Information Processing and Management 58 (2021) 102554

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/infoproman

Characterizing the dissemination of misinformation on social media in health emergencies: An empirical study based on COVID-19

Cheng Zhou [*], Haoxin Xiu, Yuqiu Wang, Xinyao Yu

Business School, Nankai University, 94 Weijin Road, Nankai District, Tianjin 30074, China

ARTICLE INFO

Keywords:
Misinformation dissemination during health emergencies
Health caution and advice misinformation
Health help-seeking misinformation
Emotional support
Misinformation ambiguity
Misinformation richness

ABSTRACT

The dissemination of misinformation in health emergencies poses serious threats to public health and increases health anxiety. To understand the underlying mechanism of the dissemination of misinformation regarding health emergencies, this study creatively draws on social support theory and text mining. It also explores the roles of different types of misinformation, including health advice and caution misinformation and health help-seeking misinformation, and emotional support in affecting individuals' misinformation dissemination behavior on social media and whether such relationships are contingent on misinformation ambiguity and richness. The theoretical model is tested using 12,101 textual data about COVID-19 collected from Sina Weibo, a leading social media platform in China. The empirical results show that health caution and advice, help seeking misinformation, and emotional support significantly increase the dissemination of misinformation. Furthermore, when the level of ambiguity and richness regarding misinformation is high, the effect of health caution and advice misinformation is strengthened, whereas the effect of health help-seeking misinformation and emotional support is weakened, indicating both dark and bright misinformation ambiguity and richness. This study contributes to the literature on misinformation dissemination behavior on social media during health emergencies and social support theory and provides implications for practice.

1. Introduction

In December 2019, a new type of coronavirus was identified and then an outbreak began in Wuhan, China. On February 11, 2020, the World Health Organization (WHO) renamed this disease COVID-19. With the spread of the virus around the world, on March 11, 2020, the WHO declared that COVID-19 caused a global pandemic, urging governments and organizations around the world to take action to minimize the spread of the virus.

During health emergencies, the number of people who use social media to seek health-related information, such as health advice, prevention and treatment information, is high and continues to grow (Chu et al., 2017). To date, social media has increasingly influenced people's daily lives and their health behaviors (Zhao, Da & Yan, 2020). The ubiquity of social media allows people to find useful health-related information more effectively and efficiently (Zhao, Zhang & Wu, 2019). In health emergencies, the public feels anxious and tends to search for relevant information to cope with the uncertainty caused (Lifang, Zhiqiang, ZHANG & Hong, 2020).

* Corresponding author.
E-mail address: zhoucheng1017@163.com (C. Zhou).

https://doi.org/10.1016/j.ipm.2021.102554
Received 27 September 2020; Received in revised form 18 February 2021; Accepted 19 February 2021
Available online 3 March 2021
0306-4573/

Thus, social media plays a critical role in spreading information about a health emergency (Waszak, Kasprzycka-Waszak & Kubanek, 2018).

However, due to the popularity of social media, health-related misinformation has become a critical issue in the health care system (Ghenai & Mejova, 2018; Zhao et al., 2020), especially in times of health emergencies. Chou, Oh and Klein (2018)) noted that "A piece of health-related information is false because of a lack of scientific evidence". This definition mainly focuses on misinformation on health lifestyles or how to prevent or treat diseases. In fact, health help-seeking is another type of information during health emergencies (Li et al., 2020). Thus, misinformation in health emergencies includes two main dimensions in the current study: health advice and caution and health help seeking. Health advice and caution misinformation is defined as when "A health-related advice or suggestion of how to prevent or treat diseases is absolutely false". Health help-seeking misinformation, as its name suggests, expresses misinformation, such as seeking health donations, to gain improper benefits or attract public attention. Recently, health misinformation has received increasing attention from stakeholders (e.g., the health industry, social media platforms, and academia) because it, as an important kind of information, has been frequently disseminated on social media and can mislead people's health behaviors. Consequently, understanding the spread mechanism of misinformation in health emergencies on social media has been a key issue that attracts much attention.

As misinformation dissemination in health emergencies on social media can have adverse effects on public health, the previous literature has proposed specific ideas and examined interventions to curb misinformation diffusion. For example, Ozturk, Li and Sakamoto (2015) show that misinformation warnings, such as "this posting may contain misinformation", decrease users' likelihood of reposting the misinformation. In addition, some researchers have attempted to investigate the factors of misinformation dissemination, such as individuals' information dissemination habits (Gu & Hong, 2020), personal involvement (Chua & Banerjee, 2018) and healthy literacy (Oh & Lee, 2019), but most of them have used questionnaire methods to test hypotheses. Thus, there is a lack of research that uses quantitative analysis of secondary data extracted from social media platforms. More importantly, limited studies have attempted to specify how different types of misinformation affect individuals' dissemination behavior in health emergencies.

To address this research gap, this study draws on social support theory because online health misinformation can be treated as providing false social support for individuals to disseminate misinformation. Based on this theory, this study classifies such support into informational support and emotional support (Biyani, Caragea, Mitra & Yen, 2014; Chen, Guo, Wu & Ju, 2020b; Liu, Ren, Shi, Li & Zhang, 2020b). Informational support can be seen as offering incorrect health advice or caution for the public to prevent a disease or providing unverified health help-seeking messages to attract public attention or evoke societal concerns. Emotional support refers to empathy, encouragement, and caring for people (Krause, 1986). The existing literature on the health care system has mainly treated informational support as a holistic concept (Chen et al., 2020b); thus, this method cannot provide a detailed perspective of how various types of misinformation can influence individuals' dissemination behavior on social media in times of health emergencies. Consequently, based on the content features of health misinformation, this study further identifies two dimensions of informational support: health caution and advice misinformation and health help-seeking misinformation. The former is defined as "a piece of health-related information (such as prevention or treatment tips on how to deal with diseases) has not been verified or a lack of scientific evidence", and the latter means that a piece of information is fabricated in health emergencies to seek health donation or gain improper benefits.

Conroy, Rubin and Chen (2015) indicate that most misinformation creators use specific writing strategies to avoid being detected. Some studies have shown that one of the greatest features of rumors is ambiguity (Oh, Agrawal & Rao, 2013; Starbird et al., 2016). Thus, a trusted creator is more likely to use assertive words and less likely to use hedging words (Rashkin, Choi, Jang, Volkova & Choi, 2017), and a deceiver shows more "uncertainty and ambiguity" in his or her creation (Buller & Burgoon, 1996). Thus, misinformation creators may use many ambiguous words to reduce the likelihood of detection and extend the reach to the target audience. In this study context, if a piece of health misinformation contains many ambiguous words, people may feel it is suitable for themselves or their friends. For example, a piece of health misinformation says "someone has said that smoking can prevent COVID-19 infection in extent". In this sentence, "someone" and "in extent" are ambiguous words because they do not state details. Accordingly, ambiguity can be seen as a dark side of misinformation because it can mislead people and make them feel that misinformation is useful, while it may also benefit people. For example, Liu et al. (2020b) demonstrated that the uncertain words used by physicians positively moderate the relationship between treatment-related health information and patients' perceived usefulness. Surprisingly, little research has examined the bright side of ambiguity in misinformation dissemination during health emergencies. Thus, this paper proposes misinformation ambiguity and further explores whether it shapes the relationships between informational support, emotional support and health misinformation dissemination.

In addition, the representational richness of a piece of information can affect its credibility and argument quality (Yin & Zhang, 2020). Currently, development technologies enable people to create and use multimedia content more easily. Content can be posted in various formats on social media, such as text-only, text + images or text + videos. Thus, individuals are more likely to be attracted by that vivid information and will repost such information. The richness of information may lead individuals to be involved in information processing (Yin, Sun, Fang & Lim, 2018). Shi, Hu, Lai and Chen (2018) indicate that information richness is positively related to individuals' information dissemination behavior. However, previous studies have primarily discussed this feature in the accurate information context, and little attention has been given to misinformation. Thus, this study proposes misinformation richness, which is defined as "the display format of misinformation on social media" and examines whether it will shape the linkage between social support and misinformation dissemination.

Focusing on the COVID-19 pandemic, this study attempts to address two key aspects of the dissemination of misinformation on social media: 1) the determinants of misinformation dissemination in health emergencies and 2) whether misinformation ambiguity and richness shape the relationship between the determinants and individuals' dissemination behavior. Drawing on the existing literature and text mining methods, this study proposes a theoretical model associated with five main hypotheses to answer the above two questions. We collected 12,101 pieces of misinformation about the COVID-19 pandemic from Sina Weibo, one of the influential social media platforms in China, to test the model. This study makes several contributions. First, although misinformation has received many scholars' attention, most prior studies have used questionnaires or simulations. This study takes a new step to explore how misinformation content affects individuals' dissemination behavior by using object data retrieved from social media platforms, which enriches the literature on health emergency management. Second, inspired by social support theory, this research develops the determinants of misinformation dissemination and enriches the literature on health emergency management by mining the text features of health misinformation. To the best of our knowledge, this study is one of the first to apply social support theory to misinformation dissemination in health emergencies. Third, this study takes the first step to explore how the moderating effect of misinformation ambiguity and richness shapes misinformation dissemination behavior in the social media context. Accordingly, our findings provide some important implications for information practice and emergency management.

This study is structured as follows: In the second part, we review the literature on misinformation and its dissemination on social media, and the existing literature on social support is also elaborated. In the third part, the influence mechanism among the relationships of informational support, emotional support, misinformation ambiguity and richness, and misinformation dissemination is analyzed, and hypotheses are proposed. In the fourth part, we describe the research method and report the empirical results of the research. Finally, in part of the discussion, the main findings, theoretical and practical implications, limitations of current research, and possible future research directions are discussed based on the results.

2. Theoretical background

2.1. Information seeking and misinformation dissemination in health emergencies

Advancements in Internet technologies have immensely enhanced access to information during times of health emergencies (Cole, Kleine & Watkins, 2016). In a health emergency, people usually suffer from health anxiety and concern about their health condition; thus, they appear to search for health-related information more frequently on the Internet (McMullan, Berle, Arnáez & Starcevic, 2019). Health information-seeking behavior (HISB) is described as "a process of gathering health-related information" (Mukherjee & Bawden, 2012). Various motivations influence individuals' beliefs in seeking information during health emergencies, such as anxiety about their health or engaging in controlling and preventing the disease (Pesälä et al., 2017). Currently, the rise of social media has provided another effective channel for people to obtain information in health emergencies (Zhang et al., 2017a)). Miller and Bell (2012) have indicated that social media has great potential for health-related information seeking. Furthermore, the existing literature has shown the benefits of social media in health emergencies, such as sharing available information, increasing public engagement, and providing social support (Chen et al., 2020b; Moorhead et al., 2013; Rousseau et al., 2015). However, the lack of gatekeepers on social media also encourages the dissemination of misinformation (Bode & Vraga, 2018). Some researchers have realized the relationship between social media and misinformation during times of health emergencies (Hou, Du, Jiang, Zhou & Lin, 2020; Pennycook, McPhetres, Zhang, Lu & Rand, 2020). For example, Pennycook et al. (2020) observed that since COVID-19 emerged, a large amount of misinformation (i.e., preventive tips on how to address the virus) has proliferated on social media.

According to Bode and Vraga (2015), misinformation has gained much attention from academia. It is defined as "the factually incorrect information that is not backed up with evidence". Because misinformation is easily available, its spread is rooted in information practices (Ruokolainen & Widén, 2020). Ma, Lee and Goh (2013) indicated that individuals' information-seeking behavior has been associated with using social media for news dissemination. Thus, individuals wish "to be in the know" results in the dissemination of misinformation on social media (Duffy, Tandoc & Ling, 2020). Although the dissemination of misinformation is not a new phenomenon, many researchers indicate that the emergence of social media has made the spread of misinformation quicker and easier among people (Del Vicario et al., 2016; Vosoughi, Roy & Aral, 2018), especially during times of health emergencies, such as the current COVID-19 pandemic. The advent of social media, which allows people to share information almost without restriction, has intensified the dissemination of misinformation in health emergencies (Apuke & Omar, 2020). In recent years, misinformation has been a vital issue in health ecosystems (Li, Cheung, Shen & Lee, 2019; Zhao et al., 2019). According to Chou et al. (2018), health-related misinformation is defined as "a health-related claim that is false because a lack of scientific evidence". Recently, the dissemination of misinformation on social media in health emergencies has gained increasing attention because dissemination can pose threats to public health. When facing health emergencies, people often experience health anxiety (Oh & Lee, 2019); thus, they wish to find information about disease prevention and treatment and gain social support to deal with the disease (Chen et al., 2018). Due to the lack of professional medical knowledge, it is difficult to separate misinformation for people; thus, they are more likely to share misinformation without much consideration to whether the content is accurate. Apuke and Omar (2020) also reveal that people's information-seeking behavior during COVID-19 is positively related to fake news sharing on social media. Although previous studies have indicated vaccine-related misinformation in health emergencies, such as Ebola and Zika (Wang, McKee, Torbica & Stuckler, 2019; Waszak et al., 2018), there may be other types of health-related misinformation, such as incorrect health advice and fake articles on health help seeking to be disseminated on social media. More importantly, there is a lack of research focusing on misinformation dissemination on COVID-19. Thus, it is necessary to further investigate the underlying mechanism of misinformation dissemination in health emergencies.

2.2. Social support theory

To date, there is no universally accepted definition of social support. Huang, Nambisan and Uzuner (2010) advocated that social support is the exchange of verbal and nonverbal messages to communicate emotional and informational messages that reduce retrievers' stress. Rozzell et al. (2014) claim that social support reflects the information that evokes a person's feelings of being cared for, esteemed and valued. In fact, social support consists of multiple dimensions. According to Liang, Ho, Li and Turban (2011), social support includes informational support and emotional support. Informational support means the advice, suggestions and guidance that affect individuals' behaviors (Chun & Lee, 2017). For example, when an individual obtains valuable information from social media, he or she may be willing to repost it on his or her social network sites. Emotional support reflects the expressions of caring, concerns, and encouragement (Lin, Hsu, Cheng & Chiu, 2015). Such support may bring warmth to people and reduce their stress or anxiety. The role of informational and emotional support has been verified in the health care literature (Chen et al., 2020b; Liu et al., 2020b; Yan & Tan, 2014), but little research has paid attention to the dissemination of misinformation through these two support perspectives.

Furthermore, misinformation in health emergencies can be seen as false support for individuals. During health emergencies, a large amount of misinformation emerged on social media. Although previous studies have attempted to classify health-related information into various categories, such as health education (Liu, 2013) and prevention and treatment information (Liu et al., 2020b), few studies have paid attention to classifying the types of misinformation in health emergencies. Accordingly, this study measures misinformation support from a more precise approach. During emergencies, people are eager to seek health-related information related to prevention or curing disease (Pennycook et al., 2020). In addition, due to the shortage of medical resources in the short term, some medical institutions or individuals may seek support needs, such as wishes to donate materials, money, or services for disease control. These two types of health information are important components of health emergency-related information (Li et al., 2020). Therefore, this study classifies misinformation into two dimensions: health advice and caution and health help seeking. Meanwhile, emotional support is related to the words (containing misinformation) of providing encouragement, sympathy, and care to others. By doing so, this study provides a precise measure of health misinformation and explores the underlying mechanism of the spread of misinformation.

2.3. Information ambiguity

Ambiguity exists when details about situations are uncertain, unpredictable, or probabilistic (Brashers, 2001). In research on ambiguity in emergencies, some researchers have explained that ambiguous information is caused either by the inefficiency of emergency communication (Reddy et al., 2009) or the cognitive dissonance of the public (Dwivedi, Shareef, Mukerji, Rana & Kapoor, 2018). In ambiguous situations, people usually lack reliable extrinsic information to better understand the uncertain situation (Starbird, Maddock, Orand, Achterman & Mason, 2014, 2016) and are more likely to accept misinformation to fill the gap of ambiguity.

The existing literature has revealed a relationship between health concerns or anxiety and a need for health-related information (McMullan et al., 2019; Oh & Lee, 2019). Some people are concerned about their health, and they are more likely to search the Internet for health-related information (Baumgartner & Hartmann, 2011; Muse, McManus, Leung, Meghreblian & Williams, 2012). Many researchers have argued that ambiguity in the information context contributes to misinformation or rumors (Bordia & DiFonzo, 2004; Starbird et al., 2016). During health emergencies, due to the lack of professional knowledge about how to prevent and control diseases, people can actively engage with information seeking. If a piece of misinformation contains many ambiguous words or terms, people may feel it is suitable for themselves or others, which in turn encourages them to disseminate the misinformation. Starcevic and Berle (2013) have indicated that online health-related information is often incomplete and ambiguous; however, whether such ambiguity has contributed to the dissemination of health misinformation remains debatable, especially in times of health emergencies. Thus, this study proposes misinformation ambiguity and attempts to examine its moderating role in shaping the relationship between social support and misinformation dissemination.

2.4. Media richness theory

Media richness theory (MRT), proposed by Daft and Lengel (1986), emphasizes the abilities of communication media to facilitate understanding. Media richness means that the information load of the media aims to promote shared information. Later, Daft, Lengel and Trevino (1987) divided media richness into four types: face-to-face communication, telephone, written documents, and unprocessed documents. To date, advances in technology enable people to create and share multimedia content more easily. For example, individuals can post content with plain text, images or videos; thus, the media richness varies from low to high (Chen et al., 2020a; Denktaş-Şakar & Sürücü, 2020). Due to word limitations on social media (such as Twitter), individuals are likely to extend what they want to post by including complementary material, such as special tags or symbols, URLs (Castillo, Mendoza & Poblete, 2011), images or videos (Gupta, Lamba, Kumaraguru & Joshi, 2013; Jin, Cao, Zhang, Zhou & Tian, 2016). Thus, this study proposes misinformation richness to capture the features of misinformation expression and further investigates its moderating role in the relationship between social support and misinformation dissemination.

3. Hypotheses development

3.1. Social support and misinformation dissemination

Liu et al. (2020b) indicated that different types of online health information have different influences on individuals' perceived usefulness. Thus, this study also postulates that different types of health misinformation may affect its dissemination.

Existing studies have classified online health information into several suitable categories, such as symptoms, cures, and prevention

(Liu, 2007; Liu & Lu, 2010). Previous research has suggested that individuals may learn a little about a disease, so they wish to seek information on how to prevent the disease or deal with it once they have relevant symptoms (Oh & Lee, 2019). In addition, medical institutions or individuals may seek health-related support via social media (Li et al., 2020), and someone may repost such information to meet these health needs as soon as possible. In this study, we focus mainly on health emergencies, such as COVID-19. Thus, this study classifies misinformation into two dimensions: health caution and advice misinformation and health help-seeking misinformation. In great detail, health caution and advice misinformation is related to the incorrect prevention of the occurring disease. For example, a posting about COVID-19 claimed that eating garlic can prevent infection, but the WHO verified this health advice as false.[1] Health help-seeking misinformation relates to incorrect statements about seeking health-related support. For example, a posting claimed that Shanghai medical teams aiding Wuhan need donations for personal protective equipment (PPE) supplies, such as masks, protective clothing, liquid soap, etc., for COVID-19 prevention and control. However, this posting was confirmed by the government of Hubei Province to be a rumor.[2] In times of health emergencies, due to health anxiety and the lack of professional knowledge, health caution and advice misinformation make individuals believe that such misinformation may enable them to better manage their health condition, and health help-seeking misinformation enables them to feel that they need to provide support to those who seek help and contribute to emergencies. Thus, individuals are willing to repost such misinformation on social media without being aware of its accuracy. Based on the above arguments, we hypothesize the following:

H1a. . *Health caution and advice misinformation positively influences individuals' dissemination behavior.*

H1b. . *Health help-seeking misinformation positively influences individuals' dissemination behavior.*

In addition to creators' informational support for people, there is also some emotional support provided in the misinformation, which is manifested in the creators' appeasing behavior toward people. This is because in times of a health emergency, people's psychological states, such as health anxiety or worry, and sometimes these emotions may be greater than the severity of the emergency (Meggiolaro et al., 2016). At such times, in addition to health advice or help seeking information, people also need emotional support to increase their confidence or alleviate their concern. Therefore, if a piece of health misinformation contains emotional support, such as providing encouragement, care, and empathy (Bambina, 2007), it is more likely to help individuals increase their confidence and reduce their anxiety when facing a health emergency. Then they are more likely to engage with such misinformation spreading. Thus, we hypothesize that:

H2. *Emotional support provided in health misinformation positively influences individuals' dissemination behavior.*

3.2. The moderating role of misinformation ambiguity

In health misinformation, ambiguity words are widespread; misinformation ambiguity means the level of uncertainty contained in the misinformation (Oh et al., 2013). Ambiguity exists when details of situations are uncertain, unpredictable, or probabilistic (Brashers, 2001). From a cognitive perspective, when facing a health emergency, people are willing to spend effort seeking more information to mitigate their health concerns. If a piece of health misinformation includes ambiguous words, such as someone, in recent years, possible, and seems to be, people may feel that the misinformation is provided for the masses, and they believe it may be useful for them to deal with health issues. Zhang and Ghorbani (2020) indicate that specific writing strategies for misinformation used by creators attract others' attention. In this study, ambiguity word terms mean the uncertainty of health misinformation, and misinformation creators use ambiguous words to mislead people and avoid detection. Thus, misinformation creators are likely to use ambiguous words to widen the audiences for health misinformation. Previous research indicates that ambiguous words may lead to a dark side in online health information interactions (Liu et al., 2020b); by contrast, this study argues that ambiguous words may increase the dissemination of health misinformation. Thus, we hypothesize that:

H3a. . *Misinformation ambiguity strengthens the effect of health caution and advice misinformation on individuals' dissemination behavior.*

H3b. . *Misinformation ambiguity strengthens the effect of health help-seeking misinformation on individuals' dissemination behavior.*

According to Cutrona and Russell (1990), emotional support is beneficial for people who experienced or are experiencing health-related circumstances. During a health emergency, most people are experiencing health anxiety or worry, and they are eager to obtain emotional support, such as encouragement and comfort, from others to reduce their health concerns. Accordingly, when ambiguous words are contained in a piece of health misinformation, people may think such misinformation will be easier for the public to meet their emotional needs, and they will perceive the misinformation as useful; thus, they are more likely to repost it. Thus, we hypothesize that:

H3c. . *Misinformation ambiguity strengthens the effect of emotional support on individuals' dissemination behavior.*

[1] https://m.weibo.cn/5078700027/4467874712692795

[2] http://news.sina.com.cn/c/2020-02-02/doc-iimxxste8329411.shtml

3.3. The moderating role of misinformation richness

In this study, misinformation richness is defined as "the display format of misinformation". This definition is consistent with Chen et al. (2020a). Recently, many studies have examined the relationship between the richness level of information and individuals' information dissemination behavior in the context of social media (Brubaker & Wilson, 2018; Chen et al., 2020a; Ji, Chen, Tao & Li, 2019; Kim & Yang, 2017; Shi et al., 2018). For example, Shi et al. (2018) analyzed 1479,310 Twitter posts based on text mining, and the results showed that a post with images and links is more likely to be shared by individuals in the social media context. A Rahim, Ibrahim, A Salim, N and Ariffin (2019)) analyzed 2132 postings published on the Malaysian Health Department's official Facebook page, confirming that videos had a significant and positive effect on individuals' sharing behavior. Thus, according to MTR, visual content, such as images and videos, seems to grasp individual attention more easily than plain text (Guidary et al., 2019; Yin & Zhang, 2020). However, the effects of images and videos on health misinformation dissemination remain debatable. Compared to plain text with health misinformation, misinformation content that includes images or videos can provide supplemental health-related information; thus, individuals prefer to pay more attention to it and share it. Thus, this study hypothesizes that:

H4a. . Misinformation richness strengthens the effect of health advice and caution misinformation on individuals' dissemination behavior.

H4b. . Misinformation richness strengthens the effect of health help-seeking misinformation on individuals' dissemination behavior.

H4c. . *Misinformation richness strengthens the effect of emotional support on individuals' dissemination behavior.*

Finally, our research model is presented in Fig. 1. The model includes three independent variables (health advice and caution misinformation, health help-seeking misinformation, and emotional support), two moderator variables (misinformation ambiguity and misinformation richness), and one dependent variable (misinformation dissemination behavior). In addition, five control variables (length of the misinformation, number of followers of the misinformation creator, number of likes and comments on misinformation, and number of times the misinformation mentioned others) are included to eliminate the interference of other factors on the results.

4. Research methodology

4.1. Research context

In this study, we focus on the emergency health event: the COVID-19 pandemic. After the outbreak of COVID-19, a variety of health-related information was posted on social media, such as the current situation of the disease and how to prevent the disease. Social media accounts are one of the most important information sources during emergencies; however, much health misinformation is

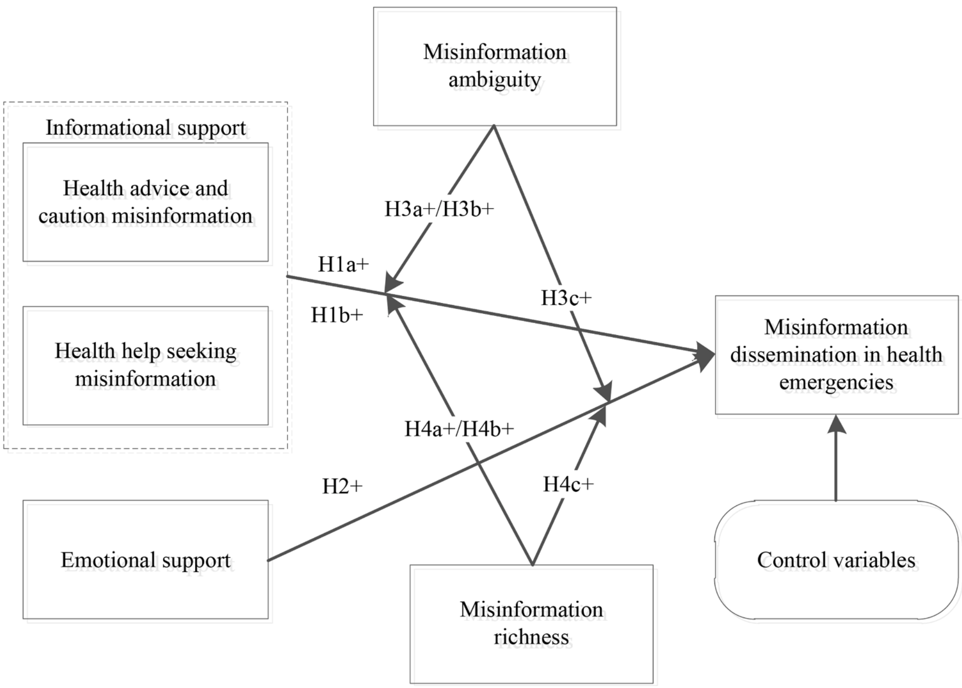

Fig. 1. The research model.

emerging. This study focuses on a leading social media platform in China, namely, Sina Weibo. The platform provides an ideal setting to investigate the health misinformation dissemination process for two reasons. First, Sina Weibo has become an influential microblog in China, and it is reported that by the end of 2019, there were over 510 million monthly active users. Thus, once an emergency event occurs, the relevant information can be disseminated in a timely manner. Second, during COVID-19, the platform built a special section to gather health misinformation, which provides data support for our research. Accordingly, the platform is suitable for our study.

4.2. Data collection

Sample data in this research were collected from Sina Weibo by crawling technology. We developed a Python-based web crawler to automatically collect health-related misinformation from January 23 to March 31, 2020. The reason for this period is that on January 23, 2020, Wuhan was locked down to control the spread of COVID-19, which was an important point in time for China's government and the public to fight the disease. At the end of March, the COVID-19 pandemic was essentially over in China. Thus, the public is eager to receive helpful information in a short time during an emergency. For each misinformation, text content, the number of reposts, likes and the number of fans of the misinformation poster are captured, and links, images, and videos are also captured, if available, to measure the misinformation richness. After collecting the initial data, we dropped 3050 texts because these posts were not original. On Sina Weibo, a post beginning with the//@ symbol indicates that the post is forwarded or reposted. Finally, the total number of 12,101 texts were left.

4.3. Operationalization for variables

Misinformation dissemination. Most previous studies have measured individuals' information dissemination behavior using quantitative indicators, such as the number of shares (Bonsón & Ratkai, 2013; Brubaker & Wilson, 2018; Chen et al., 2020a; Kim & Yang, 2017; Lifang et al., 2020). Following this logic, the number of shares can also be used as a quantitative indicator to evaluate the spread of health misinformation. The previous research has indicated that when the rumors have already been exposed to a wider audience, people are more likely to take dissemination behavior Zhao et al., 2013). Thus, the number of views may be a critical factor that influences each post reposts. In this study, due to the API of Sina-weibo does not directly provide the number of views of each post, there is an objective difficult to crawl this data. In addition, a main objective of this study is to investigate whether different types of health misinformation are a construct to influence individuals' dissemination behavior in the times of health emergencies. We have to admit that the more exposed people of the misinformation, the more times of retweets or shares. However, in this study, we assume that the misinformation has been viewed by people, namely, Weibo users were exposed to the misinformation, and further explore they how respond to such misinformation (e.g., retweet it on social media in this study). Further, if many people were exposed to a piece of misinformation, but they did not retweet it, the scope of dissemination is limited. In previous studies (A Brubaker & Wilson, 2018; Chen et al., 2020a; Khobzi, Lau & Cheung, 2019; Lifang et al., 2020; Rahim et al., 2019; Shi et al., 2018; Xu & Zhang, 2018), they also do not include the number of views in their research model to capture the contagiousness of a particular post because of the objective difficulty. In order to mitigate this bias as far as possible, the number of fans of the misinformation creator and the number of times the text of misinformation has mentioned other users are controlled. Compared to common viewers, the fans of the misinformation creator view the misinformation earlier and faster; they are more likely to disseminate the misinformation. Thus, we argue that the number of fans is related to the number of views. In addition, as Shi et al. (2018) indicate, "Mentioning" in the practice of referring to a user in a post through the use of "@username". This form aims to gain the target users' attention. We hope these two variables can mitigate the bias caused by omitting of the number of views in some degree.

Health advice and caution and help seeking misinformation. To identify the types of health misinformation, we invited three graduate students to manually label our sample data. Before manual annotation, we informed them of the labeling rules, e.g., health caution and advice terms, such as smoking can prevent viruses, and help seeking terms, such as need masks or disinfectants. Then the students performed the labeling work in two steps. Step 1: We randomly sampled 3000 texts to perform pilot tagging work and obtained an average Cohen's kappa of 0.678, which was within the substantial interval [0.60, 0.80] suggested by Landis and Koch (1977) and Li, Zhang, Tian and Wang (2018). Step 2: The remaining texts are tagged based on the agreement obtained during the first step. Eventually, the Kappa value was 0.714 for all text, indicating a high agreement in manual classification results. Finally, based on the one-hot encoding method, we built a vector distribution for each text, such as "(1,0)" denotes health caution and advice misinformation, and "(0,1)" denotes health help-seeking misinformation. In practice, health advice and caution and help-seeking words or terms may contain misinformation at the same time, because misinformation creators want to provide various content to attract public attention and avoid detection. For example, a piece of health misinformation presents "*During COVID-19, you could try to eat vitamin C to prevent infection. In addition, a local medical institution is now seeking health assistance; please forward this post to let more people know about it*". Thus, we encoded this misinformation as (1,1).

Emotional support. Following the works of Chen et al. (2020b) and Liu et al. (2020b), we performed the operationalization of emotional support in three rounds. In the first round, we recruited three graduate students to manually code work. They were informed that the purpose of the coding was to construct the dictionaries of emotional support. They highlighted the emotional words or terms from health misinformation in a sample of 3000 texts in parallel. Then, we calculated the kappa statistic (Cohen, 1960), which is used to conduct the reliability test of corpus classification, and the average value equals 0.723, which was within the substantial interval suggested by Li et al. (2018). Therefore, we constructed a first version of the emotional words dictionary with 20 words or terms. In the second round, two authors marked 2000 new postings in parallel. Similar to the first coding process, we constructed a second version of the dictionaries (the average Kappa value equals 0.734). We then compared the second version of the dictionaries with the first version and added new words or terms to the first version of the dictionaries. Based on these two procedures, the emotional dictionary expanded from the original 20 words to 35 (such as don't worry, good luck, hope, glad, fortunately, cheer up, get well soon, everything will be well, etc.). In addition, we consulted two emotional professionals and confirmed our identification of the dictionary. In the third round, we used Jieba (Sun, 2012), a Chinese text analysis tool, to automatically extract words or terms from the remaining 7101 texts based on the dictionary constructed.

Misinformation ambiguity. Because there is no mature dictionary of ambiguous words or phrases, we needed to construct such a dictionary. Although some studies have attempted to manually code ambiguity or uncertainty words in the misinformation context (Maddock et al., 2015; Starbird et al., 2014, 2016), they focused on the English context, and their method and dictionary may be inappropriate to the Chinese context. In addition, Liu et al. (2020b) adopted manual code to construct an uncertainty dictionary. However, their dictionary only included affirmation words or phrases. Zhao, Resnick and Mei (2015) indicated that interrogative words or phrases (such as "*How about you?*" and "*Really?*") could also express information ambiguity, whereas they did not pay attention to health misinformation. Based on the procedures of the emotional dictionary, we further constructed a dictionary of ambiguous words or terms, such as usually, possible, someone had said, somewhere, seems to be, truly? how about you? What do you think?, etc. The average Kappa values of the two versions are equal to 0.754 and 0.743, respectively. Finally, the ambiguity dictionary was built with 30 words or terms.

Misinformation richness. As suggested by prior research (Chen et al., 2020a; Ji et al., 2019; Yue, Thelen, Robinson & Men, 2019), this study classifies misinformation richness into three levels according to the complexity of the misinformation presentation form. The three levels ascend with richness: plain text, text + images, and text + video. Plain text is marked as a low level of misinformation richness, text + images is marked as a moderate level of misinformation richness, and text + video is marked as a high level of misinformation richness. Low, moderate and high misinformation richness are coded as 1, 2, and 3, respectively.

Control variables. To eliminate the interference of other factors on the results, the study included control variables, including the number of fans of the misinformation creator, the number of likes of each text, the number of comments of each text, the content length of each text, and the number of times the text has mentioned other users.

The definitions of the variables in this study are presented in Table 1.

4.4. Data analysis and results

STATA version 15.1 was used to analyze our data samples. The summary statistics of the variables are presented in Table 2. Then, we check for the issue of multicollinearity in Stata. As shown in Table 2, the variance inflation factor (VIF) values for all variables in this study were all below 4 (no larger than the threshold of 10), indicating that multicollinearity is not an issue in our data sample.

Based on the procedure of Zhang, Guo, Xu and Li (2020), we built two empirical models to test our hypotheses. The models are as follows:

$$\begin{aligned} MD_i = \beta_0 + \beta_1 Advice\_infor_i + \beta_2 Help\_infor_i + \beta_3 Emot\_infor_i + \beta_4 Ambiguity_i + \\ \beta_5 Advice\_infor_i * Vagueness_i + \beta_6 Help\_infor_i * Ambiguity_i + \\ \beta_7 Emot\_infor_{ii} * Ambiguity_i + \beta^{'} Z_i \end{aligned} \tag{1}$$

$$\begin{aligned} MD_i = \beta_0 + \beta_1 Advice\_infor_i + \beta_2 Help\_infor_i + \beta_3 Emot\_infor_i + \beta_4 Richness_i + \\ \beta_5 Advice\_infor_i * Richness_i + \beta_6 Help\_infor_i * Richness_i + \\ \beta_7 Emot\_infor_i * Richness_i + \beta^{'} Z_i \end{aligned} \tag{2}$$

Where Models 1 and 2 capture the moderating roles of misinformation vagueness and richness, respectively, β parameters are the coefficients to be estimated, and Z is the vector controlling the number of followers, the length of each health misinformation that the poster has released, the number of comments on each health misinformation, and the number of likes for each health misinformation.

Table 1.
Measurement of variables.

Variable name	Measure item	Description
Dependent variable		
Misinformation dissemination	*MD*	The number of reposts of each text.
Independent variables		
Health advice and caution misinformation	*Advice_infor*	Whether the text contained wrong health-related advice and caution information.
Health help seeking misinformation	*Help_infor*	Whether the text contained wrong health-related, help-seeking information.
Emotional support	*Emot_infor*	Number of emotional words or terms in each text.
Moderate variables		
Misinformation ambiguity	*Ambiguity*	Number of ambiguous words or terms in each text.
Misinformation richness	*Richness*	The richness level of each text.
Control variables		
Followers	*Fans*	Number of followers of the account that has released the text.
Likes	*Likes*	Number of likes on each text.
Comments	*Comments*	Number of comments on each text.
Length	*Length*	Length of each text.
Mentions	*Mentions*	Number of times the text has mentioned other users.

Table 2.
Variable statistics.

Variables	Mean	S.D.	Min	Max	VIF
MD	40.084	1086.278	0	76,492	
Advice_infor	0.29	0.51	0	1	2.28
Help_infor	0.06	0.32	0	1	3.78
Emot_infor	0.986	1.776	0	9	1.08
Richness	1.229	0.464	1	3	1.21
Ambiguity	1.147	0.556	0	7	1.14
Fans	25.263	618.527	0	45,331	2.41
Likes	22.801	636.506	0	48,984	5.55
Comments	12.906	174.282	0	10,518	5.85
Length	29.576	41.259	10	838	1.15
Mentions	1.051	1.443	0	14	1.12

Given that the variables vary in their initial magnitudes, we standardized the control (excluding *Mentions*) and dependent variables for the main analysis; that is, we drew on the log transformation of the control and dependent variables (Chen et al., 2020a). The models were tested hierarchically (see Table 3). First, model 1, including only the control variables, was tested, and then model 2, including the independent variables, was tested. Model 3 and model 4 with interaction terms were tested to verify the moderating effects.

As shown in Table 3, model 2 revealed that the coefficients of health caution and advice misinformation ($\beta = 0.426, p < 0.001$) and health help-seeking misinformation ($\beta = 0.175$, $p < 0.01$) are both positive and significant. This finding is consistent with our hypotheses that the various types of health misinformation are positively associated with its dissemination on social media, which indicates that H1a and H1b are supported. Meanwhile, the effect of emotional support is positive and significant ($\beta = 0.045, p < 0.001$), supporting H2.

In Model 3, the moderating effect of misinformation vagueness was tested. We found that the interaction term *Advice_infor* * *Vagueness* is positive and significant ($\beta = 0.079$, $p < 0.001$); hence, H3a is supported. Surprisingly, the interaction terms *Help_infor* * *Vagueness* ($\beta = -0.031$, $p < 0.001$) and *Emot_infor* * *Vagueness* ($\beta = -0.062$, $p < 0.001$) are both negative, and these results are contrary to our hypotheses. Thus, H3b and H3c are not supported. In addition, we also found that misinformation vagueness ($\beta = 0.664$, $p < 0.05$) is positively related to the spread of health misinformation, and this finding is consistent with Oh et al. (2013) and Starbird et al. (2016).

Model 4 focuses on the moderating role of misinformation richness. We found that the interaction term *Advice_infor* * *Richness* is positive and significant ($\beta = 0.035, p < 0.01$), whereas the interaction term between *Emot_infor* and *Richness* is negative ($\beta = -0.062$, $p < 0.001$). This means that H4a is supported and H4c is not supported. The interaction term *Help_infor* * *Richness* is not significant ($\beta = 0.015$, $p > 0.05$) and does not support H4b. Furthermore, we found that misinformation richness ($\beta = 0.517, p < 0.001$) is positively related to the spread of health misinformation.

To better understand the moderating effects, the interaction diagram was plotted based on the procedures of Aiken et al. (1991). Figs. 2-6 present the results. Fig. 2 shows that the effect of health caution and advice misinformation on health misinformation dissemination is found to be positive under both high misinformation vagueness and low misinformation vagueness. However, at low ambiguity (solid line), the dissemination of health misinformation slowly occurs compared with high ambiguity (dashed line),

Table 3.
Regression results.

DV: ln(*MD*)	Model 1	Model 2	Model 3	Model 4
Advice_infor		0.426***	0.503***	0.368***
Help_infor		0.175**	0.205***	0.095**
Emot_infor		0.045***	0.114***	0.118***
Ambiguity			0.664*	
Richness				0.517***
Advice_infor * *Ambiguity*			0.079***	
Help_infor * *Ambiguity*			−0.031***	
Emot_infor * *Ambiguity*			−0.062***	
Advice_infor * *Richness*				0.024*
Help_infor * *Richness*				−0.027
Emot_infor * *Richness*				−0.061***
Ln(Fans)	0.007***	0.006***	0.005***	0.005***
Ln(Likes)	7.75e-06	0.001*	9.85e-06	8.98e-06
Ln(Comments)	−0.001***	−0.000*	−0.001***	−0.001**
Ln(Length)	0.012***	0.009***	0.008***	0.007***
Mentions	0.042	0.032***	0.031***	0.027***
Observations	12,101	12,101	12,101	12,101
R-squared	0.356	0.415	0.447	0.440

Note: * $p < 0.05$; ** $p < 0.01$; ***$p < 0.001$; two-sided hypothesis tests.

indicating that high vagueness increases the positive effect of health caution and advice misinformation on individuals' health misinformation dissemination behavior. As shown in Fig. 3, the effect of the interaction of health help-seeking misinformation on health misinformation dissemination was weaker under high vagueness (dashed line). Fig. 4 also shows that at high vagueness (dashed line), the dissemination of health misinformation increases more slowly than at low vagueness (solid line), indicating that high misinformation vagueness weakens the positive effect of emotional support on health misinformation dissemination. Fig. 5 indicates that the positive effect of health advice and caution misinformation on individuals' dissemination behavior is stronger under high richness (dashed line). Finally, Fig. 6 reveals that high misinformation richness weakens the positive effect of emotional support on health misinformation dissemination. Overall, Figs. 2-6 provide extra support for H3a, H3b, H3c, H4a, and H4c.

4.5. Robustness check

To test the robustness of our results, we added the unoriginal postings (the procedure of data processing is similar to Section 4.3) to our data sample. The regression results are reported in Table 4. Most of the effects were quantitatively consistent with our main results reported in Table 3. Therefore, we can be more confident that the results of our analysis are solid and robust.

5. Discussion

5.1. Main findings

This study presents four key insights. First, different types of misinformation, namely, health caution and advice misinformation and health help-seeking misinformation included in this study, are positively related to their dissemination during health emergencies. In particular, the impact of health caution and advice misinformation is more significant than that of health help-seeking misinformation. This may be because people pay more attention to their health conditions during a health emergency, health caution and advice misinformation are associated with health suggestions or guidance that prevent someone from acquiring diseases in general (Li et al., 2020). People may believe that the potential value of such misinformation for health help-seeking misinformation is great; thus, they are more likely to disseminate it on social media. In addition, we find that emotional support from misinformation can positively influence its dissemination. It is acknowledged that the public wishes to obtain encouragement and comfort from others on social media (Chen et al., 2020b; Liu et al., 2020b; World Health Organization, 2020); therefore, they are likely to repost misinformation to reduce their health anxiety or stress.

Second, our research findings reveal that misinformation ambiguity strengthens the effect of health advice and caution misinformation on the dissemination of misinformation. This finding indicates that for misinformation written with more ambiguous words, health advice and caution misinformation is more likely to be disseminated on social media. This is also consistent with the finding that ambiguity is an important feature of rumor spreading (Maddock et al., 2015; Starbird et al., 2014, 2016). If a piece of health advice and caution misinformation has a high level of ambiguity, more individuals may believe that the advice is not specific to those who experience disease but can also be suitable for themselves to better know the disease. Thus, they are willing to disseminate such misinformation on social media without being aware of its accuracy. In contrast, the moderating effect of misinformation ambiguity on the relationship between health help-seeking misinformation and its dissemination is negative and significant. One possible explanation for this difference is that such misinformation is about one's needs for health support; thus, under high levels of ambiguity, individuals will believe that the misinformation is not specific and question its trustworthiness.

Third, we find that the richness of misinformation positively moderates the relationship between health advice and caution

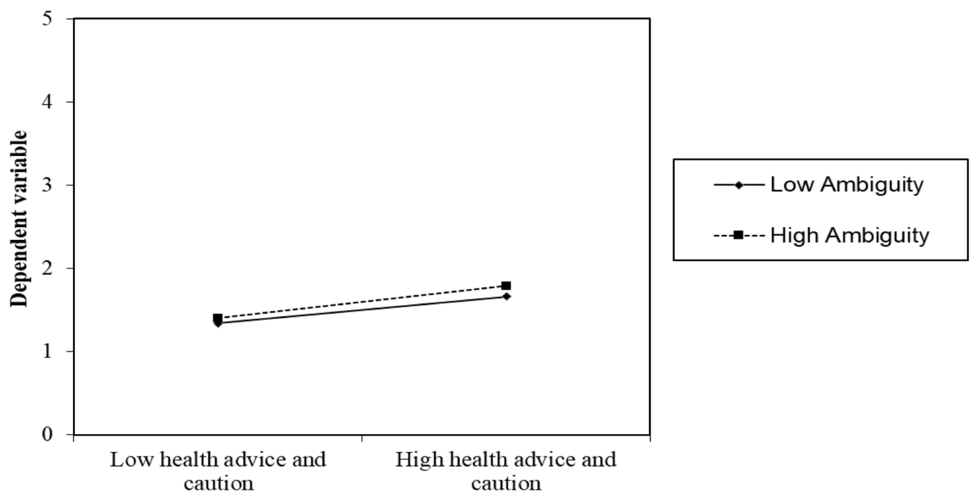

Fig. 2. The moderating effect of misinformation ambiguity on health caution and advice.

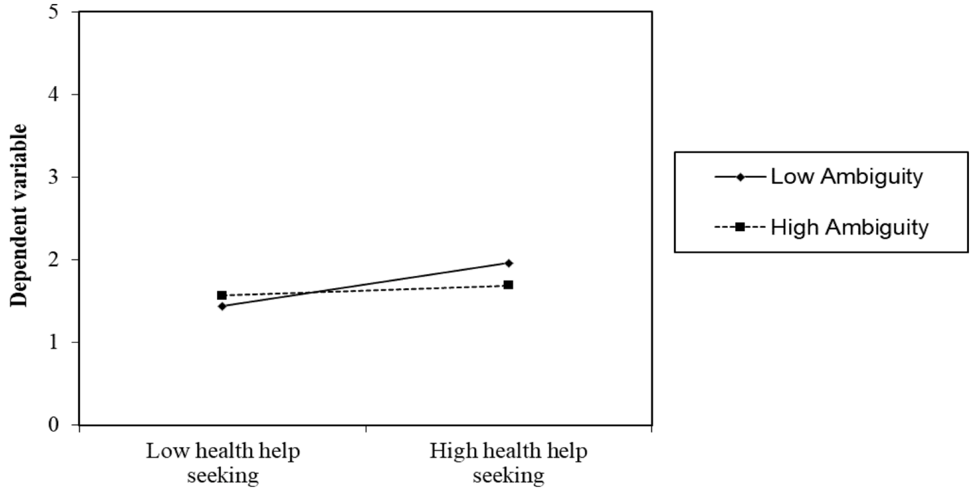

Fig. 3. The moderating effect of misinformation ambiguity on health help seeking.

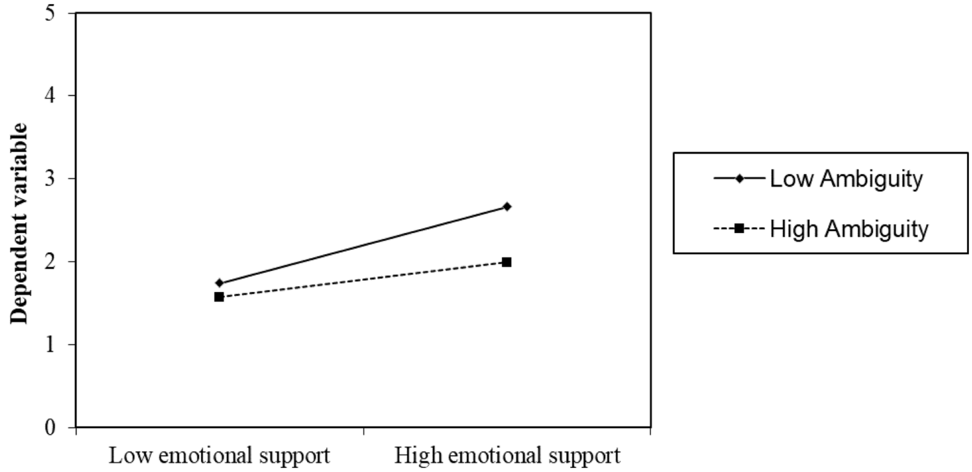

Fig. 4. The moderating effect of misinformation ambiguity on emotional support.

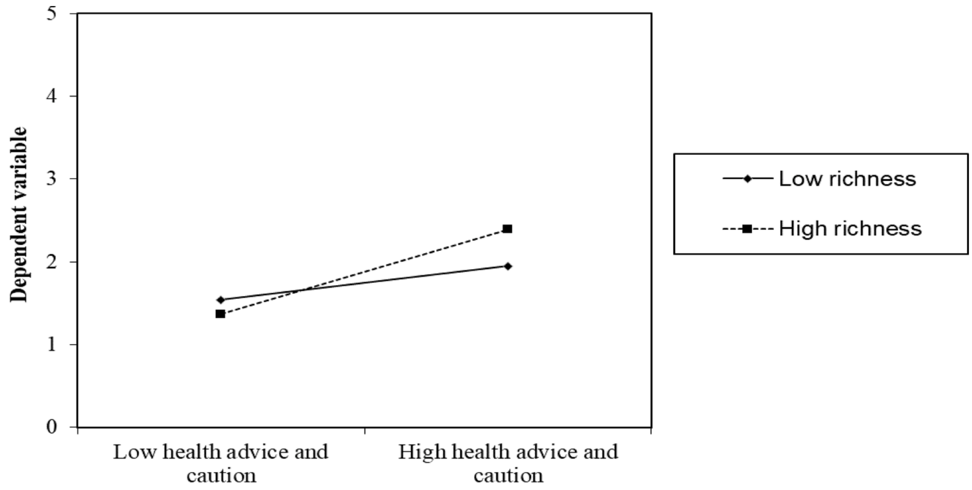

Fig. 5. The moderating effect of misinformation richness on health caution and advice.

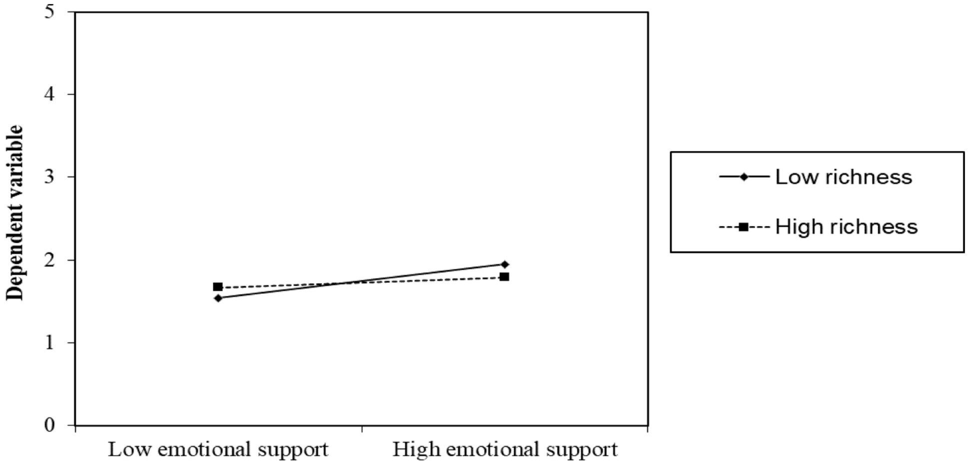

Fig. 6. The moderating effect of misinformation richness on emotional support.

Table 4.
Results of robustness check (added nonoriginal postings).

DV: ln(*MD*)	Model 1	Model 2	Model 3	Model 4
Advice_infor		0.431***	0.471***	0.596***
Help_infor		0.165**	0.159***	0.084***
Emot_infor		0.050***	0.101***	0.122***
Ambiguity			0.532*	
Richness				0.587***
*Advice_infor * Ambiguity*			0.051***	
*Help_infor * Ambiguity*			−0.008	
*Emot_infor * Ambiguity*			−0.047***	
*Advice_infor * Richness*				0.038**
*Help_infor * Richness*				−0.021*
*Emot_infor * Richness*				−0.061***
Ln(Fans)	0.010***	0.008***	0.007***	0.006***
Ln(Likes)	6.12e-06	0.004*	−0.000	−0.000
Ln(Comments)	0.005***	−0.000	0.004***	0.004***
Ln(Length)	0.000*	0.001**	0.000***	0.000***
Mentions	0.039***	0.029***	0.028***	0.023***
Observations	15,151	15,151	15,151	15,151
R-squared	0.369	0.422	0.447	0.441

Note: * $p < 0.05$; ** $p < 0.01$; ***$p < 0.001$; two-sided hypothesis tests.

misinformation and its dissemination. This is contrary to the finding that text-only can create greater citizen engagement (calculated by the number of likes, reposts, and comments) under uncertainties (Chen et al., 2020a; Lee & Xu, 2018). One plausible explanation is that visual media, such as images or videos, more easily grasp public attention than plain text (Guidry et al., 2019). A piece of health advice and caution misinformation visualized may provide more health-related content; thus, individuals are more likely to be triggered to disseminate such misinformation. However, the moderating effect of richness on the relationship between health help-seeking misinformation and its dissemination is not significant. This might be because the content of images or videos is not matched with the misinformation (Chen et al., 2020a; Daft et al., 1987); thus, individuals are less likely to disseminate it.

Fourth, the effect of emotional support on the dissemination of misinformation is weakened with the presence of misinformation ambiguity and richness. The former reveals that for misinformation presenting a high level of ambiguity during health emergencies, individuals do not obtain the emotional support provided by the misinformation very useful. This is because during health emergencies, people with health anxiety have low levels of ambiguity tolerance (Fergus, 2013; Oh & Lee, 2019), so they need emotional support from others to increase their confidence or alleviate such anxiety. As a result, if they still encounter ambiguous information when seeking emotional support, their willingness to repost will be lowered. On the other hand, the latter indicates that for misinformation presenting a high level of richness, individuals are less likely to repost it on social media. This may be because the emotional support contained in visual media is not matched with individuals' needs; thus, their emotions are not triggered.

5.2. Theoretical implications

This paper provides several insights into the existing literature. First, it contributes to the health care system by focusing on the dissemination of misinformation during health emergencies. Recently, some efforts have contributed to detecting health-related misinformation on social media (Hou, Pérez-Rosas, Loeb & Mihalcea, 2019; Sicilia, Giudice, Pei, Pechenizkiy & Soda, 2017; Zhao et al., 2020). However, little research has attempted to investigate the mechanism of misinformation dissemination in times of health emergencies. Based on text mining, this study provides an in-depth analysis of misinformation dissemination in health emergencies, which enriches the literature on individuals' information-seeking behavior.

Second, to the best of our knowledge, this is one of the first studies to apply social support theory to investigate the dissemination mechanism of misinformation in health emergencies. Although social support has identified positive effects in health ecosystems (Chen et al., 2020b; Liu, Xiao, Fang, Zhang & Lin, 2020a, 2020b; Wang, Zhao & Street, 2014), few studies have been conducted to explore how social support affects individuals' misinformation dissemination behavior on social media. Furthermore, it is different from previous studies that focused more on informational support from a whole concept (Bambina, 2007; Biyani et al., 2014; Zhang et al., 2017b). In this study, we creatively measure informational support from two aspects, including health advice and caution misinformation and health help-seeking misinformation. More importantly, we further develop a detailed view of how diverse types of misinformation can affect individuals' dissemination behavior. Our findings contribute to a deep understanding of how social support from misinformation can influence individuals' information dissemination behavior in health emergencies.

Third, this study highlights the bright and dark sides of misinformation ambiguity and richness. Previous studies have focused on the ambiguity of misinformation detection (Oh et al., 2013) and the richness of individuals' engagement behavior (Chen et al., 2020a; Shi et al., 2018). However, little research has examined the moderating effect of ambiguity and richness on misinformation dissemination. By testing the moderating role of misinformation ambiguity and richness, we found that ambiguity and richness positively moderate the relationship between health caution and advice misinformation and misinformation dissemination, while they negatively moderate the relationship between health help-seeking misinformation and misinformation dissemination. Even though the bright side of ambiguity and richness for misinformation dissemination has been verified in this article, which is consistent with the previous literature (Lee & Xu, 2018; Oh et al., 2013; Starbird et al., 2014, 2016), we also find their dark side in our research context. Accordingly, this research enriches the information ambiguity and richness literature on misinformation dissemination by disentangling the negative role of misinformation ambiguity and richness from the bright sides.

Finally, this study also contributes to the literature on health emergency management. In health emergencies, misinformation dissemination is an important issue and has gained considerable attention (Apuke & Omar, 2020). Our findings could provide social media platforms and health organizations with determinants that prompt misinformation dissemination and enable them to better manage online information in health emergencies.

5.3. Practical implications

The findings of this study also provide several practical implications. First, individuals should improve health literacy, which is defined as "individuals' cognitive and social skills to access, understand, and use information in ways which promote and maintain good health" (WHO, 1998), to decrease the dissemination of misinformation during health emergencies. Previous studies have indicated that a person with a high level of health literacy is more suspicious about online health-related information than one with low health literacy (Chen et al., 2018; Diviani, van den Putte, Giani & van Weert, 2015). Oh and Lee (2019) also highlight the importance of enhancing the level of health literacy to prevent health misinformation from spreading among social media users. Our findings indicate that health caution and advice misinformation and health help-seeking misinformation are significantly related to their dissemination. Therefore, individuals should think more about such information in health emergencies before reposting it on social media.

Second, as we found, there are bright and dark sides of misinformation ambiguity and richness. This finding informs social media platform operators of actionable interventions to decrease the dissemination of misinformation during health emergencies. For example, for health advice and caution information, operators should encourage authors to write with more certainty words or terms because such misinformation with uncertain words is more likely to be accepted by individuals and then disseminated.

Third, from the perspective of social media providers, they could develop and implement screening tools for health advice and caution and help seek relevant information during times of health emergencies. Such tools may enhance the ability the providers in detecting misinformation and further improve their manage level in timers of social media platform.

5.4. Limitations and future research directions

Although this study has provided interesting findings for both theory and practice, it has several limitations that should be considered in future research. First, although two types of health misinformation and ambiguity terms have proven to be effective and credible in this study, some biases cannot be avoided in the process of manual labeling work. Future research could improve the accuracy of the code method. Second, drawing on the research of Ji et al. (2019), emotional strength may also affect individuals' online behavior. This study only focuses on the effect of emotional valence, and subsequent research could further explore the contingent role of emotional strength. Last, the number of views of misinformation is an important determinant of reposts. This study does not include this factor in the research model because the API of Sina-Weibo does not provide such data, and there is a practical limitation of collecting data from the social media company. Accordingly, we do not articulate how many users will view the misinformation, which is crucial for the validity of analysis in this study. There are plenty of papers from econometric field pointing out similar critical issue and significant impact if it is not controlled in the analysis, and may also pose significant influence on the parameter estimation. Thus, we must acknowledge the limitations of the way this study estimates the spread of health misinformation exist. Although the number of fans and the number of times the misinformation has mentioned other users are included to reduce the adverse effects of such omission, we have to acknowledge this method is not the best. In the future, researchers could obtain the number of views to increase the validity of our results.

6. Conclusion

The dissemination of misinformation in health emergencies can have adverse effects on public health (Zhao et al., 2020). Thus, it is important to explore the underlying mechanism of misinformation dissemination during health emergencies. This study draws on text mining and social support theory to identify health caution and advice misinformation, health help-seeking misinformation, and emotional support to explore the mechanism of individuals' information dissemination behavior on social media under the contingency of misinformation ambiguity and richness. The empirical results show that the two types of misinformation proposed and emotional support are essential determinants of individuals' dissemination behavior, and misinformation ambiguity and richness strengthen the effect of health advice and caution misinformation and weaken the effect of emotional support, indicating both the bright and dark sides of themselves. Our research methodology and empirical findings contribute to the current literature on health emergency misinformation, social support theory, information ambiguity and richness, and individuals' information dissemination behavior. Furthermore, this study also provides significant practical implications for health emergency management and the design of interventions for addressing the dissemination of misinformation.

Author statement

Cheng Zhou: Conceptualization, Methodology, Writing Original draft preparation
Haoxin Xiu: Data collection, Methodology, Writing-Original draft preparation
Yuqiu Wang: Data collection, Writing-Original draft preparation
Xinyao Yu: Writing-Reviewing and Editing, Supervision

References

Apuke, O. D., & Omar, B. (2020). Fake news and COVID-19: Modelling the predictors of fake news sharing among social media users. *Telematics and Informatics*, Article 101475.

Bambina, A. (2007). *Online social support: The interplay of social networks and computer- mediated communication*. Cambria press.

Baumgartner, S. E., & Hartmann, T. (2011). The role of health anxiety in online health information search. *Cyberpsychology, Behavior, and Social Networking, 14*(10), 613–618.

Biyani, P., Caragea, C., Mitra, P., & Yen, J. (2014). Identifying emotional and informational support in online health communities. In *Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers* (pp. 827–836).

Bode, L., & Vraga, E. K. (2015). In related news, that was wrong: The correction of misinformation through related stories functionality in social media. *Journal of Communication, 65*(4), 619–638.

Bode, L., & Vraga, E. K. (2018). See something, say something: Correction of global health misinformation on social media. *Health Communication, 33*(9), 1131–1140.

Bonsón, E., & Ratkai, M. (2013). A set of metrics to assess stakeholder engagement and social legitimacy on a corporate Facebook page. *Online Information Review*.

Bordia, P., & DiFonzo, N. (2004). Problem solving in social interactions on the Internet: Rumor as social cognition. *Social Psychology Quarterly, 67*(1), 33–49.

Brashers, D. E. (2001). Communication and uncertainty management. *Journal of Communication, 51*(3), 477–497.

Brubaker, P. J., & Wilson, C. (2018). Let's give them something to talk about: Global brands' use of visual content to drive engagement and build relationships. *Public Relations Review, 44*(3), 342–352.

Buller, D. B., & Burgoon, J. K. (1996). Interpersonal deception theory. *Communication Theory, 6*(3), 203–242.

Castillo, C., Mendoza, M., & Poblete, B. (2011). Information credibility on twitter. In *Proceedings of the 20th international conference on World wide web* (pp. 675–684).

Chen, Q., Min, C., Zhang, W., Wang, G., Ma, X., & Evans, R. (2020a). Unpacking the black box: How to promote citizen engagement through government social media during the COVID-19 crisis. *Computers in Human Behavior*, 106380-.

Chen, S., Guo, X., Wu, T., & Ju, X. (2020b). Exploring the online doctor-patient interaction on patient satisfaction based on text mining and empirical analysis. *Information Processing & Management, 57*(5), Article 102253.

Chen, X., Hay, J. L., Waters, E. A., Kiviniemi, M. T., Biddle, C., Schofield, E., et al. (2018). Health literacy and use and trust in health information. *Journal of Health Communication, 23*(8), 724–734.

Chou, W. Y. S., Oh, A., & Klein, W. M. (2018). Addressing health-related misinformation on social media. *JAMA, 320*(23), 2417–2418.

Chu, J. T., Wang, M. P., Shen, C., Viswanath, K., Lam, T. H., & Chan, S. S. C. (2017). How, when and why people seek health information online: Qualitative study in Hong Kong. *Interactive Journal of Medical Research, 6*(2). e24-.

Chua, A. Y., & Banerjee, S. (2018). Intentions to trust and share online health rumors: An experiment with medical professionals. *Computers in Human Behavior, 87*, 1–9.

Chun, J. W., & Lee, M. J. (2017). When does individuals' willingness to speak out increase on social media? Perceived social support and perceived power/control. *Computers in Human Behavior, 74*, 120–129.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*(1), 37–46.

Cole, J., Kleine, D., & Watkins, C. (2016). Internet discussion forums: Maximizing choice in health-seeking behaviour during public health emergencies. In *2016 International Conference On Cyber Situational Awareness, Data Analytics And Assessment (CyberSA)* (pp. 1–4). IEEE.

Conroy, N. K., Rubin, V. L., & Chen, Y. (2015). Automatic deception detection: Methods for finding fake news. *Proceedings of the Association for Information Science and Technology, 52*(1), 1–4.

Cutrona, C. E., & Russell, D. W. (1990). Type of social support and specific stress: Toward a theory of optimal matching. *Social Support: An Interactional View*, 319–366.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management science, 32*(5), 554–571.

Daft, R. L., Lengel, R. H., & Trevino, L. K. (1987). Message equivocality, media selection, and manager performance: Implications for information systems. *MIS Quarterly, 11*(3), 355–366.

Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., et al. (2016). The spreading of misinformation online. *Proceedings of the National Academy of Sciences, 113*(3), 554–559.

Denktaş-Şakar, G., & Sürücü, E. (2020). Stakeholder engagement via social media: An analysis of third-party logistics companies. *The Service Industries Journal, 40*(11–12), 866–889.

Diviani, N., van den Putte, B., Giani, S., & van Weert, J. C. (2015). Low health literacy and evaluation of online health information: A systematic review of the literature. *Journal of Medical Internet Research, 17*(5), e112.

Duffy, A., Tandoc, E., & Ling, R. (2020). Too good to be true, too good not to share: The social utility of fake news. *Information, Communication & Society, 23*(13), 1965–1979.
Dwivedi, Y. K., Shareef, M. A., Mukerji, B., Rana, N. P., & Kapoor, K. K. (2018). Involvement in emergency supply chain for disaster management: A cognitive dissonance perspective. *International Journal of Production Research, 56*(21), 6758–6773.
Fergus, T. A. (2013). Cyberchondria and intolerance of uncertainty: Examining when individuals experience health anxiety in response to Internet searches for medical information. *Cyberpsychology, Behavior, and Social Networking, 16*(10), 735–739.
Ghenai, A., & Mejova, Y. (2018). Fake cures: User-centric modeling of health misinformation in social media. *Proceedings of the ACM on human-computer interaction, 2* (CSCW), 1–20.
Gu, R., & Hong, Y. K. (2020). Addressing health misinformation dissemination on mobile social media. In *40th International Conference on Information Systems, ICIS 2019. Association for Information Systems*.
Guidry, J. P., Meganck, S. L., Lovari, A., Messner, M., Medina-Messner, V., Sherman, S., et al. (2019). Tweeting about# diseases and# publichealth: Communicating global health issues across nations. *Health Communication, 35*(9), 1137–1145.
Gupta, A., Lamba, H., Kumaraguru, P., & Joshi, A. (2013). Faking sandy: Characterizing and identifying fake images on twitter during hurricane sandy. In *Proceedings of the 22nd International Conference on World Wide Web* (pp. 729–736).
Hou, R., Pérez-Rosas, V., Loeb, S., & Mihalcea, R. (2019). Towards automatic detection of misinformation in online medical videos. In *2019 International Conference on Multimodal Interaction* (pp. 235–243).
Hou, Z., Du, F., Jiang, H., Zhou, X., & Lin, L. (2020). Assessment of public attention, risk perception, emotional and behavioural responses to the COVID-19 outbreak: Social media surveillance in China.. In *Risk Perception, Emotional and Behavioural Responses to the COVID-19 Outbreak: Social Media Surveillance in China (3/6/2020)*.
Huang, K. Y., Nambisan, P., & Uzuner, Ö. (2010). Informational support or emotional support: preliminary study of an automated approach to analyze online support community contents. In *ICIS* (p. 210).
Ji, Y. G., Chen, Z. F., Tao, W., & Li, Z. C. (2019). Functional and emotional traits of corporate social media message strategies: Behavioral insights from S&P 500 Facebook data. *Public Relations Review, 45*(1), 88–103.
Jin, Z., Cao, J., Zhang, Y., Zhou, J., & Tian, Q. (2016). Novel visual and statistical image features for microblogs news verification. *IEEE Transactions on Multimedia, 19* (3), 598–608.
Khobzi, H., Lau, R. Y., & Cheung, T. C. (2019). The outcome of online social interactions on Facebook pages: A study of user engagement behavior. *Internet Research, 29*(1), 2–23.
Kim, C., & Yang, S. U. (2017). Like, comment, and share on Facebook: How each behavior differs from the other. *Public Relations Review, 43*(2), 441–449.
Krause, N. (1986). Social support, stress, and well-being among older adults. *Journal of Gerontology, 41*(4), 512–519.
Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 159–174.
Lee, J., & Xu, W. (2018). The more attacks, the more retweets: Trump's and Clinton's agenda setting on Twitter. *Public Relations Review, 44*(2), 201–213.
Li, L., Zhang, Q., Tian, J., & Wang, H. (2018). Characterizing information propagation patterns in emergencies: A case study with Yiliang Earthquake. *International Journal of Information Management, 38*(1), 34–41.
Li, L., Zhang, Q., Wang, X., Zhang, J., Wang, T., Gao, T. L., et al. (2020). Characterizing the propagation of situational information in social media during covid-19 epidemic: A case study on weibo. *IEEE Transactions on Computational Social Systems, 7*(2), 556–562.
Li, Y. J., Cheung, C. M., Shen, X. L., & Lee, M. K. (2019). Health misinformation on social media: A literature review. In *23rd Pacific Asia Conference on Information Systems (PACIS 2019)*.
Liang, T. P., Ho, Y. T., Li, Y. W., & Turban, E. (2011). What drives social commerce: The role of social support and relationship quality. *International Journal of Electronic Commerce, 16*(2), 69–90.
Lifang, L. I., Zhiqiang, W. A. N. G., ZHANG, Q., & Hong, W. E. N. (2020). Effect of anger, anxiety, and sadness on the propagation scale of social media posts after natural disasters. *Information Processing & Management, 57*(6), 102313-.
Lin, T. C., Hsu, J. S. C., Cheng, H. L., & Chiu, C. M. (2015). Exploring the relationship between receiving and offering online social support: A dual social support model. *Information & Management, 52*(3), 371–383.
Liu, R. L. (2007). Text classification for healthcare information support. In *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems* (pp. 44–53). Berlin, Heidelberg: Springer.
Liu, R. L. (2013). A passage extractor for classification of disease aspect information. *Journal of the American Society for Information Science and Technology, 64*(11), 2265–2277.
Liu, R. L., & Lu, Y. L. (2010). Context-based online medical terminology navigation. *Expert Systems with Applications, 37*(2), 1594–1599.
Liu, S., Xiao, W., Fang, C., Zhang, X., & Lin, J. (2020a). Social support, belongingness, and value co-creation behaviors in online health communities. *Telematics and Informatics*, 101398-.
Liu, Y., Ren, C., Shi, D., Li, K., & Zhang, X. (2020b). Evaluating the social value of online health information for third-party patients: Is uncertainty always bad? *Information Processing & Management, 57*(5), 102259-.
Ma, L., Lee, C. S., & Goh, D. H. (2013). Understanding news sharing in social media from the diffusion of innovations perspective. In *2013 IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing* (pp. 1013–1020). IEEE.
Maddock, J., Starbird, K., Al-Hassani, H. J., Sandoval, D. E., Orand, M., & Mason, R. M. (2015). Characterizing online rumoring behavior using multi-dimensional signatures. In *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing* (pp. 228–241).
McMullan, R. D., Berle, D., Arnáez, S., & Starcevic, V. (2019). The relationships between health anxiety, online health information seeking, and cyberchondria: Systematic review and meta-analysis. *Journal of Affective Disorders, 245*, 270–278.
Meggiolaro, E., Berardi, M. A., Andritsch, E., Nanni, M. G., Sirgo, A., Samorì, E., et al. (2016). Cancer patients' emotional distress, coping styles and perception of doctor- patient interaction in European cancer settings. *Palliative & Supportive Care, 14*(3), 204–211.
Miller, L. M. S., & Bell, R. A. (2012). Online health information seeking: The influence of age, information trustworthiness, and search challenges. *Journal of aging and health, 24*(3), 525–541.
Moorhead, S. A., Hazlett, D. E., Harrison, L., Carroll, J. K., Irwin, A., & Hoving, C. (2013). A new dimension of health care: Systematic review of the uses, benefits, and limitations of social media for health communication. *Journal of Medical Internet Research, 15*(4). e85-.
Mukherjee, A., & Bawden, D. (2012). Health information seeking in the information society. *Health Information & Libraries Journal, 29*(3), 242–246.
Muse, K., McManus, F., Leung, C., Meghreblian, B., & Williams, J. M. G. (2012). Cyberchondriasis: Fact or fiction? A preliminary examination of the relationship between health anxiety and searching for health information on the Internet. *Journal of Anxiety Disorders, 26*(1), 189–196.
Oh, H. J., & Lee, H. (2019). When do people verify and share health rumors on social media? The effects of message importance, health anxiety, and health literacy. *Journal of Health Communication, 24*(11), 837–847.
Oh, O., Agrawal, M., & Rao, H. R. (2013). Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises. *MIS Quarterly, 37*(2), 407–426.
Ozturk, P., Li, H., & Sakamoto, Y. (2015). Combating rumor spread on social media: The effectiveness of refutation and warning. In *2015 48th Hawaii International Conference on System Sciences* (pp. 2406–2414). IEEE.
Pennycook, G., McPhetres, J., Zhang, Y., Lu, J. G., & Rand, D. G. (2020). Fighting COVID-19 misinformation on social media: Experimental evidence for a scalable accuracy-nudge intervention. *Psychological Science, 31*(7), 770–780.
Pesälä, S., Virtanen, M. J., Sane, J., Mustonen, P., Kaila, M., & Helve, O. (2017). Health information–seeking patterns of the general public and indications for disease surveillance: Register-based study using Lyme disease. *JMIR Public Health and Surveillance, 3*(4). e86-.
Rahim, A., Ibrahim, A. I., A Salim, M. I., N, F.&, & Ariffin, M. A. I. (2019). Health information engagement factors in Malaysia: A content analysis of Facebook use by the ministry of health in 2016 and 2017. *International Journal of Environmental Research and Public Health, 16*(4), 591-.

Rashkin, H., Choi, E., Jang, J. Y., Volkova, S., & Choi, Y. (2017). Truth of varying shades: Analyzing language in fake news and political fact-checking. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing* (pp. 2931–2937).

Reddy, M. C., Paul, S. A., Abraham, J., McNeese, M., DeFlitch, C., & Yen, J. (2009). Challenges to effective crisis management: Using information and communication technologies to coordinate emergency medical services and emergency department teams. *International Journal of Medical Informatics, 78*(4), 259–269.

Rousseau, C., Moreau, N., Dumas, M. P., Bost, I., Lefebvre, S., & Atlani-Duault, L. (2015). Public media communications about H1N1, risk perceptions and immunization behaviours: A Quebec–France comparison. *Public Understanding of Science, 24*(2), 225–240.

Rozzell, B., Piercy, C. W., Carr, C. T., King, S., Lane, B. L., Tornes, M., et al. (2014). Notification pending: Online social support from close and nonclose relational ties via Facebook. *Computers in Human Behavior, 38*, 272–280.

Ruokolainen, H., & Widén, G. (2020). Conceptualising misinformation in the context of asylum seekers. *Information Processing & Management, 57*(3), 102127-.

Shi, J., Hu, P., Lai, K. K., & Chen, G. (2018). Determinants of users' information dissemination behavior on social networking sites. *Internet Research, 28*(2), 393–418.

Sicilia, R., Giudice, S. L., Pei, Y., Pechenizkiy, M., & Soda, P. (2017). Health- related rumour detection on Twitter. In *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)* (pp. 1599–1606). IEEE.

Starbird, K., Maddock, J., Orand, M., Achterman, P., & Mason, R. M. (2014). Rumors, false flags, and digital vigilantes: Misinformation on twitter after the 2013 boston marathon bombing. In *IConference 2014 Proceedings*.

Starbird, K., Spiro, E., Edwards, I., Zhou, K., Maddock, J., & Narasimhan, S. (2016). Could this be true? I think so! Expressed uncertainty in online rumoring. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (pp. 360–371).

Starcevic, V., & Berle, D. (2013). Cyberchondria: Towards a better understanding of excessive health-related Internet use. *Expert Review of Neurotherapeutics, 13*(2), 205–213.

Sun, J. (2012). Jieba chinese word segmentation tool. Accessed at: *https://github. com/fxsjy/jieba*.

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science (New York, N.Y.), 359*(6380), 1146–1151.

Wang, X., Zhao, K., & Street, N. (2014). Social support and user engagement in online health communities. In *International Conference on Smart Health* (pp. 97–110). Cham: Springer.

Wang, Y., McKee, M., Torbica, A., & Stuckler, D. (2019). Systematic literature review on the spread of health-related misinformation on social media. *Social Science & Medicine, 240*, 112552-.

Waszak, P. M., Kasprzycka-Waszak, W., & Kubanek, A. (2018). The spread of medical fake news in social media–the pilot quantitative study. *Health Policy and Technology, 7*(2), 115–118.

World Health Organization. (1998). *Health promotion glossary* (No. WHO/HPR/HEP/98.1).

World Health Organization. (2020). *Mental health and psychosocial considerations during the COVID-19 outbreak, 18 March 2020* (No. WHO/2019-nCoV/MentalHealth/ 2020.1).

Xu, W. W., & Zhang, C. (2018). Sentiment, richness, authority, and relevance model of information sharing during social Crises—The case of# MH370 tweets. *Computers in Human Behavior, 89*, 199–206.

Yan, L., & Tan, Y. (2014). Feeling blue? Go online: An empirical study of social support among patients. *Information Systems Research, 25*(4), 690–709.

Yin, C., Sun, Y., Fang, Y., & Lim, K. (2018). Exploring the dual-role of cognitive heuristics and the moderating effect of gender in microblog information credibility evaluation. *Information Technology & People, 31*(3), 741–779.

Yin, C., & Zhang, X. (2020). Incorporating message format into user evaluation of microblog information credibility: A nonlinear perspective. *Information Processing & Management, 57*(6), 102345-.

Yue, C. A., Thelen, P., Robinson, K., & Men, L. R. (2019). How do CEOs communicate on Twitter? A comparative study between Fortune 200 companies and top startup companies. *Corporate Communications: An International Journal, 24*(3), 532–552.

Zhang, L., Xu, L., & Zhang, W. (2017a). Social media as amplification station: Factors that influence the speed of online public response to health emergencies. *Asian Journal of Communication, 27*(3), 322–338.

Zhang, X., & Ghorbani, A. A. (2020). An overview of online fake news: Characterization, detection, and discussion. *Information Processing & Management, 57*(2), 102025-.

Zhang, X., Guo, F., Xu, T., & Li, Y. (2020). What motivates physicians to share free health information on online health platforms? *Information Processing & Management, 57*(2), Article 102166.

Zhang, Y., Sun, Y., & Kim, Y. (2017b). The influence of individual differences on consumer's selection of online sources for health information. *Computers in Human Behavior, 67*, 303–312.

Zhao, L., Cui, H., Qiu, X., Wang, X., & Wang, J. (2013). SIR rumor spreading model in the new media age. *Physica A: Statistical Mechanics and its Applications, 392*(4), 995–1003.

Zhao, Y., Da, J., & Yan, J. (2020). Detecting health misinformation in online health communities: Incorporating behavioral features into machine learning based approaches. *Information Processing & Management, 58*(1), 102390-.

Zhao, Y., Zhang, J., & Wu, M. (2019). Finding Users' Voice on Social Media: An Investigation of Online Support Groups for Autism-Affected Users on Facebook. *International Journal of Environmental Research and Public Health, 16*(23), 4804-.

Zhao, Z., Resnick, P., & Mei, Q. (2015). Enquiring minds: Early detection of rumors in social media from enquiry posts. In *Proceedings of the 24th International Conference on World Wide Web* (pp. 1395–1405).

Aiken, L. S., West, S. G., & Reno, R. R. (1991). Multiple regression: Testing and interpreting interactions. sage.