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Explaining education-based difference in systematic processing of COVID-19 information: Insights into global recovery from infodemic

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ABSTRACT

Systematic processing helps individuals identify misinformation during the COVID-19 pandemic and serves as an individual-level measure to fight the infodemic. Highly educated people tend to engage in systematic processing more than their less educated counterparts. We follow a major part of the risk information seeking and processing (RISP) model to explicate this gap. An online survey (N = 1,568) conducted during the early stage of the pandemic in China showed that current knowledge and perceived information gathering capacity both positively mediated the association between education level and systematic processing. Although informational subjective norms were positively associated with systematic processing, we did not observe a significant difference in these norms between highly and less educated individuals. The results clarify the psychological mechanism underlying the education-based difference in systematic processing of the COVID-19 information and corroborate a relevant part of the RISP model. Moreover, our findings offer practical implications for facilitating individuals with less educational attainment to engage in systematic processing, thereby alleviating the negative impact of exposure to misinformation on them. These insights not only apply to managing the infodemic in China, but also inform the global recovery from the infodemic.

1. Introduction

The coronavirus disease (COVID-19) outbreak has become an ongoing global pandemic and posed a severe threat to public health. Moreover, the pandemic has resulted in the first infodemic in history (Zou & Tang, 2021). According to the World Health Organization, an infodemic describes that too much information—including false or misinformation—widely circulates in digital and physical environments, causing public confusion and panic, risky behaviors, mistrust in health authorities, and other negative social impacts (World Health Organization, 2021). The infodemic has occurred in many parts of the world, and has resulted in inappropriate protective measures, public psychological issues, panic purchase, trust loss, and economic downturn (Pian et al., 2021). In particular, the wide use of social media has facilitated the spread of misinformation online and amplified the negative consequences of the infodemic (X. Han et al., 2020; Pian et al., 2021).

Prior research has shown that a lack of analytical thinking and reasoning tends to render individuals susceptible to misinformation

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and fake news (Pennycook & Rand, 2019, 2020). In other words, advancing people to engage in systematic processing may prevent them from falling for misinformation. Systematic processing is a mode of information processing that requires much cognitive effort (Chaiken et al., 1989; Eagly & Chaiken, 1993), such as evaluating the veracity of the information, cross-checking the source credibility, and assessing the relevance of the information to oneself. Compared with heuristic processing that relies on mental shortcuts to make a quick judgment, systematic processing helps individuals identify misinformation, develop sound attitude, and perform appropriate preventive behaviors (Griffin et al., 1999; Hwang & Jeong, 2021; Kharod & Simmons, 2020). Thus, facilitating systematic processing is an individual-level manner to fight the infodemic.

The degree to which an individual engages in systematic processing is susceptible to a number of factors, among which education level is a predictor that represents one's overall cognitive ability of information processing (S.-H. Lee, 2014; Riggins & Dewan, 2005). Prior research has shown that individuals with greater educational attainment tend to engage more in systematic processing than those with less educational attainment during the COVID-19 pandemic (Kim et al., 2020; Wong et al., 2021). This divide in systematic processing further leads less educated people to believe in COVID-19 misinformation more often, to have a poorer understanding of the disease symptoms, and to perform preventive behaviors less frequently, as compared with their highly educated counterparts (X. Han et al., 2020; Pickles et al., 2021; Sallam et al., 2020). These findings demonstrate a digital divide (Fuchs, 2009; Selwyn, 2004; Wei et al., 2011), in which less educated people are more vulnerable to the negative impacts of the infodemic than highly educated people, due to a lack of systematic processing. Thus, explicating the education-based difference in systematic processing can provide insights into facilitating systematic processing among individuals with low levels of education and narrowing the divide.

Because the COVID-19 pandemic suggests a great risk to various aspects of everyday life, we consider information related to the COVID-19 risk information. Thus, we apply the risk information seeking and processing (RISP) model (Griffin et al., 1999, 2013) to explain the difference in systematic processing between people with greater educational attainment and those with less educational attainment. According to the RISP model, sociodemographic characteristics such as education level tends to influence systematic processing through a number of socio-psychological factors (Griffin et al., 1999, 2013). Thus, we ask a general research question: How does education level influence systematic processing via certain socio-psychological factors? Drawing on prior research about the RISP model (Griffin et al., 1999, 2013; Z. J. Yang, Aloe, et al., 2014), we consider informational subjective norms, current knowledge, and perceived information gathering capacity three mediators between education level and systematic processing, while risk perception and negative emotions are treated as control variables. By testing such a mediating model, we try to clarify the socio-psychological mechanism underlying the education-based difference in systematic processing.

The widespread misinformation online related to the COVID-19 has become a major social issue in China (Zhang et al., 2021). Moreover, the digital divide in terms of health information utilization has been observed between less educated and highly educated individuals in China (Hong et al., 2017; Wang et al., 2013). Thus, we use survey data collected during the COVID-19 pandemic in China to test the proposed model. The findings are expected to offer some practical implications for how to facilitate people with less educational attainment to engage in systematic processing and alleviate their vulnerability to misinformation, which might serve as an individual-level strategy to narrow the digital divide and fight the infodemic. Moreover, as the pandemic has unprecedentedly increased humankinds' interconnectedness in combating the virus and the associated social problems, we also hope our findings could offer some insights into the global recovery from the infodemic.

2. Literature review

2.1. The RISP model

The RISP model is proposed to explain how a set of socio-psychological factors influence individuals' risk information seeking and processing (Griffin et al., 1999). Since its origin, the RISP model has been widely used to examine people's information seeking and processing concerning a variety of risk issues, such as health risks, environmental risks, and industrial risks, and exhibited robust predictive power (Z. J. Yang, Aloe, et al., 2014). Theoretically, the heuristic-systematic processing model (HSM) (Chen & Chaiken, 1999) and the elaboration likelihood model (ELM) (Petty & Cacioppo, 1986) largely inform the RISP model. Both the HSM and ELM are developed from dual processing theory, which differentiates between two modes of information processing (Chaiken & Trope, 1999): one represents a less effortful and superficial way of attending to information, termed as heuristic processing in the HSM or peripheral route in the ELM, while the other refers to an effort-intensive manner to digest the messages, termed as systematic processing or central route. Given that systematic processing of risk information helps individuals develop sound attitude and perform effective preventive behaviors (Griffin et al., 1999), the RISP model serves as a useful conceptual tool to help researchers and practitioners identify the relevant predictors of systematic processing.

Whether people engage in systematic processing depends on their *motivation* to go beyond the heuristic processing and their *capacity* to process the information carefully (Chen & Chaiken, 1999). Specifically, motivations for systematic processing usually involve the accuracy motivation and impression motivation: the former asserts that individuals are motivated to process information to maintain accurate beliefs, while the latter describes people's need to maintain a positive image and perform socially desirable behaviors (Chen & Chaiken, 1999). Driven by the accuracy motivation, people will use their *current knowledge* to verify the information they encounter to maintain an accurate belief (J. Z. Yang & Liu, 2021). The impression motivation characterizes another key variable in the RISP model, namely, *informational subjective norms*, which motivate people to see systematic processing as a socially desirable behavior to cope with the infodemic (J. Z. Yang, Liu, et al., 2022). Besides, *perceived information gathering capacity* represents one's confidence about his or her capacity to perform systematic processing (J. Z. Yang, Dong, et al., 2022; J. Z. Yang & Liu, 2021). Notably, the motivation and capability related variables are considered proximal predictors in the RISP model (Griffin et al., 1999).

Although perceived hazard characteristics and affective response are included in the full RISP model, they function as distal predictors and are conceptually distant from risk information seeking and processing (Griffin et al., 1999). Moreover, to highlight the role of proximal predictors, prior research examined the motivations and perceived capacity of risk information seeking and processing, while controlled for the distal predictors such as perceived hazard characteristics and affective response (J. Z. Yang & Liu, 2021). Thus, we specifically focus on three proximal predictors—informational subjective norms, current knowledge, and perceived information gathering capacity—to explain the education-based difference in systematic processing. Distal predictors such as perceived hazard characteristics and affective response are treated as control variables in the current study. Fig. 1 positions our study in the RISP model.

2.2. Education level and systematic processing

Education level is a major factor that affects one's ability to acquire and process information (S.-H. Lee, 2014; Riggins & Dewan, 2005). For instance, several studies on health communication have shown that people with greater educational attainment tend to use the Internet to seek out health-related information more skillfully than those with less educational attainment (Bhandari et al., 2020; Scheerder et al., 2017; Wang et al., 2013). Moreover, during the COVID-19 pandemic, highly educated individuals engaged in systematic processing more often than their less educated counterparts (Kim et al., 2020; Wong et al., 2021). This is because a greater educational attainment usually makes people more critical toward information and thus more likely to cross-check source credibility and evaluate the veracity of the information (J. Han et al., 2020).

The above-mentioned evidence indicates that highly educated people are more likely to perform systematic processing than the less educated. Although the RISP model suggests that individual characteristics such as education level tends to influence systematic processing indirectly via socio-psychological factors (Griffin et al., 1999), we expect that a direct link between education level and systematic processing may exist due to the prevalence of the education-based divide in terms of information utilization (Fuchs, 2009; Selwyn, 2004; Wei et al., 2011). Thus, we ask the following research question:

RQ1: Is education level directly and positively associated with systematic processing?

2.3. Informational subjective norms

Informational subjective norms represent a particular form of subjective norms, which refers to the perceived social pressure about performing a behavior (Ajzen, 1991). In the context of risk information acquisition, informational subjective norms describe one's perceived social pressure about obtaining sufficient knowledge to effectively cope with the risk (Griffin et al., 1999). This pressure mainly comes from important ones, such as family members and close friends (J. Z. Yang & Huang, 2019; Z. J. Yang, 2012; Z. J. Yang, Rickard, et al., 2014). For instance, amid the COVID-19 pandemic, an individual's family members, close friends, and other important ones all expect this person to acquire sufficient knowledge about the coronavirus to effectively prevent himself or herself from infection. Such an expectation creates a social pressure and generates informational subjective norms for this individual to actively seek and process the COVID-19 related information.

Informational subjective norms have social origins and are closely related to one's education level. In general, the education system in China is characterized by an emphasis on students' compliance with social norms (Kirkpatrick & Zang, 2011). The higher one's education level is, suggesting that the longer the one stays in the education system, the more likely that this person is to recognize the importance of following social norms. Likewise, informational subjective norms indicate an individual's perceived social norms regarding knowledge acquisition, and thus tend to be affected by the individual's education level. Moreover, prior research on the RISP model demonstrated that informational subjective norms were influenced by sociodemographic characteristics such as education level

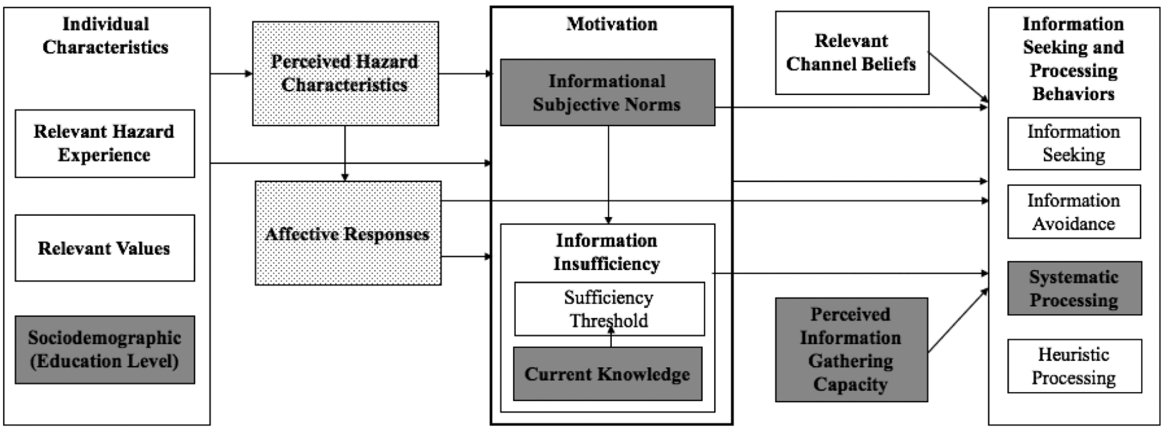

Fig. 1. Positioning our study in the RISP model.
Note. The RISP models is sketched based on Z. J. Yang, Aloe, and Feeley's (2014) work. Boxes with grey fill indicate variables under examination, while boxes with dot fill indicate control variables in this study.

(Griffin et al., 1999, 2013). Therefore, we infer that the higher one's education level is, the more likely that this person is to feel stronger informational subjective norms about getting sufficient COVID-19 knowledge.

Individual behaviors are not performed in an isolated manner; rather, subjective norms—the perceived social pressure about performing a behavior—motivate individuals to take an action (Ajzen, 1991). Systematic processing represents a planned behavior and is therefore motivated by informational subjective norms. Abundant research has shown that informational subjective norms serve as an important motive of systematic processing of risk information (Kahlor et al., 2006; Z. J. Yang, Aloe, et al., 2014). During the COVID-19 pandemic, individuals tend to feel the social pressure from family members, friends, and other important ones about obtaining sufficient knowledge to effectively cope with the virus, which motivates them to scrutinize the messages carefully.

Taken together, the literature suggests the mediating role of informational subjective norms between education level and systematic processing. Such a mediation effect is consistent with the paths outlined in the RISP model, in which individual characteristics tend to have an indirect effect on the modes of information processing through motivational factors. Moreover, prior research showed that highly educated individuals scrutinized the COVID-19 related messages more carefully than their less educated counterparts because the former group were motivated by a need to fulfil others' expectations and maintain a socially desirable image (Wong et al., 2021). Hence, we posit the first hypothesis:

H1: Informational subjective norms mediate the association between education level and systematic processing. Specifically, education level is positively associated with informational subjective norms, which in turn are positively associated with systematic processing.

2.4. *Current knowledge*

The RISP model considers current knowledge as subjective knowledge, that is, the amount of the relevant knowledge that one perceives that he or she has about a certain risk (Griffin et al., 2004; J. Z. Yang & Huang, 2019; Z. J. Yang, 2012). An individual tends to stop seek or process information once this person believes that he or she has acquired sufficient knowledge (Griffin et al., 2004). Thus, a higher level of subjective knowledge may discourage one from acquiring more information or carefully processing the information. Prior research has criticized that the RISP model solely focuses on subjective knowledge whereas ignores the impact of objective knowledge on information behavior outcomes (Manika et al., 2021). Moreover, objective knowledge, which shows how much people actually know about a topic, facilitates one to perform systematic processing to maintain an accurate belief (Denton et al., 2020). Thus, we redefine current knowledge as the objective knowledge one has about the coronavirus.

Current knowledge is largely influenced by education level. According to the knowledge gap hypothesis, individuals with higher educational attainment are overall more competent at using information and communication technologies to obtain knowledge than those with less educational attainment (Hwang & Jeong, 2009; Tichenor et al., 1970). During the COVID-19 pandemic, a plethora of information about the coronavirus has been circulating in various channels, resulting in information overload to the majority of the public (Laato et al., 2020). In such circumstances, the pre-existing difference in education level—suggesting the overall cognitive ability one has (Riggins & Dewan, 2005)—becomes a major factor that differentiates the speed of knowledge acquisition among individuals. Those with high levels of education tend to get knowledge more quickly than those with low levels of education, thus making individuals with greater educational attainment acquire more knowledge than those with less educational attainment.

One's current knowledge about a risk influences the extent to which this person engages in systematic processing. Systematic processing involves cross-checking the veracity of information (Trumbo, 1999). Because the unprecedented COVID-19 pandemic has generated a plethora of unfamiliar issues to ordinary people, evaluating information veracity thus entails a pre-understanding of the coronavirus. Therefore, the more knowledge one has about the coronavirus, the more capable this person is to perform systematic processing. Moreover, studies about climate change and nuclear power have demonstrated that objective knowledge tends to elicit thoughtful behaviors (Park & Vedlitz, 2013; Stoutenborough et al., 2013). Considering that systematic processing is a prerequisite for performing thoughtful behaviors (Y. Lee & Lin, 2021; Trumbo, 1999), these studies suggest that knowledge tends to advance systematic processing. We thus infer that a high level of current knowledge about the coronavirus is positively associated with the tendency of engaging in systematic processing.

The aforementioned pathways indicate the mediating role of current knowledge between education level and systematic processing. This mediation effect is in line with the RISP model, in which capability bridges the link between individual characteristics and information processing. Hence, we propose the following hypothesis:

H2: Current knowledge mediates the association between education level and systematic processing. Specifically, education level is positively associated with current knowledge, which in turn is positively associated with systematic processing.

2.5. *Perceived information gathering capacity*

Perceived information gathering capacity describes one's perceived behavioral control of active information seeking and careful information processing (Griffin et al., 1999). Risk issues are characterized by uncertainty and complexity, and thus require much cognitive effort to understand. Therefore, one's perceived capability of message elaboration plays an important part in facilitating systematic processing. In the present study, we define perceived information gathering capacity as the extent to which one judges that he or she is capable of thoroughly examining the information they encounter during the COVID-19 pandemic.

An individual's perceived information gathering capacity is susceptible to his or her education level. In general, individuals with high levels of education tend to be more competent at analyzing and understanding issues compared with those with low levels of education (Falch & Massih, 2011). This may lead to a difference in self-judgment of capability: highly educated individuals are likely to perceive themselves as more capable of systematically processing information than the less educated. In a similar vein, amid the COVID-19 pandemic, people with high levels of education tend to judge themselves more competent at scrutinizing the messages than those with low levels of education.

The performance of a behavior is subject to an individual's self-efficacy or perceived behavioral control (Ajzen, 1991; Bandura, 2001). Likewise, the engagement in systematic processing depends largely on individuals' perceived information gathering capacity. A number of studies have demonstrated that the stronger one judges his or her information gathering capacity, the more likely that this person is to perform systematic processing (Lo et al., 2013; Trumbo, 1999). During the COVID-19 pandemic, a large volume of misinformation was circulating on various media platforms (Kim et al., 2020). In order to identify the misinformation and reduce the harms caused by exposure to misinformation, individuals are likely to systematically process the information if they believe they are capable enough to carefully check these messages.

Taken together, perceived information gathering capacity may serve as a mediator between education level and systematic processing. This follows the assumption of the RISP model, in which perceived information gathering capacity links individual characteristics with information processing (Griffin et al., 1999; Z. J. Yang, Aloe, et al., 2014). Accordingly, a hypothesis is postulated:

H3: Perceived information gathering capacity mediates the relationship between education level and systematic processing. Specifically, education level is positively associated with perceived information gathering capacity, which in turn is positively associated with systematic processing.

2.6. Control variables

In addition to the motivational variables (e.g., informational subjective norms and current knowledge) and capability variables (e.g., perceived information gathering capacity), perceived hazard characteristics and affective responses are also included as distal predictors in the RISP model (Griffin et al., 1999). Perceived hazard characteristics describe one's cognitive evaluation of the likelihood, severity, and personal control of a given risk, while affective responses involve emotions such as worry, fear, anxiety, and hope toward the risk (Griffin et al., 2013). In terms of perceived hazard characteristics, we focus on perceived susceptibility and perceived severity of risk, given that these two indictors are widely used to predict people's risk information behaviors (Kahlor, 2010; Ter Huurne & Gutteling, 2008). Besides, although people are likely to experience positive emotions such as hope and optimism about a risk event, they feel negative emotions such as fear, anxiety, and worry more often (Kahlor, 2010; Ter Huurne & Gutteling, 2008), because risks inevitably pose a threat to their health and safety. Moreover, prior studies showed that risk perception of the coronavirus and the associated negative emotions tended to influence the degree to which people partake in systematic processing of the COVID-19 related information (Wong et al., 2021). Thus, we include perceived susceptibility, perceived severity, and negative emotions as control variables in the hypothesized model.

Fig. 2 presents the hypothesized model.

3. Method

3.1. Data collection

We commissioned Sojump, a professional online survey company in China, to recruit participants. Sojump provides a sampling service, consisting of 2.6 million registered respondents with diverse demographic features distributed throughout China. On average,

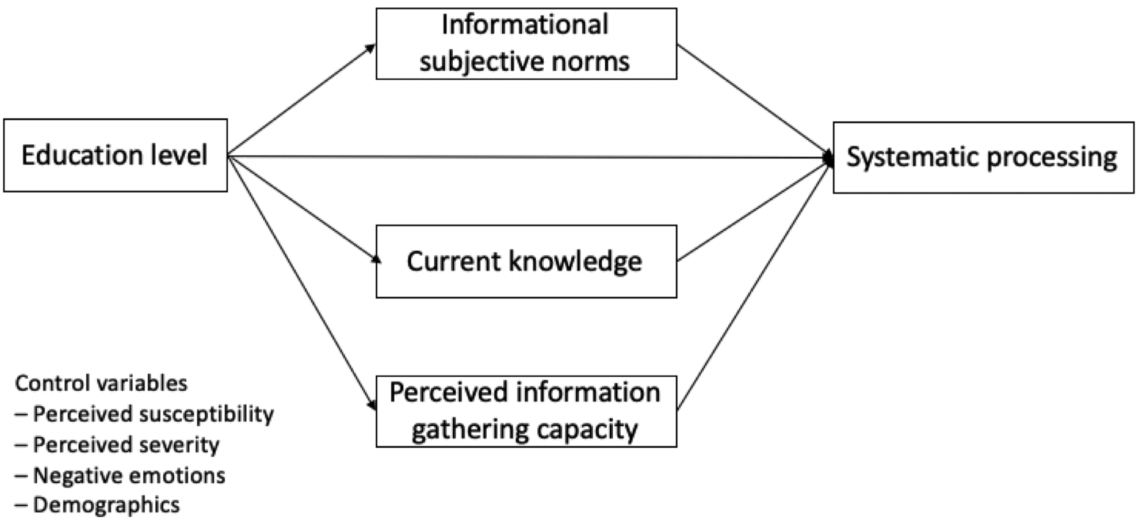

Fig. 2. The hypothesized model.

the sampling service of Sojump allows researchers to collect around 100 to 200 questionnaires each day, and this sampling technique has been used to examine people's risk information behaviors (Huang et al., 2022), media use regarding environmental issues (Huang, 2020), adoption of e-commerce (Z. Zhou et al., 2013), etc. The cross-sectional online survey was conducted from 31 January to 9 February 2020, an early phase of the COVID-19 outbreak in China. We chose this time period to collect the data because the early stage of the pandemic was characterized by a high level of uncertainty, which resulted in the widespread misinformation. For instance, the rumor that drinking wine could kill the coronavirus might lead to health risks resulting from excessive drinking (Tencent, 2021a). Besides, the misinformation about the time when residents in 31 provinces in China no longer needed to wear masks might prevent individuals from taking necessary protection and cause greater risks of infection (Tencent, 2021b). To prevent the harms resulted from falling for misinformation, systematic processing of the COVID-19 information was of great significance during the early stage of the pandemic.

In terms of the sampling procedure, each registered user in Sojump's survey pool was assigned an ID number ranging from 1 to 2,600,000, and 2,840 random integers between this value range were generated. Then, the company sent an email to these 2,840 users to invite them to participate in the online survey. The online survey was accessible through mobile phones, tabloids, and personal computers. The response rate was 58.3%, and 1,656 respondents finished the questionnaire. After deleting the invalid cases, a total of 1,568 valid cases from 31 provinces, municipalities, and autonomous regions across mainland China were used for data analysis. In terms of gender, 49.7% of the sample were females (n = 779), while 50.3% of the sample were males (n = 789). The average age of the respondents was 31 (SD = 9.00), ranging from 18 to 67 years old. On average, the household monthly income of our respondents was around 10,001~15,000 RMB. Given that this study focuses on people's systematic processing of the COVID-19 related information online, we treat Chinese netizens as the population. Table 1 compares the sample demographics to the 2020 demographics of Chinese netizens.

3.2. Measures

3.2.1. Education level

Education level was measured by asking participants to indicate the highest level of education they have received on a 9-point scale: 1 = never been to school, 2 = elementary school, 3 = middle school, 4 = high school, 5 = technical secondary school, 6 = associate's degree, 7 = bachelor's degree, 8 = master's degree, 9 = doctoral degree. Considering that a bachelor's degree is seen as the threshold for higher education in China (The Ministry of Education of the People's Republic of China, 2021), we then recoded education level as a dichotomous variable, namely, less educational attainment and greater educational attainment. The former indicator was operationalized as those who did not hold a bachelor's degree (n = 331, 21.1%), while the latter indicator was operationalized as those who held a bachelor's degree or above (n = 1237, 78.9%).

3.2.2. Informational subjective norms

Although informational subjective norms are generated by a variety of social relationships, expectations from important ones such

Table 1
Sample demographics as compared to the demographics of Chinese netizens.

Variables	Sample percentage	Chinese netizens percentage
Age		
Below 10	0%	3.1%
10-19	5.4%	13.5%
20-29	41.7%	17.8%
30-39	38.6%	20.5%
40-49	9.5%	18.8%
50-59	3.5%	15.1%
Above 60	1.3%	11.2%
Gender		
Male	50.3%	51.0%
Female	49.7%	49.0%
Level of education		
Elementary school or never attend school	0.1%	19.3%
Middle school	1.1%	40.3%
High school (including vocational school)	20.0%	31.1%
College and above	78.8%	9.3%
Household monthly income		
No income	2.1%	10.8%
Lower than RMB 1,000	1.3%	9.6%
RMB 1,000-3,000	4.8%	11.3%
RMB 3,001-10,000	41.0%	39.0%
RMB 10,001-16,000	21.2%	14.5%
More than RMB 16,000	29.7%	14.8%

Note. Demographics of the Chinese netizens by the end of 2020 were retried from the 47th China Statistical Report on Internet Development (http://www.cnnic.net.cn/hlwfzyj/hlwxzbg/hlwtjbg/202102/P020210203334633480104.pdf). Because the report only included individual monthly income, we transformed it into household income by assuming that each of the two adults in a core family have a salary.

as family members and close friends were often used to measure informational subjective norms (J. Yang, 2021; Z. J. Yang & Kahlor, 2013). Meanwhile, the differential mode of association (*chaxugeju*) in Chinese culture indicates that an individual values the expectations from closely related ones the most (Fei, 1992). Moreover, prior research used a single item to measure subjective norms in general (Hagger et al., 2002) and informational subjective norms in particular (Z. J. Yang et al., 2010). Thus, we measured informational subjective norms on a 5-point scale with one item (1 = strongly disagree, 5 = strongly agree): My family members and close friends expect me to obtain sufficient knowledge to deal with the COVID-19 outbreak ($M = 3.66$, $SD = 0.85$).

3.2.3. *Current knowledge*

We operationalized current knowledge as the objective knowledge one had about the coronavirus. Following previous research (Denton et al., 2020; Stoutenborough et al., 2013), we used a short quiz that consisted of five true/false questions to measure participants' objective knowledge. Sample questions included "Older people and those with certain medical conditions, such as lung diseases, diabetes, and heart conditions, are at a higher risk for serious infection." Participants received one point for each correct answer, while no point for a wrong answer. The total score was added to form an additive index for current knowledge ($M = 4.57$, $SD = 0.63$).

3.2.4. *Perceived information gathering capacity*

Unlike previous studies that focused on people's perceived information gathering capacity about information seeking (Liao et al., 2018; J. Z. Yang & Huang, 2019; Z. Yang et al., 2020), this study examined individuals' perceived capability of systematic processing. Drawing upon the instrument of information verification and self-efficacy (Flanagin & Metzger, 2000; Lo et al., 2013), we created a 7-item instrument of perceived information gathering capacity. Example items include "I am able to think about message creators' intentions", "If I want to, I could easily search for more information to verify the messages I encounter", etc. Participants were required to suggest the extent to which they agreed with the seven statements on a 5-point scale (1 = strongly disagree, 5 = strongly agree). These items were averaged ($M = 3.45$, $SD = 0.74$, Cronbach's $\alpha = .81$), with a higher value suggesting a stronger information gathering capacity perceived by a participant.

3.2.5. *Systematic processing*

Based on prior work (Z. J. Yang, Rickard, et al., 2014), we measured systematic processing using six items on a 5-point scale (1 = strongly disagree, 5 = strongly agree), such as "I try to relate the COVID-19 information encountered online to my personal experiences", "I think about the importance of the COVID-19 information online to my everyday life", etc. Six items were averaged ($M = 3.93$, $SD = 0.57$, Cronbach's $\alpha = .70$), with higher values indicating higher degrees of engagement in systematic processing.

3.2.6. *Control variables*

Gender was measured as a dichotomous variable (50.3% male), age as a continuous variable ($M = 31.02$, $SD = 9.00$), and

Table 2
Questionnaire items, means, standard deviations, and reliabilities of the key variables.

Items	Mean	SD	Cronbach's α
Education level (1 = never been to school, 9 = doctoral degree)	—	—	—
1. What is your highest level of education?			
Informational subjective norms (1 = strongly disagree, 5 = strongly agree)	3.66	0.85	—
1. My family members and close friends expect me to obtain sufficient knowledge to deal with the coronavirus.			
Current knowledge (1 = correct answer, 0 = wrong answer)	4.57	0.63	—
1. Older people and those with certain medical conditions, such as lung diseases, diabetes, and heart conditions, are at a higher risk for serious infection. (Right)			
2. The coronavirus appeared in Wuhan City and later spread across the country. (Right)			
3. Fever is the early symptom of the coronavirus infection in all cases. (Wrong)			
4. The coronavirus cannot be transmitted through droplets of people's respiratory fluids during exhalation. (Wrong)			
5. Smoking and drinking wine help prevent individuals from coronavirus infection. (Wrong)			
Perceived information gathering capacity (1 = strongly disagree, 5 = strongly agree)	3.45	0.74	.81
1. I am able to think about message creators' intentions.			
2. If I want to, I could easily search for more information to verify the messages I encounter.			
3. I feel capable of differentiating the commentary from the factual statement.			
4. I am able to check the message creator's identity.			
5. I am capable of confirming whether the information is the latest update.			
6. I find it easy to check whether the information is verified.			
7. I can easily examine if the information is complete.			
Systematic processing (1 = strongly disagree, 5 = strongly agree)	3.93	0.57	.70
1. I try to relate the COVID-19 information encountered online to my personal experiences.			
2. I pay attention to a few of the online COVID-19 information. (Reverse coded)			
3. I think about the importance of the COVID-19 information online to my everyday life.			
4. I spend much time to think about the COVID-19 information encountered online.			
5. I scrutinize the arguments contained in the statements about the coronavirus.			
6. I browse the COVID-19 information online quickly. (Reverse coded)			

household monthly income as an ordinal variable (Median = 7.00, or between 10,001 and 15,000 CNY, *SD* = 1.96). Following the previous instrument of risk perception (Kim & Niederdeppe, 2013), perceived susceptibility was measured by the perceived likelihood of getting the coronavirus in the near future (1 = very unlikely, 5 = very likely) (*M* = 2.03, *SD* = .86), while perceived severity was measured by perceived potential severity of the coronavirus infection for one's own health (1 = not at all serious, 5 = extremely serious) (*M* = 3.47, *SD* = 1.06). Negative emotions were measured by three items on a 5-point scale: fear, anxiety, and sadness (Kim & Niederdeppe, 2013; Seo, 2021; J. Z. Yang & Chu, 2018) (*M* = 2.68, *SD* = 0.90, Cronbach's α = .77).

Table 2 shows the measurement and descriptive statistics of the key variables.

3.3. Analytical strategy

We used PROCESS version 3.5—an SPSS macro developed by Andrew F. Hayes—to test the research hypotheses. The hypotheses constitute a mediation model with three parallel mediators. Hence, we chose Model 4 in the PROCESS templates (Hayes, 2013) to run the statistical analysis. Systematic processing was entered as the outcome variable and education level as the independent variable. Informational subjective norms, current knowledge, and perceived information gathering capacity were entered as mediators. Age, gender, household monthly income, perceived susceptibility, perceived severity, and negative emotions were entered as covariates. We tested the mediation effects with 5,000 bootstrap samples at 95% confidence intervals (Preacher & Hayes, 2008). Unstandardized coefficients were reported.

4. Results

Table 3 displays the zero-order correlations between the variables.

About 17.6% of the variance in systematic processing was explained by the model: F (10, 1557) = 33.34, $p < .001$, $R^2 = .176$. Among the control variables, gender (male = 1, female = 2) (B = –0.07, SE = 0.03, $p < .01$), household monthly income (B = 0.02, SE = 0.01, $p < .05$), perceived susceptibility (B = –0.06, SE = 0.02, $p < .001$), perceived severity (B = 0.04, SE = 0.01, $p < .01$), and negative emotions (B = 0.04, SE = 0.02, $p < .05$) were significantly associated with systematic processing.

To answer **RQ1**, the results showed that education level was directly and positively linked to systematic processing (B = 0.08, SE = 0.04, $p < .05$), indicating that people with higher educational attainment engaged in systematic processing more often than those with less educational attainment.

Education level was not significantly associated with informational subjective norms (B = 0.09, SE = 0.06, p = .11), while informational subjective norms were positively associated with systematic processing (B = 0.08, SE = 0.02, $p < .001$). The result of the bootstrap method showed the indirect association between education level and systematic processing via informational subjective norms was not significant (B = 0.01, SE = 0.005, CI [–.002, .02]). Thus, **H1** was not supported.

To test the mediating role of current knowledge, education level was positively linked to current knowledge (B = 0.20, SE = 0.04, $p < .001$), which was in turn positively correlated to systematic processing (B = 0.05, SE = 0.02, $p < .05$). In line with **H2**, the bootstrap method demonstrated that education level was indirectly linked to systematic processing via current knowledge (B = 0.01, SE = 0.01, CI [.001, .02]).

In terms of the mediating role perceived information gathering capacity, we observed a positive association between education level and perceived information gathering capacity (B = 0.11, SE = 0.05, $p < .05$), as well as between perceived information gathering capacity and systematic processing (B = 0.24, SE = 0.02, $p < .001$). Moreover, the result of the bootstrap method showed that perceived information gathering capacity significantly mediated the relationship between education level and systematic processing (B = 0.03, SE = 0.01, CI [.003, .005]). Therefore, **H3** was supported.

Table 4 presents the mediation of the relationship between education level and systematic processing via informational subjective norms, current knowledge, and perceived information gathering capacity. Fig. 3 depicts the final model.

Table 3
Zero-order correlations between the variables.

	1	2	3	4	5	6	7	8	9	10	11
1. Education level		.07**	.16***	.10***	.12***	–.16***	–.05	.28***	–.01	–.03	.11***
2. ISN			.002	.24***	.21***	.02	.003	.10***	–.04	.07**	.05*
3. CK				.01	.07**	–.07**	.01	.06*	–.01	.03	.07**
4. PIGC					.36***	–.04	.03	.09***	–.02	.05*	.09**
5. Systematic processing						.04	–.04	.13***	–.07**	.10***	.10***
6. Age							.14***	.29***	–.02	.08**	–.09**
7. Gender								.08**	–.04	.03	–.14***
8. Income									–.04	–.002	–.01
9. Perceived susceptibility										.19***	.22***
10. Perceived severity											.23***
11. Negative emotions											

Notes. *$p < .05$, **$p < .01$, *** $p < .001$. ISN = informational subjective norms. CK = current knowledge. PIGC = perceived information gathering capacity. Gender: female = 1, male = 2.

5. Discussion

Based on the survey data collected during the COVID-19 early outbreak in China, we tested a relevant part of the RISP model and explicated why individuals with greater educational attainment engaged more in systematic processing of the COVID-19 information than individuals with less educational attainment. According to the findings, this gap in systematic processing partially resulted from the fact that highly educated individuals acquired more knowledge about the coronavirus and perceived themselves to have greater information gathering capacity than their less educated counterparts. Although informational subjective norms facilitated individuals to engage in systematic processing, we did not observe a significant difference in these norms between people with greater and less educational attainment. Taken together, the findings not only advance our understanding of people's systematic processing of risk information, but also offer insights into facilitating the less educated to perform systematic processing during the infodemic. Implications are discussed below.

5.1. Theoretical implications

Examining people's risk information seeking has long been the focus of the RISP studies in various contexts (Z. J. Yang, Aloe, et al., 2014). Nevertheless, other information behaviors outlined in the model (e.g., information processing and information avoidance) has received limited attention. To echo the call for extending the seeking-oriented research to a broader category of people's risk information behaviors (Ford et al., 2022; Link, 2021; X. Zhou et al., 2021), this study is one of the few studies guided by the RISP model to explore systematic processing (Lu et al., 2021; J. Z. Yang, Dong, et al., 2022; J. Z. Yang & Liu, 2021) among people with varying degrees of education. Overall, our model demonstrates that the major predictors of risk information seeking outlined in the RISP model can also predict systematic processing in the context of the COVID-19 pandemic. Implications of each predictor for understanding the RISP model are discussed below.

First, our study included education level—a sociodemographic factor—as an antecedent that led to the difference in the motivation and capacity of systematic processing. Compared with previous RISP research that treated education level as a control variable (Griffin et al., 2004; Lu et al., 2020; Wong et al., 2021; J. Z. Yang & Zhuang, 2020; Z. J. Yang, 2012), this study extends our attention from the psychological mechanism underlying systematic processing to the sociodemographic predictor of this mechanism. In other words, systematic processing is not only a cognitive response to information (Griffin et al., 1999, 2013), but also a process that is susceptible to sociodemographic influence. Moreover, the direct link between education level and systematic processing revealed in this study indicates that education level may not only serve as a distal predictor but also a proximal predictor of systematic processing in the RISP model. Given that the education-based difference in systematic processing represents a digital divide in terms of information utilization (van Dijk, 2005), research on digital divide could complement the psychology-based RISP model.

Second, inconsistent with our expectation, there was no significant difference in informational subjective norms between highly educated and less educated individuals, which caused the non-significant mediating role of informational subjective norms between education level and systematic processing. This may be because informational subjective norms during a crisis differ from social norms in everyday settings. In everyday life, one's willingness to follow social norms is closely related to his or her education level, considering that the education system in China has consistently emphasized the importance of complying with norms (Kirkpatrick & Zang, 2011). However, when a public health emergency breaks out, individuals from all demographic sectors tend to feel the pressure

Table 4
Mediation of the association of education level with systematic processing via ISN, CK, and PIGC.

	ISN		CK		PIGC		Systematic processing	
Control variables	*B* (*SE*)	*p*	*B* (*SE*)	*p*	*B* (*SE*)	*P*	*B* (*SE*)	*p*
Age	0.001 (0.003)	.99	–0.004 (0.001)	$<$ .05	–0.005 (0.002)	$<$ .05	0.003 (0.002)	.06
Gender	–0.001 (0.04)	.97	0.04 (0.03)	.27	0.07 (0.04)	.07	–0.07 (0.03)	$<$ .01
Income	0.04 (0.01)	$<$ .01	0.01 (0.01)	.15	0.03 (0.01)	$<$ .01	0.02 (0.01)	$<$ .05
Perceived susceptibility	–0.06 (0.03)	$<$ .05	–0.02 (0.02)	.32	–0.04 (0.02)	.12	–0.06 (0.02)	$<$ .001
Perceived Severity	0.06 (0.02)	$<$ .01	0.02 (0.02)	.33	0.03 (0.02)	.09	0.04 (0.01)	$<$ .01
Negative emotions	0.04 (0.03)	.10	0.04 (0.02)	$<$ .05	0.07 (0.02)	$<$ .01	0.04 (0.02)	$<$ .05
Antecedents								
Education level	0.09 (0.06)	.11	0.20 (0.04)	$<$ .001	0.11 (0.05)	$<$ .05	0.08 (0.04)	$<$ .05
ISN	—	—	—	—	—	—	0.08 (0.02)	$<$ .001
CK	—	—	—	—	—	—	0.05 (0.02)	$<$ .05
PIGC	—	—	—	—	—	—	0.24 (0.02)	$<$ .001
Model	R^2 = .023, *F* (7, 1560) = 5.14, *p* $<$ .001		R^2 = .033, *F* (7, 1560) = 7.49, *p* $<$ .001		R^2 = .030, *F* (7, 1560) = 6.18, *p* $<$ .001		R^2 = .176, *F* (10, 1557) = 33.34, *p* $<$ .001	
Effect	Boot Effect		Boot *SE*		Boot LL 95% CI		Boot UL 95% CI	
Total indirect effect	0.04		0.01		.01		.07	
Direct effect	0.08		0.04		.01		.15	
Total effect	0.12		0.04		.05		.20	

Notes. ISN = informational subjective norms, CK = current knowledge, PIGC = perceived information gathering capacity; Gender: female = 1, male = 2. LL = lower limit; UL = upper limit; CI = confidence interval.

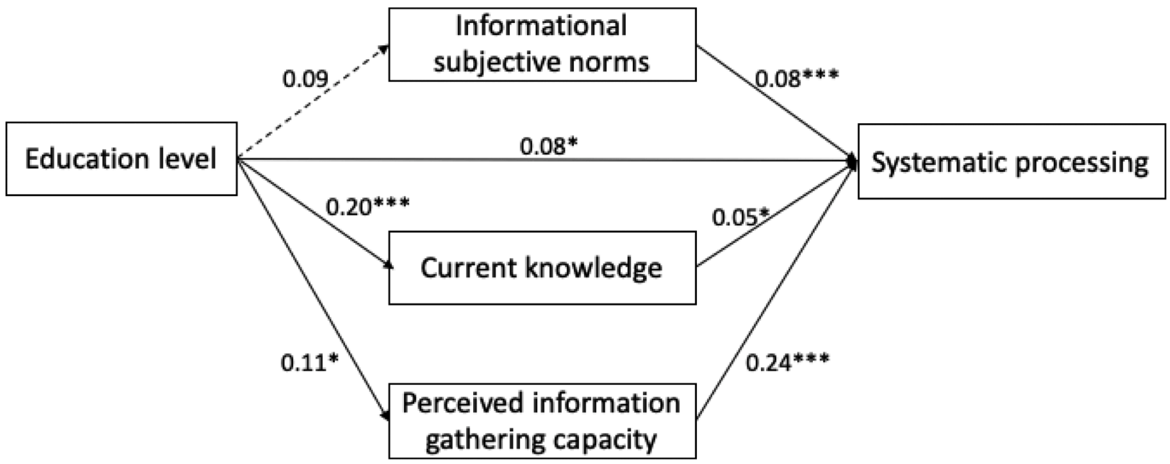

Fig. 3. The final model based on statistical results.
Note. *p < .05; ***p < .001. Unstandardized coefficients were reported.

to protect themselves from the severe threat (Seo, 2021), including the informational subjective norms of acquiring sufficient knowledge to stay safe. In other words, it is the life-threatening nature of the pandemic instead of one's education level that largely determines individuals' inclination to recognize and follow informational subjective norms.

Third, different from treating current knowledge as subjective knowledge in the RISP model, we redefined current knowledge as the objective knowledge one has about the coronavirus. Objective knowledge denotes one's ability to adequately process issue-specific information (Manika et al., 2021). Compared with subjective knowledge, objective knowledge has a stronger influence on attitude and subsequent behaviors (Denton et al., 2020). This indicates the necessity to differentiate between objective knowledge and subjective knowledge in the RISP model and compare their effects on risk information behaviors. Notably, prior research has shown that as people acquire more knowledge about a risk issue, their cognitive heuristics and biases also increase, which does not necessarily lead to a greater reasoning of the issue message (Kahan et al., 2009, 2012). In relation to this study, obtaining more knowledge about the coronavirus also indicates that people may use more heuristics to complement their reasoned judgment (Lu et al., 2021). These findings remind us to cautiously view the mediating role of current knowledge between education level and systematic processing. Fostering less educated individuals' objective knowledge may facilitate them to engage in systematic processing; however, heuristics generated in this process may also weaken their tendency of performing systematic processing.

Fourth, the mediating role of perceived information gathering capacity between education level and systematic processing not only echoes research on the education-based difference in information utilization (Falch & Massih, 2011), but also corroborates a relevant path in the RISP model in recent studies (Lu et al., 2021; J. Z. Yang, Dong, et al., 2022; J. Z. Yang & Liu, 2021). Moreover, the mediation effect of perceived information gathering capacity was stronger than that of current knowledge, which suggested that perceived information gathering capacity served as a more powerful predictor to explicate the education-based difference in systematic processing than current knowledge did. Accordingly, cultivating the literacy regarding information verification may be more effective than fostering issue-specific knowledge for advancing the less educated to engage in systematic processing.

To sum up, the mediation model proposed in this study corroborates that motivation and capacity are two prominent factors that drive systematic processing (Chen & Chaiken, 1999) among people with varying levels of education. Through specifying the accuracy motivation as current knowledge and impression motivation as informational subjective norms, our findings suggest that the accuracy motivation may play a more important role than the impression motivation in explicating the education-based difference in systematic processing. The results offer some insights into the adaptation of the RISP model to better understand the difference in systematic processing between different demographic segments.

5.2. Implications for global recovery from the infodemic

The education-based difference in systematic processing is present across the globe (Hong et al., 2017; Pickles et al., 2021; Wang et al., 2013). As long as the difference exists, individuals with less educational attainment are more vulnerable to the negative impacts of the infodemic due to a lack of systematic processing than those with greater educational attainment. Thus, alleviating the negative consequences of misinformation to the less educated plays an important part in the global recovery from the infodemic. To address this gap and facilitate individuals with less educational attainment to engage in systematic processing, our model has several implications.

First, the mediating role of current knowledge between education level and systematic processing indicates that practitioners should facilitate individuals with less educational attainment to acquire more knowledge about the coronavirus through effective scientific communication. Specifically, knowledge about the coronavirus and the associated prevention measures can be delivered in a straightforward manner, such as cartoons or short-form videos, thus making it easier for the less educated to understand the information and increase their current knowledge.

Second, the mediating role of perceived information gathering capacity between education level and systematic processing denotes that practitioners should strengthen the ability of information verification among the less educated. For instance, workshops about cultivating information literacy can be delivered to individuals with less educational attainment, thereby increasing their capacity of gathering information. Meanwhile, social workers could encourage the less educated to consult professional sources in face or through web-mediated manners to solve confusions related to the pandemic. This may help less educated individuals get a sense of self-control, thus increasing their perceived information gathering capacity.

Third, although informational subjective norms were not susceptible to education level, increasing these norms could advance individuals to engage in systematic processing, regardless of education level. This can be achieved in two aspects. On the one hand, practitioners could employ a community-based method—teaming up with family members and neighbors—to inform the less educated about the importance of obtaining sufficient knowledge to protect themselves from the threat. On the other hand, public service advertisements that emphasize the importance of getting enough coronavirus knowledge help create a social norm that pressures the less educated to follow the norm and process the information in an effortful manner.

5.3. Limitations and future research

5.3.1. Conceptual limitations and future research

According to the RISP model, in addition to informational subjective norms, information insufficiency is another important motive for risk information seeking and processing (Griffin et al., 1999, 2013). Despite that the relationship between information insufficiency and information seeking has been widely examined (Z. J. Yang, Aloe, et al., 2014), a very few studies have suggested the association between information insufficiency and systematic processing (Lu et al., 2021). Thus, not including information insufficiency in this study is a conceptual limitation. To overcome this limitation, future research could test whether information insufficiency mediates the relationship between education level and systematic processing.

Besides, the partial mediation effect of current knowledge and perceived information gathering capacity indicates that there could be other mediating mechanisms underlying the association between education level and systematic processing. In addition to information insufficiency, the RISP model and other related theories—such as the framework of risk information seeking (Ter Huurne & Gutteling, 2008) and the planned risk information seeking model (Kahlor, 2010)—all suggest that affective response serves as a proximal predictor of risk information seeking. Thus, researchers could test the mediating role of affective response between education level and systematic processing.

5.3.2. Methodological limitations and future research

First, compared with the latest demographics of Chinese netizens, individuals with greater educational attainment—those with a bachelor's degree or above—were overrepresented in this study. This was due to the sampling strategy used in the present study, in which highly educated participants constituted the majority of the sampling pool (Sojump, 2021). Noticeably, we asked participants to report their highest level of education in the survey, while the demographics of Chinese netizens suggested the current level of education netizens had at the end of 2020. Besides, approximately 16.6% of the population were teenager netizens who were middle school or high school students when the survey was conducted (China Internet Network Information Center, 2021). In other words, this group constituted a considerable portion of the netizens with less educational attainment. Thus, although our results favored individuals with greater educational attainment, the findings could somewhat inform our understanding of the education-based difference in systematic processing among Chinese netizens as the teenager group grows up and acquires a higher level of education. Additionally, the non-normality of a given variable tends not to bias the regression coefficient if the sample size is large (Knief & Forstmeier, 2020). Therefore, considering the relatively large sample size in this study ($N = 1{,}568$), the relationships between education level and other examined variables might be not highly biased. Nevertheless, readers should cautiously generalize the findings to the population.

Second, although informational subjective norms mainly come from important ones such as family members and close friends (J. Yang, 2021; Z. J. Yang & Kahlor, 2013), the single-item measurement decreased the validity of informational subjective norms. To increase the validity, researchers could use multiple items, including the influence from colleagues, acquaintances, and the majority of others in society to complement the single-item measurement of informational subjective norms.

Third, we could not claim causality between the examined variables based on the cross-sectional survey data. To strictly test the relevant causal link in the RISP model, we advise researchers to use a longitudinal design. Specifically, informational subjective norms, current knowledge, perceived information gathering capacity and other potential mediators can be measured in the first-wave survey. Then, the same respondents participate in the second-wave survey and their frequencies of engaging in systematic processing are measured. Thus, the causality of the model can be tested.

Fourth, considering that the coronavirus has become a global pandemic, future research could test our model in other countries or regions to explain the education-based difference in systematic processing. Given that the divide in information utilization is prevalent in developing countries (Chang et al., 2015; Mathrani et al., 2021), the proposed model may be particularly relevant to understand the gap in systematic processing between highly educated and less educated individuals in these countries. Hopefully, testing this model in other countries could offer implications and measures for the global recovery from the infodemic.

6. Conclusions

Although a plethora of studies have examined how to manage the COVID-19 misinformation and fight the infodemic (Larson, 2020;

Patwa et al., 2021; The Lancet Infectious Diseases, 2020), limited attention has been paid to how to help the less educated individuals avoid the harms caused by exposure to misinformation. People with less educational attainment are more vulnerable to the negative impacts of the infodemic than their highly educated counterparts. Assuming highly educated individuals are more likely to engage in systematic processing than less educated individuals, our study explicates the psychological mechanism underlying the education-based difference in systematic processing. The findings indicate that increasing current knowledge, perceived information gathering capacity, and informational subjective norms among the less educated are effective ways to facilitate their systematic processing. Compared with increasing one's education level to advance his or her systematic processing, our measures are more feasible. Considering that the infodemic has become a global issue, we hope that this study could offer approaches to alleviate less educated individuals' vulnerability to misinformation, especially in developing countries, thereby contributing to the global recovery from the infodemic.

Author statement

We confirm that neither the manuscript nor any parts of its content are currently under consideration or published in another journal. Both authors have approved the revised manuscript and agreed with its submission to this special issue of *Information Processing & Management*.

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