Thus, the sample satisfied the requirements of our research. The recordings were transcribed verbatim by carefully listening to each audio file and cross-referencing with the interview notes, resulting in a total of approximately 110,000 words, with an average of over 2900 words per transcript.

Data analysis

Identification of factors affecting personalized health information avoidance

According to grounded theory, the primary data analysis strategy involves coding the data to develop a theory through three stages: open coding, axial coding, and selective coding.[92,93] During the process of coding analysis, it is essential to fix one's attention only on the original data, relinquishing prior experiences, viewpoints, speculations, and assumptions.[94] Concurrently, the investigators remain cognizant of theory, in this case utilizing NVivo software to continually refine and summarize the data for theory development.

Open coding. Open coding is a methodical process that entails a meticulous line-by-line analysis of the original data. Through the refinement and integration of original statements, it gives rise to new concepts that closely approximate the nature of the original data.[95] By systematically coding the interview text, and through an iterative comparative analysis of key statements, we formulated initial concepts, which were then categorized based on their characteristics and connotations. During the open-coding stage, we obtained 63 initial concepts and then generalized the features of these concepts to yield 22 basic categories. Examples of the initial concepts and dimensions formed by the open coding and their representative original statements are shown in Table 2.

Axial coding. The purpose of axial coding is to systematically classify, abstract, and synthesize the most predominant and crucial factors referred to by users, establishing potential logical connections between categories and concepts, and distinguishing between main categories and subcategories. Simultaneously, it verifies the associative relationships utilizing raw data.[96] We reorganized the factors influencing the avoidance of personalized health information, consolidated the redundant factors, summarized the conceptual categories, and ultimately constructed six principal categories: health characteristics and cognition, decision-making cognition, negative emotions, information

factors, social factors, and avoidance behavior, as shown in Table 3. Clearly, most of these factors are closely related to the personalized characteristics of health information on WeChat.

Selective coding. Selective coding involves refining categories and discovering relationships among concepts. During selective coding, core categories can be extracted from major categories, along with the influential relationships between them.[97] By repeatedly comparing categories, carefully considering the original statements, and thoughtfully examining the relationships among categories, it became evident that avoiding personalized health information was the core category. This avoidance behavior was influenced by six principal categories (the sixth of which marked the distinction between active and passive factors), which were further subdivided into 20 subcategories.

As presented in Table 4, the factors influencing personalized health information avoidance can be broadly categorized into three groups: personal, informational, and social factors. Personal factors, which are internal drivers, include health characteristics and cognition, decision-making cognition, and negative emotions. Specifically, health characteristics and cognition encompass health status, health optimism preference, negative health experiences, and health information literacy. Decision-making cognition includes the four factors of perceived control, anticipated cost, perceived risk, and cognitive dissonance. Emotional factors have a significant impact and include anxiety, fear, worry, sadness, and irritation, as well as fatigue. Informational factors are important external drivers of avoidance, consisting of information overload, content accuracy, content relevance, and information utility. Social factors, also external drivers, come from the social environment; they include social ties and subjective norms.

This study sequentially employed open coding, axial coding, and selective coding of the original interview texts to extract the initial concepts and construct the principal and core categories. A detailed summary of the data coding is presented in Table 4.

Theoretical saturation test. Theoretical saturation is an evaluation of the accuracy and reasonability of the concepts and categories formed by researchers through concept extraction and category delineation.[98] It is the stage when no new categories or relationships can be discerned in the data.[91,92] To verify whether theoretical saturation was achieved, an additional six participants were interviewed, but no new concept categories or relationships were identified. Therefore, it was concluded that the coding results had reached theoretical saturation.

Table 2. Examples of the initial concepts and dimensions formed through open coding.

Representative original statement (P)	Initial concepts (a)	Initial category (A)
P1. During the period of postpartum depression, the whole person is resistant of things related to mental illness and depressed. I often inexplicably began to cry, being sad. What's more, I do not want to see health information related to this at all. Neither do other health information. (I10)	a1 Objective physical health problems a2 Perceived physical health status	Health status A1
P2. People in their 20s and 30s who are optimistic may neglect to get in touch with this health information and don't read it if they don't think it has anything to do with them; but for middle-aged people like us in their 40s and 50s, they may still be more to reserve this health information knowledge. (I02) P3. If a person suffers from a very serious disease, or the hope of a cure is very slim, it will change that person's mentality. The problem will not be solved even if we get in touch with health information every day. What's worse, the mood will also be affected. (I33)	a3 Stay optimistic a4 Mind-blowing a5 Escapist mentality	Health optimism preference A2
P4. I have had a serious thyroid disease before, which left a deep shadow on me. During that time, it was very painful both physically and mentally, and the follow-up treatment and rehabilitation was also very troublesome. So now I see the first response to thyroid-related health promotion is to have such a painful life before, and my heart will be very resistant. (I20) P5. I will resist in my heart. I feel that it involves a past that I don't want to mention before, and it is still a not-so-good experience. If I pull out the bad memories and emotions of the past, I will avoid it. (I02)	a6 Bad experience associations a7 Painful memories a8 Psychological shadows	Negative health experiences A3
P6. It's okay if the statements are consistent, but if the statements are inconsistent, you will be confused. I don't know which one is right and which one to listen to and obey. (I11) P7. The things on the Internet are true and false, and I can't tell which ones are true and which are false. (I12)	a9 Comprehension a10 Self-management a11 Learning ability a12 Judgment ability	Health information literacy A4
P8. Sometimes WeChat sends me information like cancer prevention and treatment. I can't control this, and I don't know the pathology. Even if you tell me, I may not understand it and don't know what to do. (I08)	a13 Powerless a14 Super content	Perceived control A5
P9. I also know that smoking and drinking alcohol are harmful, but it is even more difficult for me to stop smoking or drinking since it has lasted for so many years. The cost of quitting smoking and drinking is too great. Sometimes I feel regrettable when I click on it. (I28)	a15 Behavior cost a16 Time cost a17 Stubborn habits (difficult to change)	Anticipated cost A6
P10. Recently, there are more and more people staying up late. With more public accounts focusing on this issue, I have known that staying up late can also cause cardiovascular and cerebrovascular diseases, as well as	a18 Symptoms related to perceive (consciousness) a19 Likelihood	Perceived risk A7

(continued)

Table 2. Continued.

Representative original statement (P)	Initial concepts (a)	Initial category (A)
some gastrointestinal disorders. It scares me when I suddenly discover that I am facing so many risks of health problems, especially the cardiovascular and cerebrovascular diseases. (I13) P11. I'm afraid to know that I might be at risk after seeing it. I'd rather not know anything and steal for a while. If I saw it, I would be frightened and I might live a few more years. (I12)	a20 Severity a21 Maintain uncertainty	
P12. I have never felt that drinking milk tea will be so harmful. Although I know that it must add something harmful in it, I don't think it will endanger life. (I20) P13. I do prefer to drink beer and eat crayfish, but these health tips definitely tell me not to eat seafood and not to drink, which will create a more contradictory state. I want to eat when I am constantly reminded that I can't eat. There will be some undesirable consequences if I eat, which is irritable. (I29)	a22 Contradictory mentality a21 Confusion a23 Disagreement a24 Psychological gap	Cognitive conflict A8
P14. Sometimes if you are in a particularly bad mood and an anxious state, you will deliberately not read some health information. (I17) P15. If I push such information to me at this time, I might avoid it. Since if I can't do it, I will start to be a little anxious. And if it keeps reminding me about this, I will be even more anxious. (I34)	a25 Anxiety about health status a26 Anxiety about potential health threats a27 Anxiety caused by cognitive conflicts	Anxiety A9
P16. Such a title is very scary, and it will be very uncomfortable and scary when you read it. (I02) P17. I don't read disease-related information on WeChat since I'm afraid to know that I might be at risk after seeing it, and I would rather not know anything. (I32)	a28 Fear of information contents (disgusting pictures, descriptions) a29 Fear of unknown risks	Fear A10
P18. Because I am still a little worried that staying up late will cause some health problems, especially about the sudden death of young people in the news some time ago. (I01) P19. Generally speaking, I don't want others to know if I have any illness, especially some people who are actually not familiar with me on WeChat. I am worried about other people's gossip. (I03)	a30 Health concerns a31 Information privacy concerns a32 Concerns about personal abilities	Worry A11
P20. Seeing this kind of disease-related information will make me uncomfortable and sad since there are people around me who have died of these diseases, so I will avoid it. (I17)	a33 Sad a34 Depressed a35 In a bad mood	Sadness A12
P21. It is very irritable to watch everything when the mood of menopause comes up. You may click on a push when you encounter it, but you don't want to watch anything when you are upset. (I22) P22. We don't understand those that are related to cancer. What's worse, we will feel uncomfortable and panic after seeing it. (I19)	a36 Irritability caused by health a37 Irritability caused by overload a38 Mental discomfort a39 Dislike	Irritation A13

Table 2. Continued.

Representative original statement (P)	Initial concepts (a)	Initial category (A)
P23. Sometimes too many such pushes can also be a psychological burden. You may feel tired even if you just click in. (I13) P24. Even with excellent content, moderation is essential. Excessive words can lead to visual fatigue. (I15)	a40 Visual fatigue a41 Psychological burden	Fatigue A14
P25. In the family group, there will often be health information forwarded by uncles and aunts. Sometimes they will be specially @you. If you are under more pressure, you will indeed feel tired. (I01)	a42 Excessive group messages a43 Insufficient processing capacity	Information overload A15
P26. In some WeChat groups, the headline of the push will scare people, but the contents inside are lack of factual basis. It will be better if you don't read it since the quality is not good. (I35)	a44 The reliability of the information source a45 The accuracy of the content a46 Content contradictory	Content accuracy A16
P27. If what WeChat pushes me is the harm caused by smoking, but I don't smoke, and there are no smokers around me, then this has nothing to do with me, so I will definitely not go to see it. (I15)	a47 The degree of relevance to one's own situation a48 The degree of information matching	Content relevance A17
P28. I am very depressed. I think doctors and the psychotherapist talks are useless. Information on the Internet is useless to me anyway. (I30)	a50 Information usefulness a51 Practical operational significance	Information utility A18
P29. There have been cases when family and friends have had related bad experiences. When they see related health information, they feel uncomfortable and avoid this type of health information. (I21) P30. In addition, there are some friends on WeChat. My social circle should relax me, but it shouldn't make me more anxious. (I16)	a52 Family relationship, friend relationship a53 Social circle	Social ties A19
P31. People on WeChat are basically acquaintances, not everyone is familiar with some mental illnesses, such as affective disorders or bipolar disorder. Many people even don't accept this. Under these circumstances, I will not repost or discuss it with them because I'm worried that they think I have a problem. (I13)	a54 Be consistent with others a55 Fear strange vision	Subjective norms A20
P32. If I am more confident in my information processing ability, I know when there is too much information, or I can distinguish which information is true and false, in this case I will have a choice to avoid some unnecessary information. (I16)	a56 Active filtering a57 Saving time a58 Active information avoidance a59 Maintaining inner consistency	Active avoidance A21
P33. If a person encounters information that he doesn't want to read, he passively avoids it and change nothing, which is a kind of self-deception. Sometimes I was like this, because I was anxious and didn't want to watch it. After I avoided it, I began to think about it and felt anxious again. (I17)	a60 Ostrich mentality a61 Remaining uncertain a62 Complete avoidance a63 Self-deception	Passive avoidance A22

Note: The "I + sequence number" denotes the respondent.

Table 3. Examples of the main dimensions formed through axial coding.

Principal category	Initial categories	Connotations
Health characteristics and cognition B1	A1 Health status	The physical and psychological health status of users
	A2 Health optimism preference	Users' optimistic, neutral, or negative attitudes toward their own health status
	A3 Negative health experiences	Negative and painful illnesses that users have experienced
	A4 Health information literacy	The individuals' ability to obtain, identify, and use health information
Decision-making cognition B2	A5 Perceived control	Users' perceived degree of control over health information and related health outcomes
	A6 Anticipated cost	The cost of behavioral changes entailed by the health information acquired by an individual
	A7 Perceived risk	The likelihood and severity of an individual's perceived health threat
	A8 Cognitive conflict	Psychological contradictions or conflicts due to discrepancies between original cognitive structure and the content of health information
Negative emotions B3	A9 Anxiety	Individuals' anxiety about potential health risks and excessive health information
	A10 Fear	Individuals' fear of their health status and health information content
	A11 Worry	Individuals' worries about their health and information privacy concerns
	A12 Sadness	Sadness caused by individuals' unhappy associations with health information
	A13 Irritation	Anxiety and depression when facing health information

(continued)

Table 3. Continued.

Principal category	Initial categories	Connotations
	A14 Fatigue	Psychological sense of burden and fatigue when facing excessive health information
Information factors B4	A15 Information overload	Health information that exceeds the scope of individual acceptance and effective use
	A16 Content accuracy	Accuracy and reliability of health information content
	A17 Content relevance	The degree of the relevance of health information content to an individual's condition
	A18 Information utility	The degree of the usefulness of the health information for making health decisions
Social factors B5	A19 Social ties	Interrelationships formed by individuals in society
	A20 Subjective norms	Social pressure on individual information behavior; degree of influence of others or groups
Avoidance behavior B6	A21 Active avoidance	Avoidance of a part of health information, due to a positive mental state, in order to improve the efficiency of health information acquisition and processing and to make correct health decisions
	A22 Passive avoidance	Individuals' failure, when encountering health information they don't want to see, to take measures to avoid unnecessary interference; instead, they retreat from all the information and compromise the utility of their original search, which can lead to serious consequences.

Table 4. Summary of the data coding.

The core category	Principal categories	Subcategories	
WeChat health information avoidance behavior C1	Health characteristics and cognition B1	A1 Health status	
		A2 Degree of health optimism preference	
		A3 Negative health experiences	
		A4 Health information literacy	
	Decision-making cognition B2	A5 Perceived control	
		A6 Anticipated cost	
		A7 Perceived risk	
		A8 Cognitive conflict	
	Negative emotions B3	A9 Anxiety	
		A10 Fear	
		A11 Worry	Worry about health
			Worry about privacy
		A12 Sadness	
		A13 Irritation	
		A14 Fatigue	
	Informational factors B4	A15 Information overload	
		A16 Content accuracy	
		A17 Content relevance	
		A18 Information utility	
	Social factors B5	A19 Social ties	
		A20 Subjective norms	
	Avoidance behavior B6	A21 Active avoidance	
		A22 Passive avoidance	

Construction of ISM model

Based on Moughari's research, the interpretive structural modeling approach includes four steps: constructing the adjacency matrix, constructing the reachable matrix, dividing the hierarchical relationship, and developing the ISM model.[99]

Constructing the adjacency matrix. An adjacency matrix reflects the logical relationships among influencing factors. The twenty subcategories identified through grounded theory were entered into the adjacency matrix as influencing factors. Within the matrix, each value represents the impact of a factor in a given row, F_i, on a factor in the corresponding columns, F_j. The 20×20 adjacency

Table 5. Results of the level partitions.

Influencing factors	Antecedent set $Q(F_i)$	Reachable set $R(F_i)$	Interaction set	Level
F1	F1	F1, F2, F4, F6, F9, F10, F11, F13, F18	F1	L4
F2	F1, F2, F3, F8	F2, F4, F5, F6, F9, F10, F11, F15, F17, F18	F2	L3
F3	F3	F2, F3, F4, F9, F10, F11, F13, F18	F3	L4
F4	F1, F2, F4, F5, F7, F8, F18	F4, F9, F10, F11, F13	F4	L2
F5	F5	F4, F5, F9, F10, F11, F12, F13	F5	
F6	F1, F2, F6	F6, F9, F11, F13	F6	
F7	F7, F8	F4, F7, F9, F10, F11, F13, F14, F16, F18	F7	
F8	F8	F4, F7, F8, F9, F10, F11, F13, F14, F16, F17, F18	F8	L4
F9	F1, F2, F3, F4, F5, F6, F7, F8, F9, F15, F17, F19, F20	F9	F9	L1
F10	F1, F2, F3, F4, F5, F7, F8, F10, F16, F17, F18, F19	F10	F10	
F11	F1, F2, F3, F5, F6, F7, F8, F11, F15, F16, F18, F19, F20	F11	F11	
F12	F5, F12, F19	F12	F12	
F13	F1, F2, F3, F4, F5, F6, F7, F8, F13, F15, F16, F17, F18, F20	F13	F13	
F14	F7, F8, F14, F15	F14	F14	
F15	F2, F15	F9, F11, F13, F14, F15, F	F15	L2
F16	F7, F8, F16	F9, F10, F11, F13, F16, F18	F16	
F17	F2, F8, F17	F9, F10, F13, F17	F17	
F18	F1, F2, F7, F8, F16, F18	F4, F9, F10, F11, F13, F18	F18	
F19	F19	F9, F10, F11, F12, F19	F19	
F20	F20	F9, F11, F13, F20	F20	

As shown in Table 5, the extracted top-level factors are L_1 = {F9, F10, F11, F12, F13, F14}. After removing these six top-level factors, the second-level factors were L_2 = {F4, F5, F6, F7, F15, F16, F18, F19, F20}. When the same approach was repeated to complete the hierarchical division, all the factors were classified into four levels, which are also shown in Table 5.

matrix is directional, based on values of 0 or 1.[100] Zero denotes that the ith row (F_i) has no impact on the jth column (F_j), and 1 indicates that the ith row (F_i) has no direct influence on the jth column (F_j). These relationships are expressed as follows:

$$A_{ij} = \begin{cases} 1, & F_i \text{ has direct effect on } F_j \\ 0, & F_i \text{ has no direct effect on } F_j \end{cases} \quad (1)$$

where A_{ij} is the value of the factor in row i and column j of the adjacency matrix, F_i is the factor represented by the ith

row, and F_j is the factor in the jth column.

Furthermore, the adjacency matrix registers only direct relationships among the influencing factors, as extracted from terms such as "resulted in," "generated," "helped to," and "increased" in the interview transcripts, without accounting for indirect impactful relationships.

$$A = \begin{array}{c} F1 \\ F2 \\ F3 \\ F4 \\ F5 \\ F6 \\ F7 \\ F8 \\ F9 \\ F10 \\ F11 \\ F12 \\ F13 \\ F14 \\ F15 \\ F16 \\ F17 \\ F18 \\ F19 \\ F20 \end{array} \begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

F1 = health status; F2 = health optimism preference; F3 = negative health experiences; F4 = perceived control; F5 = anticipated cost; F6 = perceived risk; F7 = cognitive conflict; F8 = health information literacy; F9 = anxiety; F10 = fear; F11 = worry; F12 = sadness; F13 = irritation; F14 = fatigue; F15 = information overload; F16 = content accuracy; F17 = content relevance; F18 = information utility; F19 = social ties; F20 = subjective norms.

Constructing the reachable matrix. To further capture indirect relationships among the influencing factors, the transitivity principle was employed to construct the reachable matrix M. That is, if the first factor relates to the second factor, and the second factor relates to the third factor, then the first factor is transitively related to the third factor. The transitivity check continues until the transitivity of all factors in the matrix has been examined. The reachable matrix can be calculated according to the following Boolean rules:

$$M = (A) + (I^r) = (A) + (I^{r-1}) \neq (A+I)^{r-2} \neq \ldots \neq (A+I),$$
$$r \leq 20$$

(2)

where

M = the final calculated reachable matrix
$A = (A_{ij})_{n \times n}$ = the adjacency matrix (the order is 20)
I = unit matrix
$(A + I)^r$ = intermediate reachability matrix with r intermediates.

Since there are 20 factors influencing personalized health information avoidance behavior, MATLAB R2020b was utilized to perform several power operations to obtain the reachable matrix M. (The operation code is attached in the last Appendix). In the reachable matrix, 1 indicates the existence of a reachable path between corresponding factors, while 0 shows the absence of both direct and indirect connections between the corresponding row and column factors.

$$M = \begin{array}{c} F1 \\ F2 \\ F3 \\ F4 \\ F5 \\ F6 \\ F7 \\ F8 \\ F9 \\ F10 \\ F11 \\ F12 \\ F13 \\ F14 \\ F15 \\ F16 \\ F17 \\ F18 \\ F19 \\ F20 \end{array} \begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Dividing the hierarchical relationship of influencing factors.
According to the reachable matrix M, we obtained the antecedent set $Q(F_i)$, the reachable set $R(F_i)$, and the intersection set $Q(F_i) \cap R(F_i)$. The antecedent set $Q(F_i)$ is composed of a given factor, F_i, and other factors that may reach factor F_i, including all row factors with a value of 1 in column F_i of the reachable matrix. The reachable set $R(F_i)$ consists of the factor F_i and other factors influenced by F_i, including all column factors with a value of 1 in the F_i row of the reachability matrix. The interaction set comprises factors that are common to both the reachable set and the antecedent set.

$$Q(F_i) = \{F_j | F_j \in M, \ m_{ji} = 1\} \ i, j = 1, 2, \ldots, n \quad (3)$$

$$R(F_i) = \{F_j | F_j \in M, \ m_{ij} = 1\} \ i, j = 1, 2, \ldots, n \quad (4)$$

$$C(F_i) = Q(F_i) \cap R(F_i), \quad (5)$$

where $Q(F_i)$ is the antecedent set, $R(F_i)$ is the reachable set, $C(F_i)$ is the intersection set, and m_{ji} and m_{ij} = the values of the factors in reachable matrix M.

A top-level factor is a factor achieved with the assistance of all other factors, but one that does not contribute to any factor beyond those at the same level.[101] A top-level factor is identified when $C(F_i) = R(F_i)$. Once the top-level factors are marked, they are removed from the reachable set of other factors, and this procedure is repeated until a hierarchical classification has been established for all the factors in the matrix.

Developing the ISM model. A four-level ISM model of the factors that influence personalized health information avoidance behavior was developed, as displayed in Figure 2, which is based on the hierarchical division and the interactions involving each influencing factor in matrix *M*. The model illustrates the hierarchical relationships of the twenty influencing factors from the bottom to the top. Levels 3 and 4 consist of fundamental factors that directly affect the factors at level 2 (anticipated cost, perceived control, perceived risk, cognitive conflict, content accuracy, information utility, content relevance, information overload, social ties, and subjective norms). Level 2, in turn, directly affects level 1. Additionally, the four levels can be divided into three layers: a top layer (level 1), a middle layer (level 2), and a bottom layer (levels 3 and 4). Direct and indirect influences operate between layers, ultimately forming chains of factors that contribute to personalized health information avoidance behavior.

MICMAC analysis

A MICMAC analysis was conducted to understand and identify critical factors, based on their driving power and dependence power. According to Mohapatra's method,[102] the former was calculated by summing the value of each row, namely, the values of the influencing factors in the reachable matrix M, while the dependence power was derived by adding the values in each column of factors. Then, all 20 factors were divided into autonomous, independent, linkage, and dependent factors to form a four-quadrant, dependency/driving force classification diagram (see Figure 3).
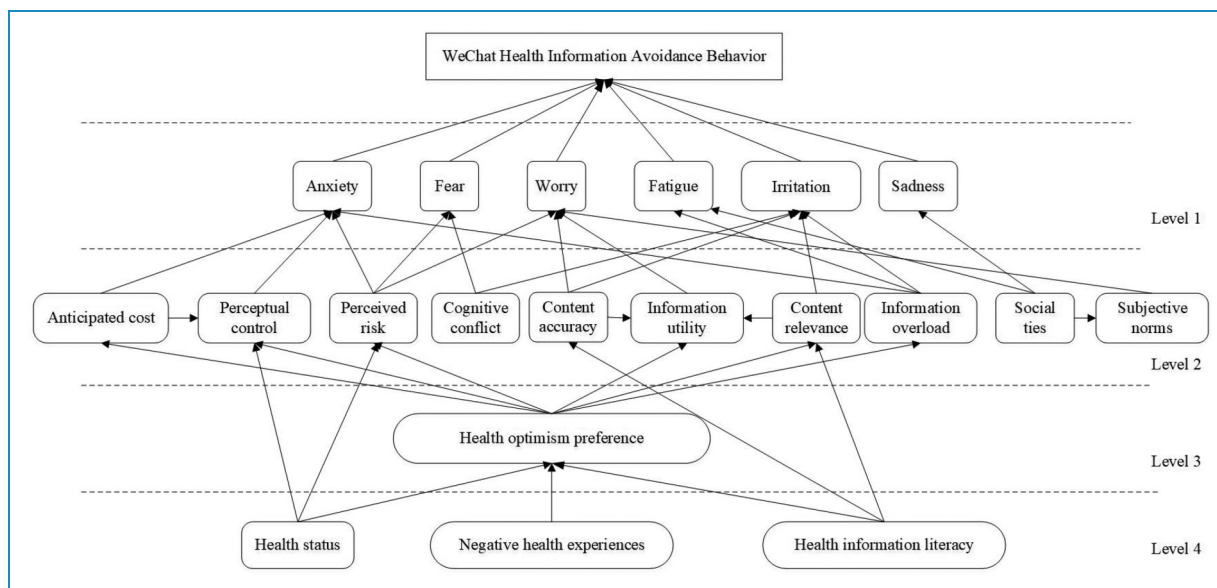
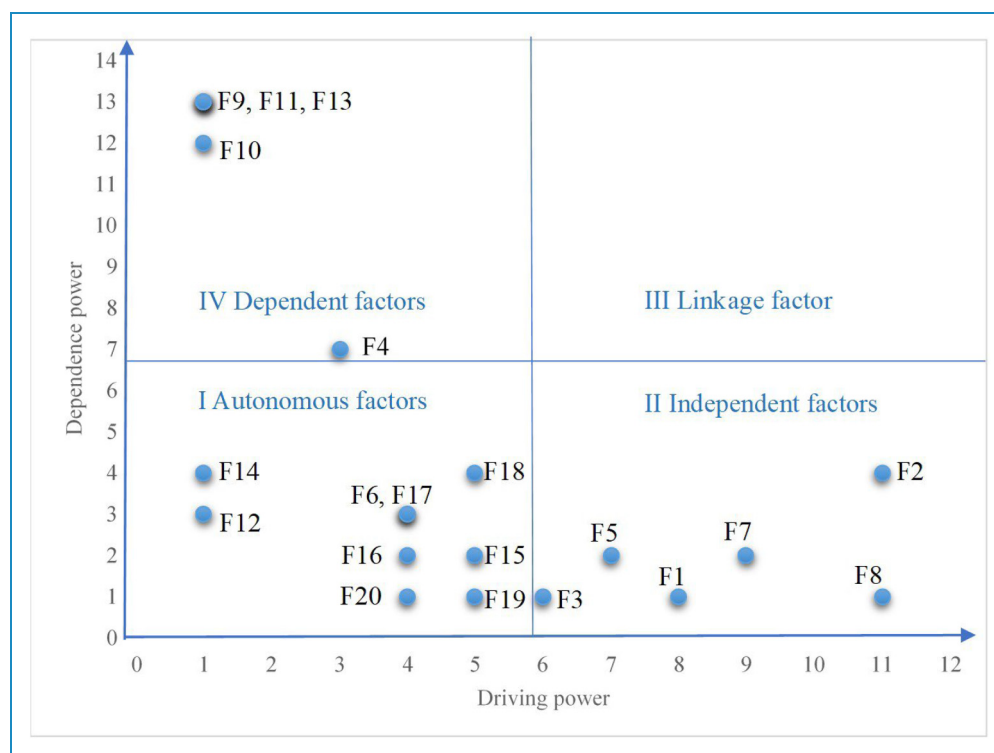**Figure 2.** ISM model diagram of influencing factors.

Figure 3. Dependence-driving force classification diagram.
F1 = health status; F2 = health optimism preference; F3 = negative health experiences; F4 = perceived control; F5 = anticipated cost; F6 = perceived risk; F7 = cognitive conflict; F8 = health information literacy; F9 = anxiety; F10 = fear; F11 = worry; F12 = sadness; F13 = irritation; F14 = fatigue; F15 = information overload; F16 = content accuracy; F17 = content relevance; F18 = information utility; F19 = social ties; F20 = subjective norms.

Quadrant I contains the autonomous factors, (F6, F12, F14, F15, F16, F17, F18, F19, and F20), which usually have low dependence and driving power, with minimal influence on WeChat health information avoidance behavior. Most of these are located in the middle layer of the ISM model, including most cognitive factors, information

factors, and social factors, which are indirect influencing factors. Autonomous factors are generally relatively stable. The impact of lower-level factors on them usually takes a while to appear, although changes in autonomous factors can lead to more direct and rapid impacts on upper-level factors.[103,104]

Quadrant II displays the independent factors (F1, F2, F3, F5, F7, and F8), which are critical factors with low dependence and high driving power. The results of the ISM show that most of the independent factors are distributed in levels 3 and 4, likely eliminating or weakening the impact of factors at other levels.[105]

Quadrant III typically holds linkage factors, which have both high dependence and driving force; however, no influencing factors fall into this quadrant. This is highly likely attributable to the high instability of linkage factors, as they easily impact other factors and are impacted in turn.[106]

Quadrant IV displays the dependent factors (F4, F9, F10, F11, F13), which generally have high dependence and low driving power. These mainly consist of negative affective and emotional factors found at level 1 in the ISM model, and they are easily influenced by other factors and require the support of other factors in the current scenario.[107]

To sum up, the classifications arrived at through the MICMAC analysis are generally in line with the ISM model, where the driving power of direct factors in the surface layer is weak and their dependence is high, whereas the driving power and dependence of indirect factors in the middle layer are relatively low. What's more, the dependence of basic factors in the root layer is weak, but these factors exert a strong driving power on WeChat health information avoidance behavior.

Results and discussion

This study identifies and prioritizes twenty predictors classified into four levels, each of which has a different impact on health information avoidance.

The top-layer enablers of health information avoidance

The top-layer factors are related to negative emotions, including anxiety, fear, worry, irritation, sadness, and fatigue. This suggests that emotional discomfort is a direct cause of personalized health information avoidance behavior, which is consistent with Kleiber's point of view toward stress and coping theory, namely, that information avoidance is an emotional management coping style in stressful situations.[108] The RPA model posits that people, in order to alleviate discomfort,[75] tend to avoid information that can increase negative emotions or diminish positive emotions; in other words, information avoidance is expressly a way to regulate negative emotions, such as anxiety, fear, and worry. For instance, when confronted with unfavorable information regarding an increased risk of

breast cancer and the associated anxiety,[26] people may resist breast cancer screening and avoid corresponding information. Similarly, fear and anger associated with COVID-19 can induce information avoidance.[109] However, other individuals, driven by sadness and the fear of illness, actively seek out health information rather than try to protect themselves against negative emotions by avoiding it.[52] The decision of individuals to avoid health information primarily depends on the perception of emotional effects before and after acquiring such information.[26] When individuals perceive that the emotional gains from not knowing are greater than those from being informed, they are more likely to exhibit avoidance. Hence, it is evident that the impact of emotions on the avoidance of health information is complex and conditional.

The middle-layer enablers of health information avoidance

The middle-layer factors, found in the second tier of the ISM model, can be divided into three dimensions: (1) decision-making cognitive factors (perceived control, anticipated cost, perceived risk, and cognitive conflict), (2) informational factors (information overload, content accuracy, content relevance, and information utility), and (3) social factors (social ties and subjective norms), which have been confirmed by previous research to be antecedents that contribute to information avoidance.[110] A study by Melnyk and Shepperd[111] revealed that individuals are more likely to engage in information avoidance when the processing of irrelevant health information requires more resources; for instance, information overload was a known reason that people avoided seeking information about COVID-19 during the 2020 pandemic. Individuals who perceive injunctive and descriptive avoidance norms are more inclined to avoid health information.[65] However, our results indicate that cognitive, informational, and social factors at the middle level do not exert a direct impact on information-avoidance behavior. Instead, they contribute to heightened information uncertainty, which might be a proximal cause of negative emotions that directly trigger information avoidance.[26] This also explains nicely why certain studies have found that social norms and cognitive factors have no impact on information avoidance.[112,113] Additionally, anticipated cost (F5) and cognitive conflict (F7) fall into the quadrant of driving factors, and these are the key determinants of information avoidance. This finding aligns with the literature, indicating that individuals often tend to avoid information that conflicts with their knowledge and beliefs[66,67] and content of low quality and value.[114]

The bottom-layer enablers of health information avoidance

The bottom-layer enablers, involving level 3 and level 4 factors in the ISM model, have strong driving power. These factors include health status, negative health

experience, health information literacy, and health optimism preference, all of which are not influenced by other factors in the system but have indirect or direct effects on middle-level personal cognitive and informational factors. Specifically, health status directly influences perceived control, perceived risk, and health optimism preference. This is supported by the findings of Elliot et al., who proposed bidirectional associations among perceived control, health risk, and positive/negative emotions.[115] Moreover, health information literacy has been associated with content accuracy, content relevance, and health optimism preference, which means that individuals with higher information literacy find health information easier to comprehend,[60,73,116] possess greater health self-efficacy, and have a more optimistic perception of their own health status. Also, our study supports the idea that patients' negative health experiences (F3), such as bad prior experiences with serious illness or with doctors' not examining them thoroughly,[20,117] tend to lower their level of health optimism, thereby increasing the likelihood that they will avoid health information.[19]

Types and results of WeChat health information avoidance

From the results of the interviews, it can be observed that many people engage in information avoidance to some extent, but their situations and their reasons for doing so vary.[118] Moreover, avoidance behavior is regarded as a way to manage information uncertainty and involves active and passive strategies.[119] Active avoidance, typically rooted in high health-information literacy, develops as a response to false, unreliable, or useless information. Exercised with a high level of self-control and self-efficacy, it enhances efficiency in seeking and utilizing health information.[120,121] In contrast, passive avoidance, often associated with negative emotions, involves health information that might bring about cognitive conflicts, cognitive overload, comprehension difficulties, or social pressures.[122] Passive avoidance is merely a temporary emotional comfort; it not only diminishes the utility of information but also can lead to adverse consequences such as delays in diagnosing a disease. This, in turn, further intensifies negative emotions like anxiety and fear; therefore, it is necessary to reduce unreasonable and irrational information avoidance.[19]

Conclusion

Theoretical implications

This study makes two important theoretical contributions. First, despite the considerable amount of research on health information avoidance,[18,123,124] there is still a gap in studies conducted on everyday encounters with personalized health information on social media. Health information avoidance is a diverse and complex phenomenon shaped by a combination of individual, informational, and social factors.[26,118] Moreover, the avoidance of personalized health information differs significantly from general or average patterns of health information avoidance; the driving factors of personalized health information avoidance are highly individualized. Among the 20 factors identified, 14 are personal factors and only 4 relate to information characteristics and 2 to social contexts. These personal factors fall into three categories: health status and cognition, decision-making cognition, and emotional responses. Personalization contrasts not only with generality, in terms of greater relevance to the individual and deeper personal engagement,[26] but also with the average patterns of other avoidance behaviors. For example, compared to average disease prevalence rates, personal health examination results have a more pronounced influence on individual health assessments and decision making.[16] Consequently, personal factors play a critical role in shaping personalized information avoidance behaviors.

Second, this study used in-depth interviews and grounded theory analysis to explore the avoidance of personalized health information in everyday life contexts, overcoming the limitations of controlled experiments and predefined hypotheses. The findings comprehensively summarize the multidimensional influencing factors and enrich the literature on information-avoidance behavior. Moreover, the paper stands as a pioneering attempt to introduce the ISM-MICMAC method to construct a four-level hierarchical structure of the factors that influence health information avoidance behavior on social media and to investigate the interdependence of these factors and their impacts on health information avoidance. The causal relationships revealed by the structural framework, grounded in driving power and dependence power, are in keeping with the stimulus-organism-response (SOR) model,[125–127] which describes how health characteristics and cognition can act as stimuli to arouse an organism (through decision-making cognition, negative emotions, informational factors, and social factors) and lead to health information avoidance. Thus, the findings clarify the logical relationships among the factors that influence health information avoidance on social media and serve as a valuable guide for further research and practical applications.

Practical implications

The data analysis results show that six negative emotional factors directly impacted avoidance behavior, while another six influencing factors (health status, health optimism preference, negative health experiences, anticipated costs, cognitive conflicts, and health information literacy) exerted strong driving forces, followed by information overload, information utility, and social ties. Therefore, the article puts forward noteworthy practical implications.

First, health information avoidance, as an adaptive strategy for dealing with uncertainty, may enhance the efficiency of information seeking, but it may also lead individuals to overlook health information that is beneficial to them.[26,117] Hence, it is imperative to guide user behavior toward rational avoidance. To counteract or alleviate negative emotions such as anxiety and fear, individuals might start by mitigating their perceptions of threat.[128,129] Introducing elements of music, games, and entertainment into health information can foster curiosity[130] and induce positive emotions—for instance, offering emotionally engaging, interesting, and persuasive videos rather than explanatory text, or developing entertaining mini-games on WeChat to disseminate health knowledge. Additionally, self-regulation techniques can be considered,[131] such as using the psychological contrast between negative future outcomes and positive present realities to effectively alleviate the information avoidance related to specific diseases.

Second, individuals need to recognize the crucial roles of health status, negative health experiences, and health literacy in health information avoidance. On one hand, people need to actively monitor their physical condition, assess and control their health status objectively and in a timely manner, understand the costs associated with the behavioral changes prompted by health information, and act to prevent information avoidance due to excessive optimism or pessimism. On the other hand, to enhance the health-information literacy of WeChat users, governments could collaborate with communities, schools, libraries, hospitals, and health commissions to regularly organize activities to disseminate health knowledge.[28] For example, they could set up dedicated public accounts or video channels on WeChat that offer regular courses on health-information literacy and provide targeted training for information-poor groups such as the elderly, low-income individuals, farmers, and people with low education levels.[27]

Third, the abundance of health information on the WeChat platform may lead to information overload and reduce information utility,[121,132] which is not conducive to effective health-information seeking.[65] The dissemination of a large amount of misinformation and disinformation can cause information overload; therefore, WeChat should provide users with health information that is clearly sourced[133] and matches their needs. Specifically, the platform could require information senders to cite sources to enhance the credibility of health information and use human-AI collaboration methods to identify fake or misleading information, semantically and contextually, while also promptly debunking information through official accounts and removing false information. These measures would strengthen users' perception of the utility of health information available on WeChat. Additionally, governments could enact and enforce stricter policies to reduce the dissemination of health misinformation and disinformation on social media.[134]

Limitations and future research

Although this study involved a fairly comprehensive analysis of the factors that influence people's health information avoidance on WeChat, it had certain limitations. First, it should be noted that grounded theory relies on small-scale data that primarily capture subjective user experiences. Therefore, the conclusions drawn from this study have not been validated with a large-scale dataset. Future research could integrate large datasets and machine-learning methods to conduct a more in-depth investigation. Second, the interview sample encompasses a variety of groups, however, the limited number of participants from each group may result in insufficient representation of certain populations, potentially limiting the generalizability of the research findings. Future studies could optimize the conclusions by expanding the sample size or integrating quantitative methods. Third, despite that our theoretical model passed the saturation test, there is still the possibility that certain factors were missed. Future research could benefit from expanding the scope of the study to encompass a broader population to extend the findings currently found in the literature. Fourth, this study did not account for the dynamic adaptability of information-avoidance behavior, nor did it categorize different types of health information. Future research could integrate experimental and survey methods to meticulously investigate the adaptive strategies of information avoidance adopted by WeChat users in various contexts.

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References

1. Chen J and Wang Y. Social media use for health purposes: systematic review. *J Med Internet Res* 2021; 23: e17917.
2. Fallatah KU, Harvey MA and Rutter S. Health information post-encountering behaviours on social media platforms. *Inf Res* 2024; 29: 253–274.
3. Wu M, Wu T and Pei Y. What drives health information exchange on social media? Social media affordances and social support perspectives. *Health Commun* 2024; 39: 3365–3379.
4. Chen Y, Liu M, Chen M, et al. Determinants of patients' service choice in online health communities: an elaboration likelihood model perspective. *Libr Hi Tech* 2024; 42: 1863–1879.
5. Ming Y. *Impacts from intentional and incidental online health information seeking and eHealth literacy on shared decision-making and information avoidance among diabetic patients*. Kent, OH: Kent State University, 2023.
6. Wang Y and Zhang J. Impact of social media on public health. *Annal Soc Sci Manage Stud* 2019; 3: 38–40.
7. Atarere JO, Onyeaka HK, Chido-Amajuoyi OG, et al. Social media use and health promotion among cancer survivors. *Psycho-Oncology* 2024; 33: e6299.
8. Zhang X, Wen D, Liang J, et al. How the public uses social media WeChat to obtain health information in China: a survey study. *BMC Med Inform Decis Mak* 2017; 17: 71–79.
9. Wang Y, Li C, Zhang J, et al. Using social media for health education and promotion: a pilot of WeChat-based prize quizzes on China national malaria day. *Malar J* 2022; 21: 381.
10. Min H, Li J, Di M, et al. Factors influencing the continuance intention of the women's health WeChat public account: an integrated model of UTAUT2 and HBM. *Front Public Health* 2024; 12: 1–12.
11. Bian D, Shi Y, Tang W, et al. The influencing factors of nutrition and diet health knowledge dissemination using the WeChat official account in health promotion. *Front Public Health* 2021; 9: 775729.
12. Zhao Q, Qiu X, Liu W, et al. Application of a WeChat Mini Program to provide pharmaceutical care for cancer pain patients: a randomized controlled trial. *Digital Health* 2024; 10: 1–11.
13. Zhang K, Cao B, Fang Y, et al. Comparing the efficacy of 2 WeChat Mini programs in reducing nonmarital heterosexual contact by male factory workers: randomized controlled trial. *J Med Internet Res* 2024; 26: e49362.
14. Ye JC. Transforming and facilitating health care delivery through social networking platforms: evidences and implications from WeChat. *JAMIA Open* 2024; 7: ooae047.
15. Zhang L and Jung EH. Wechatting for health: an examination of the relationship between motivations and active engagement. *Health Commun* 2019; 34: 1764–1774.
16. Crainich D and Eeckhoudt L. Average willingness to pay for disease prevention with personalized health information. *J Risk Uncertain* 2017; 55: 29–39.
17. Liu J, Li H, Shen W, et al. How to cope with the negative health information avoidance behavior in a pandemic: the role of resilience. *Behav Inf Technol* 2024; 2: 1–17.
18. Gustafson CR, Brooks KR, Meerza SIA, et al. Emotional responses to COVID-19 stressors increase information avoidance about an important unrelated health threat. *PloS ONE* 2023; 18: e0286712.
19. Sun H, Li J, Cheng Y, et al. Developing a framework for understanding health information behavior change from avoidance to acquisition: a grounded theory exploration. *BMC Public Health* 2022; 22: 1115.
20. Orom H, Stanar S, Allard NC, et al. Reasons people avoid colorectal cancer information: a mixed-methods study. *Psychol Health* 2023; 11: 1–23.
21. Sweeny K, Melnyk D, Miller W, et al. Information avoidance: who, what, when, and why. *Rev Gen Psychol* 2010; 14: 340–353.
22. Howell JL and Shepperd JA. Behavioral obligation and information avoidance. *Ann Behav Med* 2013; 45: 258–263.
23. Soroya SH, Farooq A, Mahmood K, et al. From information seeking to information avoidance: understanding the health information behavior during a global health crisis. *Inf Process Manag* 2021; 58: 102440.
24. Swar B, Hameed T and Reychav I. Information overload, psychological ill-being, and behavioral intention to continue online healthcare information search. *Comput Human Behav* 2017; 70: 416–425.
25. Zhang X, Ma L, Zhang G, et al. An integrated model of the antecedents and consequences of perceived information overload using WeChat as an example. *Int J Mobile Commun* 2020; 18: 19–40.
26. Foust JL and Taber JM. Information avoidance: past perspectives and future directions. *Perspectives Psychol Sci* 2023: 1–23.
27. Ding Q, Gu Y, Zhang G, et al. What causes health information avoidance behavior under normalized COVID-19 pandemic? A research from fuzzy set qualitative comparative analysis. *Healthcare* 2022; 10: 1381.
28. Soroya SH and Faiola A. Why did people avoid information during the COVID-19 pandemic? Understanding information sources' dynamics among Pakistani Z generation. *Libr Hi Tech* 2023; 41: 229–247.
29. Sultana T, Dhillon G and Oliveira T. The effect of fear and situational motivation on online information avoidance: the case of COVID-19. *Int J Inf Manage* 2023; 69: 102596.
30. Zhang X, Gong N, Li N, et al. Why breast cancer patients avoid communicating disease-related information to their dependent children: a qualitative study. *J Clin Nurs* 2023; 32: 1230–1239.

31. Orom H, Ramer NE, Allard NC, et al. Colorectal cancer information avoidance is associated with screening adherence. *J Behav Med* 2024; 47: 504–514.

32. Guo C, Si L and Sun Y. Research on the process and influencing factors of online diabetes information users' avoidance behavior: a qualitative study. *Behav Sci* 2023; 13: 267.

33. Dong X, Tang Z and Wang H. Understanding the impact of government social media on citizens' unverified information avoidance behavior during health crises: the health belief model. *Online Inf Rev* 2024; 9: 1–24.

34. Huang Q, Lei S and Ni B. Perceived information overload and unverified information sharing on WeChat amid the COVID-19 pandemic: a moderated mediation model of anxiety and perceived herd. *Front Psychol* 2022; 13: 837820.

35. Xu X, Lin CA and Chen H. Exploring COVID-19 vaccine misinformation exposure, beliefs, fear, and information avoidance via the stimulus–organism–response framework. *Sci Commun* 2023; 45: 824–850.

36. Jia C and Li P. Generation Z's health information avoidance behavior: insights from focus group discussions. *J Med Internet Res* 2024; 26: e54107.

37. Zhong F and Gu C. The impact of health information echo chambers on older adults avoidance behavior: the mediating role of information fatigue and the moderating role of trait mindfulness. *Front Psychol* 2024; 15: 1412515.

38. Sheeran P and Webb TL. The intention–behavior gap. *Soc Personal Psychol Compass* 2016; 10: 503–518.

39. Wang J and Wu L. A comparison of health communication effectiveness and the improvement of management strategies: taking two Chinese traditional medicine hospitals' WeChat public accounts as examples. *BMC Health Serv Res* 2020; 20: 1–8.

40. Sweeny K and Miller W. Predictors of information avoidance: when does ignorance seem most blissful? *Self Identity* 2012; 11: 185–201.

41. Link E, Baumann E, Czerwinski F, et al. Of seekers and non-seekers: characteristics of COVID-19-related information-seeking behaviors. *World Med Health Policy* 2022; 14: 276–294.

42. Howell JL, Lipsey NP and Shepperd JA. Health information avoidance. In: *The Wiley encyclopedia of health psychology*. Hoboken, NJ: Wiley, 2020, pp.279–286.

43. Howell JL, Crosier BS and Shepperd JA. Does lacking threat-management resources increase information avoidance? A multi-sample, multi-method investigation. *J Res Pers* 2014; 50: 102–109.

44. Atkin CK. Instrumental utilities and information seeking. In: *New models for mass communication research*. Oxford, England: Sage, 1973, p.307.

45. Skovsgaard M and Andersen K. Conceptualizing news avoidance: towards a shared understanding of different causes and potential solutions. *Journal Stud* 2020; 21: 459–476.

46. Skovsgaard M and Andersen K. News avoidance. *SAGE Publications Thousand Oaks* 2022; 1: 1099–1103.

47. Link E. Health information as "fodder for fears": a qualitative analysis of types and determinants of the nonuse of health information. *Health Commun* 2024; 39: 3225–3237.

48. Smith SM, Fabrigar LR and Norris ME. Reflecting on six decades of selective exposure research: progress, challenges, and opportunities. *Soc Personal Psychol Compass* 2008; 2: 464–493.

49. Hart W, Albarracín D, Eagly AH, et al. Feeling validated versus being correct: a meta-analysis of selective exposure to information. *Psychol Bull* 2009; 135: 555–588.

50. Jensen JG, Petersen E and Frandsen TF. Seeking and avoiding information: a qualitative study of the information behaviour of cancer patients. *Inf Res* 2022; 27: 2209.

51. Narayan B, Case DO and Edwards SL. The role of information avoidance in everyday-life information behaviors. *Proce Am Soc Inform Sci Technol* 2011; 48: 1–9.

52. Song S, Yao X and Wen N. What motivates Chinese consumers to avoid information about the COVID-19 pandemic?: the perspective of the stimulus-organism-response model. *Inf Process Manag* 2021; 58: 102407.

53. Chae J. Who avoids cancer information? Examining a psychological process leading to cancer information avoidance. *J Health Commun* 2016; 21: 837–844.

54. Link E, Baumann E and Leuppert R. Clarifying the relationship between information seeking and avoidance: longitudinal analyses of information behaviors and their normative influences. *Health Commun* 2024; 39: 1038–1052.

55. Golman R, Hagmann D and Loewenstein G. Information avoidance. *J Econ Lit* 2017; 55: 96–135.

56. Senna PP, Ferreira LMD, Barros AC, et al. Prioritizing barriers for the adoption of industry 4.0 technologies. *Comput Ind Eng* 2022; 171: 108428.

57. Çelik F, Yıldız SY, Ozkara BY, et al. Exploring the temporal effect of ad clutter on digital ad avoidance: a two-wave longitudinal study. *Glob Knowl Mem Commun* 2024: 1–19.

58. Arantes A and Ferreira LMD. Development of delay mitigation measures in construction projects: a combined interpretative structural modeling and MICMAC analysis approach. *Prod Plan Control* 2023; 35: 1164–1179.

59. St. Jean B, Jindal G and Liao Y. Is ignorance really bliss?: exploring the interrelationships among information avoidance, health literacy and health justice. *Proce Assoc Inform Sci Technol* 2017; 54: 394–404.

60. McCloud RF, Jung M, Gray SW, et al. Class, race and ethnicity and information avoidance among cancer survivors. *Br J Cancer* 2013; 108: 1949–1956.

61. Kuhlthau CC. A principle of uncertainty for information seeking. *J Doc* 1993; 49: 339–355.

62. Kuang K and Wilson SR. A meta-analysis of uncertainty and information management in illness contexts. *J Commun* 2017; 67: 378–401.

63. Laato S, Islam AN, Islam MN, et al. What drives unverified information sharing and cyberchondria during the COVID-19 pandemic? *Eur J Inf Syst* 2020; 29: 288–305.

64. Li J. Information avoidance in the age of COVID-19: a meta-analysis. *Inf Process Manag* 2023; 60: 103163.

65. Link E. Information avoidance during health crises: predictors of avoiding information about the COVID-19 pandemic among German news consumers. *Inf Process Manag* 2021; 58: 102714.

66. Camaj L. From selective exposure to selective information processing: a motivated reasoning approach. *Media and Communication* 2019; 7: 8–11.

67. Hyman HH and Sheatsley PB. Some reasons why information campaigns fail. *Public Opin Q* 1947; 11: 412–423.

68. McCloud RF, Okechukwu C, Sorensen G, et al. Cigarette graphic health warning labels and information avoidance among individuals from low socioeconomic position in the US. *Cancer Causes Control* 2017; 28: 351–360.

69. Khaleel I, Wimmer BC, Peterson GM, et al. Health information overload among health consumers: a scoping review. *Patient Educ Couns* 2020; 103: 15–32.

70. Chen Q, Song S and Zhao Y. The impact of information overload on user information evasion in public health emergencies: an empirical study based on COVID-19 information prevalence. *Information and Documentation Services* 2020; 41: 76–88.

71. Nelissen S, Beullens K, Lemal M, et al. Fear of cancer is associated with cancer information seeking, scanning and avoiding: a cross-sectional study among cancer diagnosed and non-diagnosed individuals. *Health Information & Libraries Journal* 2015; 32: 107–119.

72. Ye J, Shim R and Rust G. Health care avoidance among people with serious psychological distress: analyses of 2007 Health Information National Trends Survey. *J Health Care Poor Underserved* 2012; 23: 1620–1629.

73. Link E and Baumann E. Explaining cancer information avoidance comparing people with and without cancer experience in the family. *Psycho-Oncology* 2022; 31: 442–449.

74. Chen X, Kreps LM and L G. Double burden of COVID-19 knowledge deficit: low health literacy and high information avoidance. *BMC Res Notes* 2022; 15: 1–7.

75. Rimal RN and Real K. Perceived risk and efficacy beliefs as motivators of change: use of the risk perception attitude (RPA) framework to understand health behaviors. *Hum Commun Res* 2003; 29: 370–399.

76. Addison CV. *The issue of avoidance: information avoidance in the context of personal health concerns*. Vancouver, Canada: University of British Columbia, 2017.

77. Seidel S and Urquhart C. On emergence and forcing in information systems grounded theory studies: the case of Strauss and Corbin. *J Inf Technol* 2013; 28: 237–260.

78. Glaser B and Strauss A. *Discovery of grounded theory: strategies for qualitative research*. New York: Routledge, 2017.

79. Strauss A and Corbin J. *Basics of qualitative research*. Newbury Park, CA: Sage, 1990.

80. Charmaz K. *Constructing grounded theory: a practical guide through qualitative analysis*. Sage, 2006.

81. Matavire R and Brown I. Profiling grounded theory approaches in information systems research. *Eur J Inf Syst* 2013; 22: 119–129.

82. Boychuk Duchscher JE and Morgan D. Grounded theory: reflections on the emergence vs. forcing debate. *J Adv Nurs* 2004; 48: 605–612.

83. Rieger KL. Discriminating among grounded theory approaches. *Nurs Inq* 2019; 26: e12261.

84. Warfield JN. Developing interconnection matrices in structural modeling. *IEEE Trans Syst Man Cybern* 1974; 4: 81–87.

85. Han Y, Geng Z, Zhu Q, et al. Energy consumption hierarchical analysis based on interpretative structural model for ethylene production. *Chin J Chem Eng* 2015; 23: 2029–2036.

86. Das D and Sengar A. Analysis of factors inhibiting the customer engagement of eHealth in India: modeling the barriers using ISM-fuzzy MICMAC analysis. *Int J Med Inf* 2023; 178: 105199.

87. Chavalala MM, Bag S, Pretorius JHC, et al. A multi-method study on the barriers of the blockchain technology application in the cold supply chains. *J Enterp Inf Manag* 2024; 37: 745–776.

88. Rana NP, Luthra S and Rao HR. Assessing challenges to the mobile wallet usage in India: an interpretive structural modelling approach. *Inf Technol People* 2023; 36: 1533–1554.

89. Ullah S, Jianjun Z, Hayat K, et al. Exploring the factors for open innovation in post-COVID-19 conditions by fuzzy delphi-ISM-MICMAC approach. *Eur J Innov Manage* 2024; 27: 1679–1703.

90. Rubin HJ and Rubin IS. *Qualitative interviewing: the art of hearing data*. Sage, 2011.

91. Barriball KL and While A. Collecting data using a semistructured interview: a discussion paper. *J Adv Nurs-Institut Subscription* 1994; 19: 328–335.

92. Glaser BG. *Theoretical sensitivity*. University of California, 1978.

93. Strauss A and Corbin J. *Basics of qualitative research techniques*. Sage Publications, 1998, pp.105–127.

94. Swendiman RA, Hoffman DI, Bruce AN, et al. Qualities and methods of highly effective surgical educators: a grounded theory model. *J Surg Educ* 2019; 76: 1293–1302.

95. Yang H, Wei H, He X, et al. User experience evaluation of cross-channel consumption: based on grounded theory and neural network. *Wirel Commun Mob Comput* 2021; 12: 1133414.

96. Zha X, Wang X, Yan Y, et al. Exploring influencing mechanism of herd behavior in academic information use: the perspective of cognitive load. *J Acad Librarianship* 2023; 49: 102705.

97. Sun G, Sun J and Li F. Influencing factors of early termination for PPP projects based on multicase grounded theory. *J Constr Eng Manag* 2022; 148: 04022120.

98. Zhang C, Yang Q, Tong L, et al. Investigate the influencing factors of industrial design platform demand: from the perspective of emotional interaction. *Front Psychol* 2022; 13: 892771.

99. Moughari MM and Daim TU. Developing a model of technological innovation for export development in developing countries. *Technol Soc* 2023; 75: 102338.

100. Hong J, Quan Y, Tong X, et al. A hybrid ISM and fuzzy MICMAC approach to modeling risk analysis of imported fresh food supply chain. *J Business Industrial Market* 2024; 39: 124–141.

101. Ali S, Baseer S, Abbasi IA, et al. Analyzing the interactions among factors affecting cloud adoption for software testing: a two-stage ISM-ANN approach. *Soft COmput* 2022; 26: 8047–8075.

102. Mohapatra B, Tripathy S, Singhal D, et al. Significance of digital technology in manufacturing sectors: examination

of key factors during COVID-19. *Res Transport Econ* 2022; 93: 101134.

103. Ben Ruben R, Vinodh S and Asokan P. ISM and Fuzzy MICMAC application for analysis of Lean Six Sigma barriers with environmental considerations. *Int J Lean Six Sigma* 2018; 9: 64–90.

104. Palaniappan A, Vinodh S and Ranganathan R. Analysis of factors influencing AM application in food sector using ISM. *J Mod Manage* 2020; 15: 919–932.

105. Fan C, Binchao D and Yin Y. Hierarchical structure and transfer mechanism to assess the scheduling-related risk in construction of prefabricated buildings: an integrated ISM–MICMAC approach. *Eng Constr Architect Manag* 2023; 30: 2991–3013.

106. Tandon A, Aggarwal AG and Aggarwal S. Understanding the determinants of reviewer credibility: an interpretive structural modeling and artificial neural network approach. *Ann Oper Res* 2023: 1–21.

107. Agarwal R, Bhadauria A, Kaushik H, et al. ISM-MICMAC-based study on key enablers in the adoption of solar renewable energy products in India. *Technol Soc* 2023; 75: 102375.

108. Kleiber C, Montgomery LA and Craft-Rosenberg M. Information needs of the siblings of critically ill children. *Child Health Care* 1995; 24: 47–60.

109. Kahlor LA, Olson HC, Markman AB, et al. Avoiding trouble: exploring environmental risk information avoidance intentions. *Environ Behav* 2020; 52: 187–218.

110. Yang ZJ, Aloe AM and Feeley TH. Risk information seeking and processing model: a meta-analysis. *J Commun* 2014; 64: 20–41.

111. Melnyk D and Shepperd JA. Avoiding risk information about breast cancer. *Ann Behav Med* 2012; 44: 216–224.

112. Ford JL, Douglas M and Barrett AK. The role of pandemic fatigue in seeking and avoiding information on COVID-19 among young adults. *Health Commun* 2023; 38: 2336–2349.

113. Kim HK, Ahn J, Atkinson L, et al. Effects of COVID-19 misinformation on information seeking, avoidance, and processing: a multicountry comparative study. *Sci Commun* 2020; 42: 586–615.

114. Thon FM and Jucks R. Believing in expertise: how authors' credentials and language use influence the credibility of online health information. *Health Commun* 2017; 32: 828–836.

115. Elliot AJ, Mooney CJ, Infurna FJ, et al. Perceived control and frailty: the role of affect and perceived health. *Psychol Aging* 2018; 33: 473–481.

116. Karim M, Widen G and Heinstrom J. Influence of demographics and information literacy self-efficacy on information avoidance propensity among youth. *Inf Res* 2019; 24: colis1909.

117. Barbour JB, Rintamaki LS, Ramsey JA, et al. Avoiding health information. *J Health Commun* 2012; 17: 212–229.

118. Heinstrom J, Nikou S and Sormunen E. Avoiding negative information as a strategy for emotion regulation. *Inf Res* 2022; 27: isic2229.

119. Sairanen A and Savolainen R. Avoiding health information in the context of uncertainty management. *Inf Res* 2010; 15: 372–379.

120. WA A and Weiner JL. Toward a theory of motivated information management. *Commun Theory* 2004; 14: 167–190.

121. Gallotti R, Valle F, Castaldo N, et al. Assessing the risks of 'infodemics' in response to COVID-19 epidemics. *Nature Human Behaviour* 2020; 4: 1285–1293.

122. Wolgast M, Lundh L-G and Viborg G. Experiential avoidance as an emotion regulatory function: an empirical analysis of experiential avoidance in relation to behavioral avoidance, cognitive reappraisal, and response suppression. *Cogn Behav Ther* 2013; 42: 224–232.

123. Taghizadeh SK, Rahman SA, Nikbin D, et al. Factors influencing students' continuance usage intention with online learning during the pandemic: a cross-country analysis. *Behav Inf Technol* 2022; 41: 1998–2017.

124. Berdida DJE and Grande RAN. Academic stress, COVID-19 anxiety, and quality of life among nursing students: the mediating role of resilience. *Int Nurs Rev* 2023; 70: 34–42.

125. Mehrabian A and Russell JA. *An approach to environmental psychology.* MIT Press, 1974.

126. Mkedder N, Bakir M and Lachachi A. Investigating the antecedents of purchase intention toward local dairy products: an empirical study based on the SOR model. *Central European Management Journal* 2021; 29: 124–148.

127. Mkedder N and Das M. Metaverse integration challenges: an in-depth ISM and MICMAC analysis. *J Retailing Consumer Serv* 2024; 77: 103684.

128. Hua J and Howell JL. Coping self-efficacy influences health information avoidance. *J Health Psychol* 2022; 27: 713–725.

129. Chae J, Lee CJ and Kim K. Prevalence, predictors, and psychosocial mechanism of cancer information avoidance: findings from a national survey of US adults. *Health Commun* 2020; 35: 322–330.

130. Horn S, Litovsky Y and Loewenstein G. Using curiosity to counter health information avoidance. *Soc Sci Med* 2024; 340: 116383.

131. Yang MZ, King WC, Oettingen G, et al. Evidence that mental contrasting reduces health information avoidance. *Ann Behav Med* 2023; 57: 687–692.

132. Bawden D and Robinson L. The dark side of information: overload, anxiety and other paradoxes and pathologies. *J Inf Sci* 2009; 35: 180–191.

133. Le XC. Determinants of health information acceptance to COVID-19 avoidance: the lens of information acceptance model and elaboration likelihood model. *The Bottom Line* 2023; 36: 29–51.

134. Renjith R. The effect of information overload in digital media news content. *Commun Media Stud* 2017; 6: 73–85.

Appendix

Appendix 1. Interview outline.

Index	Key elements	Themes
1	Demographic characteristics of the participants: gender, age, educational background, frequency of and proficiency with WeChat use.	1. Participants' experiences related to WeChat health information avoidance behavior 2. Factors that influence WeChat health information avoidance behavior
2	Have you ever experienced information-avoidance behavior when faced with various types of health information on WeChat? Please give specific examples.	
3	Under what circumstances do you usually choose to avoid health information on WeChat? What are your reasons for avoiding health information on WeChat in this situation? What motivates you to avoid health information? Under what circumstances would you not normally choose to avoid health information on WeChat? What are the reasons for not avoiding at this time?	
4	How would you rate your previous health information avoidance behavior on WeChat? Do you think this avoidance behavior has had the desired effect on you? What impact did it have on your health perceptions and health behaviors?	
5	In what ways do you avoid health messages on WeChat?	
6	Apart from the reasons mentioned above, do you think there are any other factors that cause you to avoid health messages on WeChat?	