Information Processing and Management 59 (2022) 102769

Contents lists available at ScienceDirect

Information Processing and Management

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

Recognizing fake information through a developed feature scheme: A user study of health misinformation on social media in China

Yuelin Li [a,b], Zhenjia Fan [a,b,*], Xiaojun Yuan [c], Xiu Zhang [b,d]

[a] Department of Information Resources Management, Business School, Nankai University, Tianjin 300071, China
[b] Research Center for Human Information Behavior, Nankai University, Tianjin 300071, China
[c] College of Emergency Preparedness, Homeland Security and Cybersecurity, University at Albany, State University of New York, NY 12222, USA
[d] Tianjin Ren Ai College, Tianjin 301636, China

ARTICLE INFO

Keywords:
Health information behavior
Health misinformation
Social media

ABSTRACT

This study aims at helping people recognize health misinformation on social media in China. A scheme was first developed to identify the features of health misinformation on social media based on content analysis of 482 pieces of health information from WeChat, a social media platform widely used in China. This scheme was able to identify salient features of health misinformation, including exaggeration/absolutes, induced text, claims of being unique and secret, intemperate tone or language, and statements of excessive significance and likewise. The scheme was then evaluated in a user-centred experiment to test if it is useful in identifying features of health misinformation. Forty-four participants for the experimental group and 38 participants for the control group participated and finished the experiment, which compared the effectiveness of these participants in using the scheme to identify health misinformation. The results indicate that the scheme is effective in terms of improving users' capability in health misinformation identification. The results also indicate that the participants' capability of recognizing misinformation in the experimental group has been significantly improved compared to those of the control group. The study provides insights into health misinformation and has implications in enhancing people's online health information literacy. It informs the development of a system that can automatically limit the spread of health misinformation. Moreover, it potentially improves users' online health information literacy, in particular, under the circumstances of the COVID-19 pandemic.

1. Introduction

Nowadays, the digital world is enriched with information and misinformation, given the massive amount of unregulated user-generated content on the internet, especially on social networks (Garrett, 2020; Zarocostas, 2020). "Misinformation" is defined as information that is untrue, inaccurate, incomplete, lacking evidence, intended to deceive, or otherwise demonstrably false (Case & Given, 2016). Scanfeld, Scanfeld, and Larson (2010) examined 1000 randomly selected tweets mentioning antibiotics and found that

* Corresponding author.
E-mail addresses: yuelinli@nankai.edu.cn (Y. Li), fanzhenjia@nankai.edu.cn (Z. Fan), xyuan@albany.edu (X. Yuan), myzhangx@126.com (X. Zhang).

https://doi.org/10.1016/j.ipm.2021.102769
Received 2 April 2021; Received in revised form 1 August 2021; Accepted 19 September 2021
Available online 5 October 2021
0306-4573/

700 (about 70%) contained medical misinformation or malpractice. Another concern arising from the COVID-19 outbreak is that health misinformation has been widely distributed on the web, especially on social media (Ma, Vervoort & Luc, 2020). This phenomenon is now called an "information epidemic." How to deal with an information epidemic resulting from COVID-19 has been a significant challenge for the general public (da Silva & Toledo, 2020).

Some studies have revealed that the quality of online health information is low, with a great deal of misinformation in circulation (e.g. Nsuangani & Perez, 2006). Specific issues, including accuracy and trustworthiness of information, privacy concerns, the proliferation of "junk" websites, and the difficulty of locating relevant information have also been addressed (Lee et al., 2014; Oh, Byun & Krishnamoorthy, 2018; Rubin, 2019). More seriously, misinformation can mislead users' judgement on the quality of health information and behavior, and lead them to make poor health choices when it is incorporated into a consumer's decision-making process (Pariera, 2012), especially when users are at a low level of health information literacy (HIL). Tragedies including damaged health and life loss have occurred as a result of online health misinformation being taken at face value (e.g., Cornish & Moraes, 2015). Recently, the COVID-19 pandemic has pressed an urgent need to identify misinformation, particularly health misinformation. As Ma, Vervoort and Luc (2020) highlight, all social media (e.g., Twitter) platforms are faced with their share of unvalidated information related to COVID-19. Some people even believe that it can prevent coronavirus infection by taking hot baths, smoking, or drinking liquors with high alcohol content (Ma, Vervoort & Luc, 2020). Cuan-Baltazar et al. (2020) employed the major measure tools of health information globally, including HONcode, JAMA, and DISCERN, to measure the quality and readability of online information related to COVID-19. They found that only 1.8% of the top 110 websites (selected by Google Trends in English and Spanish) had the HONcode seal; 39.1% of these sites did not meet any of the criteria required by the JAMA benchmark, and only 10.0% of the sites met the four quality criteria required by JAMA; 70.0% of the sites were classified with a low score, and none had a high score according to DISCERN scores. These studies address the pressing need to recognize and control the spread of health misinformation online.

One way to limit the spread of misinformation is to help users adopt credible health information. How to evaluate credibility of online information has been investigated for decades. Checklists and guidelines have been widely used to evaluate the quality of online information sources (Metzger, 2007; Mandalios, 2013; Zhang & Ghorbani, 2020), and demonstrated as effective (Hsieh et al., 2011; Iskeceli-Tunc & Oner, 2016). Meanwhile, algorithms have been developed to automatically detect misinformation to prevent its dissemination (Kumar & Geethakumari, 2014; Zhang, Zhang, Li & Thai, 2015; Søe, 2018; Song et al., 2021). Furthermore, researchers have attempted to prevent misinformation from propagating with accurate information in the same networks, so users can access high-quality information (Nguyen et al., 2012; Budak, Agrawal & Abbadi, 2011; Fan et al., 2013; Zhao, Da & Yan, 2021). These methods tried to prevent misinformation from reaching out to users. On the other hand, researchers realized that it is essential to educate users and improve their online HIL, and thus in turn enhance their capabilities in assessing health misinformation online. Users have been using social media as sources of health information and assessing the quality of information by themselves (De Choudhry, Morris & White, 2014; Li, Wang, Lin & Hajli, 2018). However, the quality of information found on social media is of great concern (Li, Zhang & Wang, 2018); particularly, existing systems lack effective approaches or criteria to help users search for information from a user perspective, which is the focus of this study.

This study aims to develop a feature scheme of health misinformation and evaluate its usefulness from users' perspectives. We specifically address the following research questions (RQs):

RQ1: What are the salient features of health misinformation on social media in contrast to accurate health information?

RQ2: How useful are the identified features for helping people recognize health misinformation on social media?

To address the research questions, a two-phase study was conducted. In Phase I, a feature scheme of health misinformation was developed via content analysis to answer the RQ1. In Phase II, the usefulness of this scheme was evaluated in a user experiment via an experimental and control group design to examine RQ2.

The major contributions of this study to the field of information science are as follows. (1) The study generates a feature scheme to identify misinformation from social media and empirically evaluate its usefulness. (2) It expands the body of knowledge of health misinformation and potentially improves users' online health information literacy, in particular, under the circumstances of the COVID-19 global pandemic. (3) It also provides insights of potential use to health information service providers, who may be able to improve their service by screening out misinformation. (4) It provides empirical evidence to inform automatic health misinformation filtering on social media. (5) It inspires thoughts on how to design health information systems to help people in the COVID-19 global pandemic.

The rest of the paper is organized as follows: we first review the related studies. Guided by the research questions, we then examine the features of health misinformation. We develop a feature scheme, followed by a user study to evaluate the usefulness of the scheme. At the end, we analyze and discuss the results and, finally, conclude the paper.

2. Literature Review

Misinformation can cause confusion, (potentially) damage users' health, as well as affect the usefulness and credibility of online health information. It is critical to improve users' online HIL by enhancing their capability of recognizing health misinformation. This section reviews related studies on approaches to help users identify misinformation on the web and online HIL.

2.1. Approaches to identify misinformation

2.1.1. Checklists or guidelines

Checklists and guidelines have been proposed to help users identify misinformation and obtain high-quality information. For example, Mandalios (2013) proposes a RADAR approach to help students identify high quality information online. RADAR is the acronym of Relevance, Authority, Date, Appearance, and Reason for writing. An empirical study indicates the effectiveness of using RADAR to evaluate information quality (Mandalios, 2013). However, some criteria, for instance, 'reason for writing', are not easy to understand and cause confusion. CARS, an acronym of Credibility, Accuracy, Reasonableness, and Support, is a framework proposed by Harris (2010) to evaluate online information sources. It has been widely used to educate or train students to discriminate high or low-quality information online. Lloyd (2011) points out that CARS is acceptable as a useful tool for college students. It is useful for evaluating information quality online (Hsieh et al., 2011; Iskeceli-Tunc & Oner, 2016). However, little research has been carried out to examine whether CARS is also useful for evaluating health information on social media. The usefulness of CARS is still lacking support of empirical evidence. Some other checklist approaches have been proposed and provided to users. Nevertheless, these approaches cannot successfully help them identify high quality information from the Web (Mandalios, 2013). Meola (2004) has devised a 'contextual approach' and tried to overcome the shortcomings of the checklists. However, it is challenging to be implemented in practice (Mandalios, 2013).

Zhang and Ghorbani (2020) extensively reviewed current approaches to detect fake news. Features for fake news representation have been characterized into creator/user-based features, new content-based features, and social context-based features. A more detailed typology in terms of each type of feature was developed. Some practical-based approaches, including online fact-checking resources and social practical guides for fake news detection were reviewed. However, the survey addresses fake news detection on social media, rather than health misinformation. Obviously, the content and features of health misinformation and fake news are different. As a consequence, new approaches or tools to help users identify health misinformation are still called for.

2.1.2. Features and automatic approaches to detect fake information

Fake news has been viewed as a threat to democracy (Zhou & Zafarani, 2020). Oehmichen et al. (2019) found that misinformation accounts have different features and behavior from regular accounts and the content of misinformation is more novel, polarized and appears to change through coordination. Also, false news was diffused significantly farther, faster, deeper, and more broadly than the truth. Moreover, humans, not robots, make false news spread more quickly than the truth (Vosoughi, Roy, & Aral, 2018). Therefore, how to detect fake news has drawn a lot of attention in recent years. From a data mining perspective, Shu et al. (2017) gave a comprehensive review of fake news detection on social media. They pointed out that traditional ways to identify fake news do not work well for fake news distributed on social media, while fake news detection on social media is facing big challenges, regardless of manual or automatic approaches. Feature extraction is a core issue for fake news detection. For fake news on social media, both news content features and social context features should be considered for modeling fake news detection. The former involves linguistic-based and visual-based features; the latter includes user-based, post-based, and network-based features. News content models, including knowledge-based and style-based models are existing approaches; existing social context models include stance-based and propagation-based models. However, few studies have examined fake news detection using social context features. Song et al. (2021) propose a multi-modal fake news detection framework. This framework can selectively extract the relevant information related to a target modality from another source modality while maintaining unique information of the target modality. It can also mitigate the influence of noise information that may be generated by cross-modal fusion components.

In addition to fake news issues, some general misinformation/disinformation detection has also been examined. According to Kumar *et al* (2020), different types of algorithms have been proposed to detect misinformation, including feature-, graph-, and time-based algorithms for opinion-based false information, and feature engineering and propagation based for fact-based false information. Among them, the majority of algorithms are feature-based. These approaches rely on developing efficient features that distinguish between true and false information individually or jointly. These features were developed based on the analyses of the text that show the differences in properties of the two types of information. The study indicates that it is critical to single out the features of misinformation for identifying and filtering misinformation online. Søe (2018) found that disinformation and misinformation had two salient features, including intention/intentionality and non-misleadingness/misleadingness, with the latter as the primary feature to develop an algorithm. Ruokolainen and Widén (2020) propose a Social Information Perception (SIP) model, which includes different elements in social, cultural and historical aspects, and situations and contexts. These elements get involved in the mental process of users and determine whether they perceive information as accurate information, misinformation or disinformation.

Automatic health misinformation detection has also been studied. For example, Sicilia et al. (2017, 2018) developed a novel rumor detection system to target health-related rumors about Zika on Twitter as well as a new feature subset. The method was tested and verified as a useful one. Zhao, Da and Yan (2021) aimed to explore automatically identified health misinformation on social media. They proposed a health misinformation detection model by machine learning, incorporating the central-level features, including topic features and the peripheral-level features, such as linguistic, sentiment, and user behavioral features. The results indicate that behavioral features were more informative than linguistic features in detecting misinformation.

The aforementioned studies suggest that feature identification of misinformation is a critical step to develop an effective misinformation detection system or tool. However, in terms of health misinformation, empirical studies on the features are still lacking, especially from users' perspectives.

2.2. Online health information literacy (HIL)

Online HIL refers to the ability of users to seek, find, understand, and appraise health information from online resources and apply such knowledge to address or solve a health problem (Stellefson et al., 2011). Users do not believe that the internet is a good source for accessing health information (Magnezi, Bergman & Grosberg, 2014). They are seriously concerned about the accuracy of health information posted on the Web (Nsuangani & Pérez, 2006; Prybutok & Ryan, 2015; Zhang & Ghorbani, 2020). However, their online HIL is problematic (e.g., Stellefson et al., 2011). Whether a user can benefit from online health information depends on their health literacy (Viviani & Pasi, 2017). However, many users lack online HIL skills (Stellefson et al., 2011), including the ability to obtain online health information (Escoffery et al., 2005; Redmond, 2008; Zhao, Da & Yan, 2021), and to evaluate the credibility of such information (Nsuangani & Pérez, 2006; Freeman & Spyridakis, 2009). In particular, Luk et al. (2020) found that exposure to health misinformation claiming that smoking/alcohol drinking can protect against COVID-19 was associated with self-reported increases in tobacco and alcohol consumption in China during the pandemic. Moreover, users usually overestimate their HIL (Hanik & Stellefson, 2011).

The factors that affect the HIL level include educational level, hometown location, health level, gender, family income, major, and grade. For example, people with a higher educational level are more likely to obtain health information and to evaluate it more effectively (Gokyildiz et al., 2014). Redmond (2008) reports that urban college students could obtain online health information better than rural students, but no significant difference was found in their capability to evaluate information. Health literacy levels among college students varied with their health levels (Yilma, 2016). Feng (2016) found that college students with higher family income and higher grades have higher health literacy levels, as do students whose major subject area is in medicine. In addition, labor-intensive factory workers' health information literacy is also problematic. A survey concerned with their knowledge, attitudes, and practices regarding the COVID-19 pandemic in China indicated that less than 30% of respondents disagreed that gargling with salt water effectively protects against COVID-19 (Li et al., 2020).

These studies suggest that it is imperative to help users improve their online HIL, especially under the circumstances of the COVID-19 pandemic.

2.3. A summary of related studies

In summary, the related studies indicate that various websites and social media platforms have been recognized as useful sources of health information. However, the information is somewhat unreliable, and even misleading. Users prefer to seek health information online, while having noticed the credibility issue of online health information. Some automatic detection approaches provide insights to health misinformation. However, such automatic detection methods cannot completely filter health misinformation and are still facing many challenges; for example, real-time misinformation flow, and users' capability in the evaluation of information credibility is still very important. This calls for research on how to effectively help people to identify health misinformation.

The previous studies indicate that various factors affect users' evaluation of information credibility and usefulness. These studies have shown that many users lack online HIL, which is a big concern since a great deal of health misinformation has been distributed online, especially during the COVID-19 pandemic. Therefore, it is necessary to develop an effective approach or tool to help users recognize health misinformation, and thus in turn to improve their online HIL. However, few studies have been undertaken to examine this issue.

The present study aims to (1) identify the features of health misinformation in social media; (2) develop a feature scheme, and (3) employ the scheme as a tool to help users improve their capability in recognizing health misinformation on social media, and thereby enhance their online HIL. With the outbreak of COVID-19, health misinformation has been widely spread online, including social media. It is imperative to help users improve their online HIL in such circumstances. The scheme developed in this study extracts general features of health misinformation, and thus has potential to assist people to fight the infodemic through improving their online HIL.

3. Research Design

We designed a two-phase study. Phase I targeted RQ1 to develop a feature scheme of health misinformation on social media; Phase II designed an experiment to answer RQ2, that is, to examine the usefulness of the feature scheme in improving users' capability of recognizing health misinformation. This section elaborates the research design.

3.1. Phase I. Developing a feature scheme of health misinformation

To address RQ1, we extracted and analyzed health information from WeChat's "Moments", a component of the WeChat platform, then identified the features of health misinformation via open coding and content analysis. We then compared the features of accurate information and misinformation, using chi-square tests to evaluate the differences. Significantly different features were extracted to create a feature scheme for health misinformation in Chinese context (Li, Zhang & Wang, 2018).

3.1.1. Participants

Many health conditions become more prevalent with age, which drives demographic trends in health information behavior. According to Pálsdóttir (2011), middle-aged and older adults collect health information more frequently and reliably than young people. Therefore, to collect health information samples more efficiently, we recruited 19 participants aged 50 years or older and extracted health information from “Moments” in their WeChat accounts. Their demographic characteristics are shown in Table 1. In total, 529 pieces of health information were collected. After excluding duplicates, 482 items remained.

3.1.2. Data Analysis

We first categorized the information as reliable information versus misinformation via the following three steps (Li, Zhang & Wang, 2017; 2018).

Step 1. Rumor websites were used, including Shanghai Rumor Buster (http://piyao.jfdaily.com/), Inner Mongolia Online Rumor Buster (http://py.hlnmg.com/), Zhejiang United-Media Websites Rumor Buster (https://py.zjol.com.cn/), Beijing United-Websites Rumor Buster (http://py.qianlong.com/), and Rumor filter by WeChat. The reasons to choose these sites are two-fold: (1) most of these sites are provided by or related to the local government and the information posted is authoritative and credible; (2) the information in these sites is rich and updated. Via these sites, we can observe whether the information had been identified as a rumor. If so, the information was categorized as misinformation; if not, it was retained for second-round identification.

Step 2. Two health experts were recruited (a physician and a doctoral student in pharmacy) to independently assess information that could not be referred to rumor websites. We took their agreements into account and left items on which they disagreed for a third round.

Step 3. The third health expert was recruited (a medical big data specialist) to assess the remaining information as real or misinformation.

Finally, if a piece of health information earns two ‘fake’ votes, it will be assessed as fake or misinformation; otherwise, if it earns two ‘real’ votes, it will be assessed as ‘real’ information. Via this three-step procedure, all the health information collected in this study was categorized as "real" or "misinformation" for further analysis.

Then, we analyzed the text via open coding, adopting the CARS framework proposed by Harris (2010). This framework was adopted because it involves a set of characteristics of low-quality web information, such as lack of credibility, lack of accuracy, lack of reasonableness, and lack of support. These criteria are appropriate as a preliminary coding scheme of this study.

A pair of coders worked in the first two stages to code the 482 pieces of health information. First, they coded the text based on the CARS list. However, since the CARS list was generated in an English context, some indicators were not appropriate for a Chinese context. Moreover, some appropriate indicators for low credibility in a Chinese context may have been missed. Therefore, during the open coding process, indicators appropriate for a Chinese context were added to the coding scheme, including "mixed usage of simple and traditional Chinese characters," "under the guise of authority or government," "inappropriate typographic space." A new coding scheme was then generated (see Table 2). Based on this new scheme, the two coders independently coded the sample. Subsequently, the research group discussed the results of the two coders to check whether the codes were appropriately assigned, and then developed categories for similar codes, assigned labels to these categories, and finally identified the features of health misinformation.

To identify the salient features of misinformation compared to real information, we performed chi-square tests (Li, Zhang & Wang, 2018), and then used these features to create a feature scheme.

3.2. Phase II: Evaluating the usefulness of the feature scheme

To answer whether the feature scheme could help improve people’s health information recognition capabilities on social media, it is necessary to compare the effectiveness between the feature scheme and some materials unrelated to the feature scheme on the participants’ capability in recognizing health misinformation. Therefore, a between-subjects user experiment was carried out.

3.2.1. Participants

Considering that college students have been an important user group of online health information and they search for health information not only for themselves, but also for family and close friends (Prybutok & Ryan, 2015), we recruited participants for an experimental group (52 participants, nos. E01–52) and a control group (45 participants, nos. C01–45) from a public university in China. Totally, 44 participants in the experimental group and 38 participants in the control group completed the experiment.

Chi-square tests were employed to analyze the difference between the two groups, see Table 3. The demographic variables were selected from previous studies and have been demonstrated as, to some extent, affecting users’ health information behavior (e.g.,

Table 1
Demographic characteristics of 19 WeChat users.

Category	Participants	Number of pieces of information extracted	Percentage	
Gender	Male	8	51	11%
	Female	11	431	89%
Age	50–54	12	309	64%
	55+	7	173	36%
Education level	HS Diploma	11	261	54%
	Bachelor	4	199	41%
	Doctor	4	20	4%
Occupation	Farmer	5	56	12%
	Retired	5	257	53%
	Employed	9	169	35%

Table 2
Coding scheme for the features of health misinformation (revised based on CARS).

Dimensions	Feature
Lack of credibility	Exaggeration/absolutes
	Induced text
	Agitated propaganda and promotion
	Claims of unique and secret information
	Negative meta-information
Lack of accuracy	Problematic punctuation
	Inappropriate typographic space
	Typos
	Bad grammar
	Unfair opinions
	Incomplete content
	Mixed usage of simple and traditional Chinese characters
Lack of reasonableness	Statements of excessive significance
	Intemperate tone or language
	Over-claims
	Unmatched title and text
Lack of support	Numbers/statistics presented without identified source
	Absence of source documentation
	Under the guise of authority or government

Table 3
Participants' demographic information.

		Experimental group No.(%)	Control group No.(%)	χ^2
Gender	Male	17 (38.64)	17 (44.74)	0.313
	Female	27 (61.36)	21 (55.26)	
Grade	Freshman or Sophomore	37 (84.09)	7 (18.42)	35.363*
	Junior or Senior	7 (15.91)	31 (81.58)	
Health status	Good	38 (86.36)	33 (86.84)	0.004
	Fair	6 (13.64)	5 (13.16)	
Hometown	Rural	12 (27.27)	12 (31.58)	1.067
	Town	15 (34.09)	9 (23.68)	
	Urban	17 (38.64)	17 (44.74)	
Family income (yuan/annually)	$\leq$ 80,000	21 (47.72)	16 (42.11)	0.260
	$>$ 80,000	23 (52.28)	22 (57.89)	
Frequency to browse "Discovery"	0–5	27 (61.36)	24 (63.16)	0.028
	Above 6	17 (38.64)	14 (36.84)	
Pay attention to health information in "Discovery"	Yes	24 (54.55)	19 (50.00)	0.681
	No	20 (45.45)	19 (50.00)	
Self-evaluation of health information recognition	Very strong	2 (4.55)	0 (0.00)	0.118
	Strong	26 (59.09)	15 (39.47)	
	Fair	15 (34.09)	21 (55.26)	
	No good	1 (2.27)	2 (5.26)	

* $p<0.05$.

Donelle et al., 2009; Eriksson-Backa et al, 2012; Diviani et al., 2015). Table 3 shows that only the grade levels were significantly different between the two groups: there were more higher-grade students in the control group than in the experimental one. Statistical results indicated that the difference at grade level did not generate significant difference in the score they earned. Therefore, the two groups' demographic characteristics are quite similar. It is critical to further compare the two groups and test the usefulness of the scheme. We then compared the performance of the two groups before and after learning the feature scheme and examined the scheme's effectiveness.

3.2.2. Experimental Design

To explore whether the developed feature scheme can help improve users' capability to identify health misinformation on social media, we first categorized 482 pieces of information collected in Phase I into two groups: real information (R) and misinformation (M). We then randomly selected 16 pieces of information each from these two groups. Totally, 32 pieces of information were tested in the experiment.

To reduce the participants' workload, we first assigned 16 pieces of information into four groups for the pre-test. These were labelled A1–A4 (3R/1M), B1–B4 (1R/3M), C1–C4 (2R/2M), and D1–D4 (2R/2M), with each group containing both real and misinformation items as indicated. The other 16 pieces of information were assigned to four post-test groups: E1–E4 (2R/2M), F1–F4 (2R/2M), G1–G4 (2R/2M), and H1–H4 (2R/2M). Real and misinformation items in each group were combined to test participants' assessment. In addition, the total length of the text in a given group was controlled to reduce bias. The format of each item was "text +

picture" or plain text.

3.2.3. Procedure

The experiment was conducted in a computer lab. Before the pre-test, the participants were asked to fill out a consent form and an entry questionnaire that elicited demographic information and users' experience with health information and social media. In the pre-test for the experimental group, participants randomly selected one group of health information (A, B, C or D) and assessed each piece of information as real or misinformation in the questionnaire. They earned "1" point if they made a correct judgment; otherwise, "0" point. We finally calculated their total score. Then, they were asked to read the feature scheme for 10 minutes. For the post-test, they randomly selected another group of health information (E, F, G or H) and made an assessment, following the same way to calculate their final score as mentioned above. Finally, participants were presented with a post-experiment questionnaire to evaluate their satisfaction with their assessments and the usefulness of the feature scheme based on a five-point Likert scale. After they finished the experiment, they were required to write down why they assessed a piece of information as misinformation. They were also allowed to write down comments on the usefulness of the scheme or suggestions for improving it. All qualitative data were processed via open coding, finished by two coders independently.

The control group followed a similar procedure. However, in order to test the usefulness of the feature scheme, upon completing the pre-test, we asked the participants to read a movie review of the popular 2017 film *Coco*. The review is unrelated to any issues of health and completely different from the treatment in the experimental group, that is, the feature scheme. In this way, we try to eliminate the potential influence of the treatment on the participants and make sure the research results are valid and reliable. They then moved to the post-test and did not need to comment on the scheme on the post-experiment questionnaire. Figure 1 shows the experimental design of this study.

4. Results

4.1. Distribution of real health information and misinformation

Table 4 shows that 57% of the sample is health misinformation, which suggests that the quality of health information distributed on WeChat is, indeed, a serious concern.

4.2. Features of health misinformation

To identify salient features of misinformation, we calculated the frequency of each feature and performed chi-square tests to show the relationship between each feature. Table 5 shows all significant features of health misinformation; only the "business promotion" feature did not stand up as a significant feature.

In order to develop a scheme, we organized the features into a list, and then extracted typical statements from health

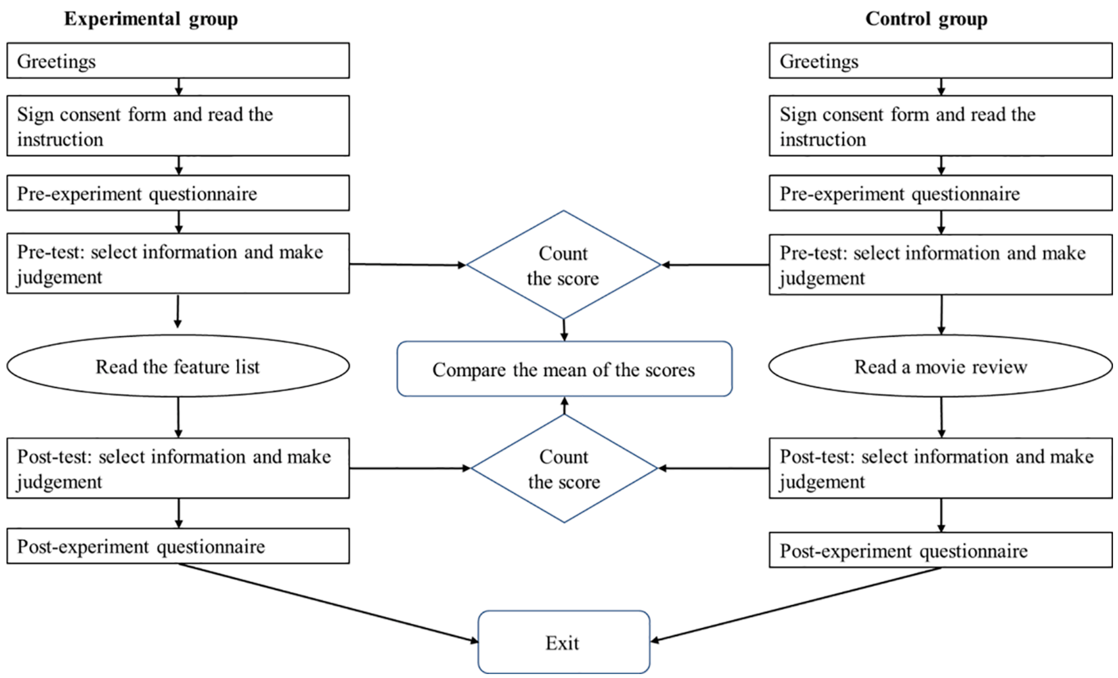

Fig. 1. Experimental design

Table 4
Distribution of real and misinformation.

Process	Methods	N	Real	Mis*	Disagreement/Cannot be judged
First-round	Rumor identification websites	482	8	73	401
Second-round	Identified by two health experts	401	196	33	172
Third-round	Identified by the third expert	172	2	170	0
Total		-	206 (43%)	276 (57%)	0

Mis*: Misinformation.

Table 5
Distribution and features of real health information and misinformation.

Dimensions	Feature	Mis (%)	Real (%)	χ^2
Lack of credibility	Exaggeration/ absolutes	157(56.88)	27(13.11)	95.783***
	Induced text	98(35.51)	24(11.65)	35.513***
	Agitated propaganda and promotion	81 (29.35)	18 (8.74)	30.700***
	Claiming unique and secret information	62 (22.46)	11 (5.34)	26.914***
	Business promotion	25 (9.06)	14 (6.8)	0.811
	Negative meta-information	17 (6.16)	1 (0.49)	10.564**
Lack of accuracy	Problematic punctuation	84 (30.43)	20 (9.71)	29.945***
	Inappropriate typographic space	37 (13.41)	13 (6.31)	6.387*
	Typos	33 (11.96)	2 (0.97)	21.140***
	Bad grammar	20 (7.25)	1 (0.49)	12.939***
	Unfair opinions	20 (7.25)	1 (0.49)	12.939***
	Incomplete content	18 (6.52)	1 (0.49)	11.351**
Lack of rationality	Statements of excessive significance	93 (33.7)	12 (5.83)	53.775***
	Intemperate tone or language	88 (31.88)	10 (4.85)	53.204***
	Over-claims	38 (13.77)	2 (0.97)	25.385***
	Unmatched title and text	31 (11.23)	6 (2.91)	11.519**
Lack of support	Numbers/ statistics presented without identified source	79 (28.62)	8 (3.88)	48.809***
	Absence of source documentation	66 (23.91)	1 (0.49)	54.095***
	Under the guise of authority or government	20 (7.25)	1 (0.49)	12.939***

misinformation in the sample. Table 6 shows the scheme, which was provided for testing in Phase II.

4.3. Recognition of health misinformation

In terms of correct answers defined as correctly identifying “real” or “fake” health information during the experiment, the ratio of correct assessments in the post-test increased 15.90% than that in the pre-test of the experimental group, but for the control group, the increase was just 9.87%.

To compare the pre-test and post-test in each group and the pre-test and the post-test between the two groups respectively, we compared the final score they earned and performed both paired-sample and independent-sample t-tests.

Table 7 shows that in the pre-test, experimental group performance was not significantly different from that of the control group. However, in the post-test, the performance of the experimental group was significantly improved after reading the scheme ($t = 2.185$, $DF = 1$, $p < 0.05$). In contrast, the control group showed no significant difference between the pre- and post-test.

The results also showed a significant difference between the pre-test and post-test in the experimental group ($t = -3.510$, $DF = 43$, $p < .05$). This means that the participants in the experimental group significantly improved their ability to differentiate real information from misinformation after they had learned the scheme. Again, for the control group, no significant improvement was observed. The results demonstrate that the scheme has a significant impact on helping improve participants’ ability to identify health misinformation.

4.4. Criteria the participants used to identify misinformation

We collected the statements written by the participants to explain how they assessed misinformation in the experiment (See Table 8). Open coding was performed to analyze the data using NVivo 11. Table 8 shows the categories, codes, frequency of the code, and text examples.

Table 8 shows that exaggeration/absolutes is the most frequently used and essential criterion for making assessment, followed by credibility, relevance, rationality, inducement, and propaganda. The frequency of other criteria is equal to or lower than 5. The participants used some criteria we identified in the scheme, for example, exaggeration/absolutes, induced text, over claim, and so on, to make assessment. This indicates that the participants, indeed, learned something from reading the scheme in the experiment, which helped them to recognize health misinformation. Thus, to some extent, the results provided empirical evidence to support the scheme. It also demonstrated that the scheme is easy to learn by the participants. We also noticed that, beyond the scheme, the participants assessed misinformation based on their experience, specific contexts, and the comparison of information from authoritative search

Table 6
Feature scheme of health misinformation.

Dimensions	Feature	Typical statements (Italic) or typical characteristics (in parenthesis)
Lack of credibility	Exaggeration/ absolutes	XX can prevent cancer in your whole life; Defeat diabetes - food control is enough; Six types of breakfast are horrible! Eating such a breakfast is equal to suicide!
	Induced text	Come here and take a careful look; God! How can you see? It is definitely worth reading; It is a great pity that so few people know it!
	Agitated propaganda and promotion	This is a very good article. Your friend definitely needs it! If you post it to your Discovery, many people will appreciate it. Prevention is better than treatment. For your friends' health, please post it to your Discovery only in 3-5 seconds.
	Claims of unique and secret information	Secret prescription; secret treatment; a secret and unique method that can cure the disease.
	Negative meta-information	The way that can help health in fact will kill you. This is in fact fish leading to cancer! Please don't eat it. The Farmers even don't eat it!
Lack of accuracy	Problematic punctuation	(Both English and Chinese punctuation are used in the same article; error punctuations)
	Inappropriate typographic space	(Redundant space within an article)
	Typos	(Typos can be seen here and there in an article)
	Bad grammar	(Grammatical errors can be seen in an article)
	Unfair opinions	All is because of money! For money they can do anything! Forget about cancer! You don't need to do any surgery or treatment, even chemotherapy.
	Incomplete content	(Lacking critical information; incomplete)
Lack of rationality	Statements of excessive significance	Very comprehensive; help you defeat cancer; ninety-nine percent of people did not know that eating those fruits and vegetables would kill them; the best treatment; very valuable medicine; cure any cancer; etc.
	Intemperate tone or language	(Use multiple exclamation marks), poison, urgent, 68 times more poisonous than arsenic
	Over-claims	The truth scares you; Brushing your teeth every day is equal to taking drugs; Eating gruel is equal to taking drugs.
	Unmatched title and text	(Title is not matched with content; title is exaggerated or content does not completely match the title)
Lack of support	Numbers/ statistics presented without an identified source	(Do not clearly write down the data source)
	Absence of source documentation	(The source is necessary but you cannot find the citation from the article)
	Under the guise of authority or government	(Claim the information is from authoritative agencies, including governmental agencies)

Table 7
Analysis of pre-test and post-test results

Group	N	Experimental group Mean/SD	N	Control group Mean/SD	t
Pre-test	44	2.48/0.976	38	2.263/1.057	0.953
Post-test	44	3.114/0/841	38	2.658/1.047	2.185*
t		-3.510 *		-1.835	

* $p < 0.05$

engines. However, compared to the features in the scheme they used, the frequency of using these criteria is much lower.

4.5. Usefulness of the scheme

In the experimental group, 42 participants (95.5%) reported that the scheme was very useful in helping them make assessments (18 marked "very useful"; 24 marked "useful"). The rest evaluated the scheme as "fairly useful," indicating that the feature scheme, indeed, assisted them with making assessments about health information.

Seventeen participants answered the open questions in the questionnaire. The answers were analyzed and categorized into "problems" and "comments or suggestions". Table 9 shows the results.

As shown in Table 9, the participants mentioned that the scheme still has some issues in terms of readability, format, and organization. They also gave suggestions to improve the scheme, such as adding examples, marking fake brands, and so on. Some also suggested that the scheme should be accessed publicly to help more people.

5. Discussion

The two-phase study investigated the importance of helping people identify health misinformation on social media. It first developed a feature scheme to identify health misinformation, and then evaluated the usefulness of this scheme in a user experiment.

Table 8
Criteria to identify misinformation

Categories	N	Codes	Code frequency	Text example
Content-based	82	Exaggeration/ absolutes	24	"Exaggerate importance on purpose" (E19); "Exaggerate by using multiple exclamation marks" (E21); "Too absolute" (E27); "(emphasize) 100%" (E35)
		Credibility	10	"Lack of credibility" (E13, E08)
		Relevance	9	"Lack of relevance" (E28)
		Rationality	8	"Lack of rationality" (E08)
		Induced text	8	"Induced, for instance, you will lose your life if you don't follow the rules, and so on, too scared" (E04)
		Propaganda	7	"Just (some) propaganda"(E41),"Propaganda and excessive promotion" (E27)
		Over-claims	5	"Over-claims" (E06, E36)
		Inappropriate language and tone	4	"Unnormal tone"(E41); "Expression out of control (not reasonable)" (E42)
		Negative information	3	"negative information" (E42)
		Accuracy	3	"Lack of accuracy" (E42)
		Authenticity	1	"Not real, lack of authenticity" (E38)
Information sources	12	Under the guise of TV	5	"Under the guise of CCTV (China Central Television, most authoritative television in China)" (E26); "Under the guise of television" (E36)
		Data without specific sources	3	"Do not indicate where the data is from" (E12)
		No source files	2	"Lack of source file, but it is necessary" (E43)
		No evidence necessary	2	"No any scientific evidence" (E19); "No evidence to support" (E18)
Text-based features	7	Unmatched title and text	2	"The title and content do not match" (E10)
		Incomplete content	2	"The content is not complete" (E25)
		Typos	2	"Typos, for example, Vitamin C5……" (E36); "Mixed use of Chinese and English characters" (E07)
		Grammatical errors	1	"Grammatical errors" (E42)
Experience	3	Experience	3	"I eat every day and don't see any problem" (E18); "Different foods provide different nutrients, no something like best food"(E38); "Barcode begins with 8 is not credible" (E05)
Consideration of individual case	1	Specific contexts	1	"Maybe my body does not accept" (E32)
Comparison	1	Helps from search engines	1	"(I) search via Bidu (to verify)" (E03)

Table 9
Comments or suggestions for improving the feature scheme

	Answers	No. (%)	Examples
Any problems?	No	10 (58.8)	"No questions." (E04, E13, E24, E26, E34) "It is a very good one." (E32) "Not need to improve. It has been a great one." (E05) "It has been great!" (E06, E35) "It is very comprehensive and easy to understand." (E45)
	Yes	3 (17.6)	"It should be more readable. The words are messy in the current version; can draw a clear table or list the number." (E17) "Should be clearer when comparing, a little messy, can give more examples." (E37) "The organization [of the list] is not good. It should be improved." (E47)
Suggestions or comments	Suggestions for improvement	2 (11.8)	"Can combine some examples [to illustrate the feature]." (E08) "(Add) Health Certification, and [the methods] to identify fake brand." (E25)
	Suggestions for publication	2 (11.8)	"Publish it." (E16) "Hope it can be a public tool and help more people, particularly, help seniors know better [about the feature list]." (E49)

The scheme was demonstrated *useful* in promoting participants' ability of identifying health misinformation, *easy to learn and use*, and thus *helpful* in improving users' online HIL.

5.1. Features of health misinformation and the scheme

Unlike other studies concerned with information quality, this study focused on recognizing features from health misinformation, by which to help users improve their capability in identifying health misinformation or fake information on social media. In the content analysis of Phase I, we identified different features of health misinformation. In Phase II, the results empirically support the CARS list proposed by Harris (2010), especially the features indicating low-quality information, for example, "exaggeration/absolutes", "over-claims", "intemperate tone or language", and so on. Beyond the CARS list, more features, especially with respect to Chinese context, for example, "under the guise of authority or government", "inappropriate typographic space", were identified. For example, if a piece of health misinformation is claimed as real, mostly its creator prefers to emphasize the support from the CCTV, the most authoritative TV station in China. However, usually, the CCTV does not endorse information related to health. If users do not know this, they may be trapped. Therefore, this feature will remind users not to believe those claims that emphasize the support from the CCTV and more verification is needed. Moreover, based on the analysis of the qualitative data the participants provided to explain the reasons why they made assessment of misinformation, we found they used some features not included in the CARS list, including their experience, comparison of searching search engines, consideration of individual cases, and so on. The results indicate that the scheme proposed in this study is helpful and useful for users to recognize misinformation. To further clarify the features of health misinformation, we grouped them as "semantic," "grammatical," or "peripheral," with examples of each dimension shown in Table 10.

Table 10 shows that, for health misinformation, there are more semantic features than grammatical or peripheral features, suggesting that health misinformation can be evaluated mainly from its semantics, but grammatical and peripheral features are also indicators that should be considered.

Based on the general framework of Harris (2010), this study has revealed the most important features of health misinformation. The results indicate that exaggeration or reliance on absolutes is a critical feature of health misinformation, appearing in most health misinformation items identified in this study. The qualitative data analysis also supported this viewpoint. Moreover, the qualitative analysis indicated that exaggeration/absolutes is the most frequently adopted criterion for assessing health misinformation. Other features—induced text, over-claims, intemperate tone or language, and problematic punctuation—each was found in more than 30% of the health misinformation items. The results indicate that health misinformation shares some features with fake news summarized by Zhang & Ghorbani (2020), especially in terms of content-based features. However, some differences are also obvious. Due to different purposes and target user groups, some specific features are different. For example, exaggeration/absolutes is the most frequently presented feature of health misinformation in this study but, for fake news, a bunch of features are salient, including the usage of punctuation, the length of sentences, stance-based features, and so on.

Interestingly, the presence of business promotion is not a typical characteristic of health misinformation; that is, both health information and misinformation were used to promote businesses. The result partly corroborated the findings of Walther, Wang, and Loh (2004), that visual advertisements on .org websites negatively affected health website credibility, whereas on .edu or .com sites the influence was positive. The mixed results suggest that some indicators of health misinformation still need to be further investigated.

Zhao, Da & Yan (2021) detected the features of online misinformation from topic, linguistic, sentiment, and behavioral features. They tried to incorporate different features and developed a new approach to help the system detect health misinformation automatically. With a different purpose, the current study targets online users and reveals that semantics, grammatical and peripheral features are typical features of health misinformation. Based on these features, a feature scheme was developed, which helps users improve their online HIL. Therefore, the current study takes a user perspective and the scheme can be directly used to promote users' understanding of health misinformation.

The results indicate that the scheme is easy to learn (especially for younger participants) and the features can be directly used to make assessment of health misinformation. After reading the scheme, users can improve their capability to identify health misinformation. Two consequential experiments following the same procedure as this study were conducted (Zhang & Li, 2019; Zhang, 2018), with participants whose age was 45-60 and above 60, respectively. The results verified the usefulness of the scheme. However, the participants used fewer features in the scheme to make assessment of health misinformation than those in the current study. Only 6% of the older adults used the scheme to make assessment. The findings indicate that, for younger users, the scheme is much easier to learn and adopt. Some new elements may need to be added to the scheme for older adults, making it more attractive for them to learn and use. In addition, new approaches need to be developed in order to get adapted to their learning behavior.

This feature scheme has implications for research on misinformation related to the COVID-19. Considering the low quality of information related to COVID-19, as Cuan-Baltazar et al. (2020) address, we are confident that the scheme proposed in this study can contribute to help users differentiate between useful information and misinformation.

5.2. *Effectiveness of the scheme as a tool to improve users' online HIL*

Previous studies found that users relied heavily on online health information (e.g., Escoffery et al., 2005), even though their online health literacy itself, was problematic (Stellefson et al., 2011). Therefore, it is imperative to help users identify health misinformation in online settings where they are likely to encounter misinformation. Some researchers have also conducted studies to examine the criteria or indicators that can help users to distinguish real information from misinformation. These studies have proposed such criteria as accuracy, authority, objectivity, and currency (e.g., Metzger, 2007), but it is not easy for a layperson to evaluate whether a piece of health information is accurate, authoritative, or objective. Therefore, for general users—who are, almost by definition, not professional users—such criteria play a quite limited role.

Based on studies of checklists and guidelines, our study took a different approach by developing a feature scheme that is somewhat more elaborate than a simple checklist. Through a two-phase study, we not only identified the features of health misinformation and developed a feature scheme with typical statements, but also experimentally tested the usefulness of the resulting scheme. Moreover, the following studies (Zhang & Li, 2019; Zhang, 2018) provided strong empirical evidence to support the feature scheme and illustrated its effectiveness.

Though some checklists and guidelines have been proposed for general use, few were available for evaluating health information quality in the specific context of social media. The current study addressed this issue and made a novel contribution both to the

Table 10
Typical features of health misinformation

Dimension	Typical features
Semantic	exaggeration/absolutes; induced text; claims of unique and confidential information; incomplete content; over-claims; unfair opinions; numbers/statistics without identified sources; statements of excessive significance
Grammatical	problematic punctuation; inappropriate typographic space; typos; bad grammar
Peripheral	agitated propaganda and promotion; negative meta-information; intemperate tone or language; unmatched title and text; absence of source documentation; under the guise of authority or government

knowledge base in this area and to health information practices, especially in terms of providing an approach to improve users' online HIL.

The results of previous studies indicate that more attention should be paid to misinformation distributed via social media (Li, Zhang & Wang, 2018), but how to help general users recognize misinformation on social media remains a challenge, especially facing the COVID-19 global pandemic. Other approaches devoted more attention to the peripheral features of a source: format, arrangement, price, and availability (Stoker & Cooke, 1994) and, to some extent, can help users identify low quality information. Zhao, Da & Yan (2021) involved more features, such as linguistic, sentiment, and user behavioral, however, they aimed to develop an automatic model, rather than improve users' online HIL. Taking a user's perspective, the current study proposes a feature scheme and makes a step forward to focus on message credibility and its incorporation of a message's semantic, grammatical, and peripheral features. Though the approach proposed in this study is based on Harris (2010), it adds new features, furnishes typical statements as examples for users, and directly targets health misinformation, thus providing a more practical tool. In particular, the scheme could be used as a tool and helps general users deal with the information epidemic resulting from COVID-19. As discussed above, the scheme can be learned quickly by younger users. It can also be employed to help people make misinformation assessments. We firmly believe that by promoting the usage of this scheme, users' online HIL can be improved, especially for younger users. If it can be used appropriately, for example, with more explanation about misusing health misinformation, it can also help older adults improve their online HIL.

Moreover, the feature scheme could be easily understood and used. Our experimental results suggest that an easily learned, easily implemented approach may be more effective than those that are too general or abstract, or that include only peripheral features of information. The developed feature scheme has proved to be an effective tool for users to improve their health misinformation recognition ability and online health literacy.

5.3. Limitations and implications

This study has limitations. First, we only analyzed "text + picture" or plaintext health information; no video items were included. Since videos about health have been increasingly distributed on social media platforms, they should be adopted in future studies. Second, the sample size is limited, in comparison to the vast amount of health information distributed on various social media platforms. Only four pieces of health information were provided to the participants in the pre-test and post-test, respectively. The limited sample size restricted the generalization of the results. Third, we did not consider the order in which texts were presented to the participants, which may also bias the results. Finally, we did not thoroughly investigate participants' prior knowledge and its influence on health information recognition.

Despite these restrictions, this study has significant implications. First, it contributes to the body of knowledge on health information research, specifically on health misinformation. Through identifying typical features of health misinformation, the present study contributes new knowledge on health misinformation theoretically. Second, the feature scheme, paired with typical statements illustrating the features, has been practically verified as an effective tool to improve users' health information recognition on social media in China. It could be further adapted to different contexts and used as an educational tool in practice to help people improve their health information literacy. Third, although the features were identified based on the analysis of health misinformation on social media in China, considering the open nature of the internet, the scheme can also be used to recognize health misinformation on the Web. Fourth, the features identified in this study have suggested a new way to achieve automatic misinformation filtering on social media which addressed the need of developing effective approaches to automatically or semi-automatically help users assess health information on social media (Viviani & Pasi, 2017). Furthermore, we will analyze the features and associated typical statements of health misinformation on social media, and then create a scheme that is more amenable to machine learning. The results may enhance the feature-based algorithm to filter misinformation addressed by Kumar *et al* (2020). Finally, because health information quality is a ubiquitous problem (Zhang, Sun, & Xie, 2015) and the presentation of such information is culture-dependent, the present study can methodologically inform similar studies in other language and cultural contexts.

6. Conclusions

The study identifies salient features of health misinformation on Chinese social media platforms, including exaggeration/absolutes, induced text, over-claims, intemperate tone or language, and problematic punctuation; in particular, some features in the Chinese context, such as under the guise of authority or government and inappropriate typographic space. Semantic features are more important indicators for health misinformation than are grammatical or peripheral features. The feature scheme will inform health information service providers on how to better serve their target users. These features will be used to develop a mechanism to help social media automatically or semi-automatically filter health misinformation and improve information quality.

Future studies will be carried out to evaluate the effectiveness of the feature scheme in helping users recognize information related to COVID-19 and deal with the information epidemic. We will continue to develop a tool that specifically targets misinformation of COVID-19, and could be implemented to social media and automatically filters obvious misinformation to protect general users. In addition, video health information will be collected and analysed to observe whether new features emerge. The newly identified features will be added to the current feature scheme and to make the scheme more robust for future use.

CRediT authorship contribution statement

Yuelin Li: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing, Validation, Funding acquisition. **Zhenjia Fan:** Methodology, Data curation, Writing – original draft, Visualization, Formal analysis. **Xiaojun Yuan:** Writing – review & editing, Validation. **Xiu Zhang:** Investigation, Writing – original draft, Formal analysis.

Acknowledgment

We appreciate the support of the National Social Science Foundation of China. This paper is written out of the Major Project of National Social Science Foundation of China (Grant No.20&ZD142). We also appreciate Dr. Nicolas J. Belkin and the reviewers for their constructive suggestions and insights, and the volunteers who participated in the experiment.

References

Budak, C., Agrawal, D., & Abbadi, A. E. (2011). Limiting the spread of misinformation in social networks. In *Proceedings of the 20th International Conference on World Wide Web, WWW 2011*. India: Hyderabad. March 28 - April 1, 2011.

Case, D. O., & Given, L. M. (2016). Looking for information: a survey of research on information seeking, needs, and behavior. *Journal of the Medical Library Association, 91*(2), 259.

Cornish, L. S., & Moraes, C. (2015). The impact of consumer confusion on nutrition literacy and subsequent dietary behavior. *Psychology & Marketing, 32*(5), 558–574.

Cuan-Baltazar, J. Y., Muñoz-Perez, M. J., Robledo-Vega, C., Pérez-Zepeda, M. F., & Soto-Vega, E. (2020). Misinformation of COVID-19 on the Internet Infodemiology Study 2020. *JMIR Public Health Surveill 2020*, e18444.

da Silva, E., & Toledo, M. M. (2020). Internet and COVID-19: information and misinformation. *InterAmerican Journal of Medicine and Health, 3*.

De Choudhury, M., Morris, M. R., & White, R. W. (2014). Seeking and sharing health information online: comparing search engines and social media. In *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems* (pp. 1365–1374). New York, NY: ACM.

Diviani, N, Putte, B V D, Giani, S, et al. (2015). Low health literacy and evaluation of online health information: A systematic review of the literature. *Journal of Medical Internet Research, 17*(5), 1–17. e112.

Donelle, L, Hoffman-Goetz, L, Gatobu, S, et al. (2009). Comprehension of Internet-based numeric cancer information by older adults. *Informatics for Health and Social Care, 34*(4), 209–224.

Escoffery, C., Miner, K. R., Adame, D. D., Butler, S., McCormick, L., & Mendell, E. (2005). Internet use for health information among college students. *Journal of American College Health, 53*(4), 183–188.

Eriksson-Backa, K, Ek, S, Niemela, R, & Huotary, M. (2012). Health information literacy in everyday life: A study of Finns aged 65-79 years. *Health Informatics Journal, 18*(2), 83–94.

Fan, L., Lu, Z., Wu, W., Thuraisingham, B., Ma, H., & Bi, Y. (2013). Least cost rumor blocking in social networks. In *2013 IEEE 33rd International Conference on Distributed Computing Systems* (pp. 540–549). IEEE.

Feng, Z. (2016). *An investigation and research of current status of health literacy of medical students in vocational college. Master dissertation*. Nanjing, China: Southeast University.

Freeman, K. S., & Spyridakis, J. H. (2009). Effect of contact information on the credibility of online health information. *IEEE Transactions on Professional Communication, 52*(2), 152–166.

Garrett, L. (2020). COVID-19: the medium is the message. *Lancet, 395*(10228), 942–943.

Gokyildiz, S., Alan, S., Elmas, E., Bostanci, A., & Kucuk, E. (2014). Health-promoting lifestyle behaviours in pregnant women in turkey. *International Journal of Nursing Practice, 20*(4), 390–397.

Hanik, B, & Stellefson, M. (2011). E-health literacy competencies among undergraduate health education students: a preliminary study. *International Electronic Journal of Health Education, 14*, 46–58.

Harris, R. (2010). Evaluating internet research sources. *Virtual Salt*. Retrieved February 28, 2020, from https://resources.saylor.org/wwwresources/archived/site/wp-content/uploads/2011/08/HIST104-7.1.2-VirtualSalt.pdf.

Hsieh, H. Y., Fung, H. C., Wang, C. J., Chin, S. C., & Wu, T. (2011). Epileptic seizures in neurofibromatosis type 1 are related to intracranial tumors but not to neurofibromatosis bright objects. *Seizure, 20*(8), 606–611.

Iskeceli-Tunc, S., & Oner, D. (2016). Use of webquest design for inservice teacher professional development. *Education & Information Technologies, 21*(2), 319–347.

Kumar, K. K., & Geethakumari, G. (2014). Detecting misinformation in online social networks using cognitive psychology. *Human Centric Computing & Information Sciences, 4*(1), 1–22.

Kumar, S., Asthana, R., Upadhyay, S., Upreti, N., & Akbar, M. (2020). Fake news detection using deep learning models: A novel approach. *Transactions on Emerging Telecommunications Technologies, 31*(2), e3767.

Lee, K., Hoti, K., Hughes, J. D., & Emmerton, L. (2014). Dr Google and the consumer: a qualitative study exploring the navigational needs and online health information-seeking behaviors of consumers with chronic health conditions. *Journal of Medical Internet Research, 16*(12), e262.

Li, Y., Zhang, X., & Wang, S. (2017). Fake vs. real health information in social media in China. In *Proceedings of the 80th American Society for Information Science & Technology Annual Meeting*. D.C.: Washington. Oct. 27- Nov.1.

Li, Y., Zhang, X., & Wang, S. (2018). Health information quality in social media: An analysis based on the features of real and fake health information. *Journal of the China Society for Scientific and Technical Information, 37*(3), 294–304 (In Chinese).

Li, Y., Wang, X., Lin, X., & Hajli, M. (2018). Seeking and sharing health information on social media: a net valence model and cross-cultural comparison. *Technological Forecasting and Social Change, 126*(1), 28–40.

Li, Z. H., Zhang, X. R., Zhong, W. F., Song, W. Q., Wang, Z. H., Chen, Q., Liu, D., Huang, Q., Shen, D., Chen, P., Mao, A., Zhang, D., Yang, F., Wu, X., & Mao, C. (2020). Knowledge, attitudes, and practices related to Coronavirus disease 2019 during the outbreak among workers in China: A large cross-sectional study. *PLoS Neglected Tropical Diseases, 14*(9), Article e0008584.

Lloyd, M. (2011). A tale of six fish: Achieving social presence through discussion forums in an offline learning environment. *Journal of Learning Design, 4*(2), 39–51.

Luk, T. T., Zhao, Z., Weng, X., Wong, Y.-H., Wu, Y. S., Ho, S. Y., Lam, T. H., & Wang, M. P. (2020). Exposure to health misinformation about COVID-19 and increased tobacco and alcohol use: a populationbased survey in Hong Kong. *Tobacco Control*. Aug 27, 2020. Retrieved Feb 23, 2021, from https://pubmed.ncbi.nlm.nih.gov/32855353/. doi:10.1136/tobaccocontrol-2020-055960.

Ma, X., Vervoort, D., & Luc, J. G. Y. (2020). When misinformation goes viral: Access to evidence-based information in the COVID-19 pandemic. *Journal of Globe Health Science, 2*(1), e13. https://doi.org/10.35500/jghs.2020.2.e13. Retrieved Feb 23, 2021, frompISSN 2671-6925•eISSN 2671-6933.

Magnezi, R., Bergman, Y. S., & Grosberg, D. (2014). Online activity and participation in treatment affects the perceived efficacy of social health networks among patients with chronic illness. *Journal of Medical Internet Research, 16*(1), e12.

Mandalios, J. (2013). *RADAR: An approach for helping students evaluate internet sources*. Sage Publications, Inc.

Meola, M. (2004). Chucking the checklist: a contextual approach to teaching undergraduates web-site evaluation. *Portal Libraries & the Academy, 4*(3), 331–344.

Metzger, M. J. (2007). Making sense of credibility on the web: Models for evaluating online information and recommendations for future research. *Journal of the American Society for Information Science & Technology, 58*(13), 2078–2091.

Nguyen, N. P., Yan, G., Thai, M. T., & Eidenbenz, S. (2012). Containment of misinformation spread in online social networks. In *ACM Web Science Conference* (pp. 213–222). New York, NK: ACM.

Nsuangani, N. M., & Pérez, M. A. (2006). Accessing web-based health related information by college students: An exploratory study. *Journal of Health Promotion, 4*(1), 64–74.

Oehmichen, A., Hua, K., Lopez, J., Molina-Solana, M., Gomez-Romero, J., & Guo, Y. (2019). Not all lies are equal. A study into the engineering of political misinformation in the 2016 US presidential election. *IEEE Access, 7*, 126305–126314.

Oh, B. M., Byun, H., & Krishnamoorthy, A (2018). Privacy issues on social media: A risky trade off of personal information. iConference 2018 Proceedings. . Retrieved September 1, 2019, http://hdl.handle.net/2142/100277.

Pálsdóttir, Á. (2011). Opportunistic discovery of information by elderly Icelanders and their relatives. *Information Research, 16*(3), 38–61.

Pariera, K. L. (2012). Information literacy on the web: How college students use visual and textual cues to assess credibility on health websites. *Communications in Information Literacy, 6*(1), 34–48.

Prybutok, G., & Ryan, S. (2015). Social media: The key to health information access for 18- to 30-year-old college students. *Cin Computers Informatics Nursing, 33*(4), 132–141.

Redmond, T. L. (2008). *Electronic (digital) health information competency: A comparative analysis of knowledge and skills of rural and non-rural freshman college students. Doctoral dissertation*. Central Michigan University.

Rubin, V. L. (2019). Disinformation and misinformation triangle. *Journal of Documentation, 75*(5), 1013–1034.

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

Scanfeld, D., Scanfeld, V., & Larson, E. L. (2010). Dissemination of health information through social networks: Twitter and antibiotics. *American Journal of Infection Control, 38*(3), 182–188.

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).

Sicilia, R., Giudice, S. L., Pei, Y., Pechenizkiy, M., & Soda, P. (2018). Twitter rumour detection in the health domain. *Expert Systems with Applications, 110*, 33–40.

Shu, K., Aliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake news detection on social media: A data mining perspective. *ACM SIGKDD explorations newsletter 19.1*, 22–36.

Søe, S. O. (2018). Algorithmic detection of misinformation and disinformation: Gricean perspectives. *Journal of Documentation, 74*(2), 309–332.

Song, C., Ning, N., Zhang, Y., & Wu, B. (2021). A multimodal fake news detection model based on crossmodal attention residual and multichannel convolutional neural networks. *Information Processing & Management, 58*(1), Article 102437.

Stellefson, M., Hanik, B., Chaney, B., Chaney, D., Tennant, B., & Chavarria, E. A. (2011). Ehealth literacy among college students: A systematic review with implications for ehealth education. *Journal of Medical Internet Research, 13*(4), e102.

Stoker, D., & Cooke, A. (1994). Evaluation of networked information sources. In *Proceedings of the 17th International Essen Symposium* (pp. 287–312). Essen.

Viviani, M., & Pasi, G. (2017). Credibility in social media: Opinions, news, and health information-a survey. *Wiley Interdisciplinary Reviews Data Mining & Knowledge Discovery* (p. e1209).

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

Walther, J., Wang, Z., & Loh, T. (2004). The effect of top-level domains and advertisements on health website credibility. *Journal of Medical Internet Research, 6*(3), 56–65.

Yilma, T. M. (2016). Health information seeking behavior among college students: A case in a developing country. In *ACM on Conference on Human Information Interaction and Retrieval* (pp. 381–383).

Zarocostas, J. (2020). How to fight an infodemic. *Lancet, 395*(10225), 676.

Zhang, H., Zhang, H., Li, X., & Thai, M. T. (2015). Limiting the spread of misinformation while effectively raising awareness in social networks. *Computational Social Networks*. London: Springer, Cham.

Zhang, X. (2018). *The capability of users in screening health information in social media. Unpublished doctoral dissertation*. Tianjin, China: Nankai University.

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

Zhang, X., & Li, Y. (2019). Ability of users in different age groups to screen health information in social media. *Journal of the China Society for Scientific and Technical Information, 38*(8), 838–848 (in Chinese).

Zhang, Y., Sun, Y., & Xie, B. (2015). Quality of health information for consumers on the web: a systematic review of indicators, criteria, tools, and evaluation results. *Journal of the Association for Information Science & Technology, 66*(10), 2071–2084.

Zhao, Y., Da, J., & Yan, J. (2021). Detecting health misinformation in online health communities: Incorporating behavioral features into machine learning based approaches. *Information Processing & Management, 58*(1), Article 102390.

Zhou, X., & Zafarani, R. (2020). A survey of fake news: Fundamental theories, detection methods, and opportunities. *ACM Comput. Surv., 53*(5), 1–40. https://doi.org/10.1145/3395046. Article 109 (September 2020)pages. Retrieved July 20, 2021, from.