Factors Affecting Prosocial Sharing of Health-Related Information on Social Media during a Health Crisis: A Dual Exchanging-Protecting Model

Long Hoang Le
The School of Business, RMIT Vietnam, Ho Chi Minh City, Vietnam
long.le18@rmit.edu.vn

Ai-Phuong Hoang
The School of Business, RMIT Vietnam, Ho Chi Minh City, Vietnam

Hiep Cong Pham
The School of Business, RMIT Vietnam, Ho Chi Minh City, Vietnam

Abstract

During a health crisis, prosocial sharing of health-related information (HRI) on social media can help deliver early warnings about new diseases, raise social awareness, exchange support, and spread health policies. Current literature has mainly focused on the factors of general sharing of HRI under normal conditions but neglected those motivations under the health crisis context. This study aims to investigate factors that influence prosocial sharing of HRI on social media during a health crisis. To obtain the objective, this study proposes a dual exchanging-protecting model derived from the fear appeal model and social exchange theory. A partial least squares analysis, carried out on surveyed data of 326 participants, suggested that online users performed two steps of threat appraisal and coping appraisal when they share HRI on social media. Specifically, both health and information risks were found to have impacts on prosocial sharing via motivational factors. Additionally, the motivations of prosocial sharing include both protecting factors (i.e., sharing efficacy, response efficacy) and an exchanging factor (i.e., reciprocity expectation). Our findings offer several theoretical implications and practical contributions for health communicators.

Keywords: prosocial sharing, health information, health problems, information quality problems, health crisis.

1 Introduction

During a health crisis, health-related (e.g., physical illness and mental health issues) and information-related problems (e.g., information overload, information uncertainty, and misinformation) have posed a serious concern to public and governmental agencies alike. For example, popular mental and psychological issues during COVID-19 have been found, including fear, anxiety, and unsafety feelings under uncertain conditions (Usher et al., 2020). Psychological distress can emerge from misleading and overloaded information (Torales et al., 2020), social distancing, unemployment, caregiving stress, and impacts of death and illness (Sritharan & Sritharan, 2020). The Director-General of the World Health Organisation, Tedros Adhanom Ghebreyesus recently emphasised that: "We are not just fighting an epidemic; we're fighting an infodemic" (World Health Organisation, 2020).

Sharing health-related information (HRI) on social media can either reduce or worsen the problems. On the one hand, sharing messages about a health promotion campaign on social media can help to enhance people's awareness about the disease, address the problems of low health literacy, or connect people with similar health concerns (Berry et al., 2017; Kye et al., 2019). Recognising the advantage of social media in health promotion and advertising, over half of the public health departments in the United States adopted social media for their campaigns (Thackeray et al., 2012). Similarly, in China, healthcare knowledge is encouraged to be shared via social networks to enhance the health literacy of online users (Zhao et al., 2020). Another worthy note is that social media can change the way HRI and healthcare advice is shared. Traditionally, sharing healthcare advice has a one-way direction from health professionals to patients. The availability of social media helps online users to exchange HRI and obtain healthcare advice not only from healthcare providers but also from other peer users – which enables "the future of mental healthcare", so-called peer-to-peer healthcare (Naslund et al., 2016; Zhao et al., 2021). On the other hand, online sharing of HRI can cause several negative problems for online users. Specifically, sharing misinformation about health on social media might cause unfavourable effects on both individuals and society. For example, sharing inaccurate health treatments can lead to wrong decisions of parents and even to children's deaths, and financial losses for society (Chen et al., 2018). Social media can translate a health crisis into a severe social crisis when spreading extensive information publicly and rapidly across communities (Kilgo et al., 2018). In a worsening situation, social media and online interactions can also fuel such information-sharing problems by transmitting misinformation and negative emotions (e.g., Chen et al., 2018).

This study focuses on *prosocial sharing of HRI* on social media during a health crisis with the belief that this behaviour can help to reduce both health and information risks aroused from the crisis. As stated above, sharing misinformation, or even sharing information "without much thought" (Marin, 2021) might even worsen a health crisis. Meanwhile, promoting online prosocial sharing of HRI, which refers to a voluntary activity that aims to help others rather than oneself and without reward anticipation (Leng et al., 2020), can provide more qualified information about the disease and health of the community.

A review of the literature on online sharing of HRI revealed several knowledge gaps. First, current literature has not differentiated domains of sharing behaviour, for example, sharing without much thought (Marin, 2021) from prosocial sharing (Dunfield, 2014). While sharing without much thought might stimulate the problems of misinformation and information overload (Marin, 2021), prosocial sharing can reduce the likelihood of sharing misinformation since online users need to consider it carefully before performing the sharing action. Specifically, sharing HRI on social media can be considered a coping strategy for psychological stress during a health crisis, such as during COVID-19 (Le et al., 2022). Lacking behavioural differentiation might reduce the understanding of contributing factors to each behaviour.

Second, during a health crisis, both health-related problems and information quality problems become a serious concern, which typically causes fear among communities (Usher et al., 2020). Under such fear of pressure, many people are likely to share extensive information on social media. Nevertheless, few studies have considered fear-aroused factors when examining the motivations for sharing HRI.

Finally, there is a lack of a theoretical framework to explain HRI-sharing behaviour during a health crisis. The popular theories used in the literature on HRI sharing (e.g., social exchange theory, social support theory) and online prosocial sharing (e.g., altruism, cognitive development, affective-driven motivations) are not sufficient to justify sharing behaviour during critical events. The motivations and mechanisms underlying prosocial behaviour have been emphasised to be difficult to investigate (Dunfield, 2014; Eisenberg, 2014) because of its various dimensions, contextual dependence, and diverse theoretical justifications. Consequently, heretofore, "although the motivation for performing prosocial actions is critical, it is often unknown" (Eisenberg, 2014).

This research aims to identify motivating factors of prosocial HRI sharing on social media in a health crisis. Specifically, this study sets to answer two research questions: (i) What factors motivate online users' prosocial sharing of HRI on social media during a health crisis?, and (ii) How do health- and information-related risks, and motivational factors affect prosocial sharing of HRI on social media during a health crisis?

The next section reviews the relevant literature about problems aroused by a health crisis and online prosocial sharing. After that, the research model and hypotheses are postulated. The method section presents the measures, sampling, and analysis techniques. In the subsequent section, data analysis and findings are reported. Finally, we discuss the results and conclude the study.

2 Literature review

2.1 Health- and information-related problems during a health crisis

A crisis is defined as "an unusual event of overwhelmingly negative significance, that carries a high level of risk, harm, and opportunity for further loss" (Seeger et al., 2003, p. 4). Gaspar et al. (2016, p. 180) provided a more specific definition of a crisis, which is the situation when "potentially stressful events associated with the emergence of health threats (e.g., epidemics, biological and chemical contamination of food), terrorist attacks, natural disasters (e.g., hurricanes, floods), industrial accidents (e.g., nuclear) or even events related with macroeconomic changes" take place. Generally, different types of crises share several similar characteristics, including the low probability of occurrence, severe negative damages and loss, informational uncertainty, and community negative emotions. A health crisis, a specific type of social crisis, has several distinctions. Health crises can be derived from natural sources such as a disease (Kilgo et al., 2018), and/or social-related sources such as cultural and political factors (Campos et al., 2006). Health crises typically put high pressure on the healthcare system and stimulate fear in the community. In the social media decade, a health crisis can be translated into a severe crisis when it is spread publicly and rapidly (Kilgo et al., 2018). Public communication under a health crisis, accordingly, might deal with both health- and information-related problems.

Literature on health crises indicates that a health crisis can cause serious harm to both physical and mental health (Bonanno et al., 2010). For example, Shanbehzadeh et al. (2021) indicate that COVID-19 patients have commonly suffered physical health problems of fatigue, pain, arthralgia, physical capacity diminishing, and negative impacts on daily activities. Besides the physical issues, psychological issues were discovered, such as fear, anxiety, and unsafety feelings (Usher et al., 2020). Especially, psychological distress can be emerged from the disease relevance such as impacts of death and illness and caregiving stress (Sritharan & Sritharan, 2020), and misinformation (Torales et al., 2020). In another example, during the Ebola outbreak in 2014, many Americans were reported to have psychological distress and perceived a high risk of the African pandemic to their health in the future (Thompson et al., 2017). In Chinese rural areas, the spread of several pandemic diseases such as HIV/AIDS and Avian Flu caused major issues in the mortality and death rates for over a decade (Dummer & Cook, 2007).

Besides the health threats, information problems also soar during a health crisis. In the early stage of a crisis, the lack of relevant information might cause information uncertainty, whereas, in the later stage of the crisis, people typically deal with information overload and poor information quality. Information overload refers to a situation when the amount of information is large and surpasses the cognitive capacity of individuals (Bawden & Robinson, 2009). Information quality refers to "the degree to which individuals believe that the health information obtained from the online environment is high quality" (Liang et al., 2017, p. 436). The characteristics of information quality include accuracy, completeness, currency, and transparency (Liang et al., 2017). In general, the quality of HRI received from online sources was found to be poor quality, i.e., inadequate, incomplete, and source ambiguity (Sudau et al., 2014).

2.2 Social media usage during a health crisis

Social media usage in health crisis communication has recently received increased attention. A study by the OECD indicated that: "social media can enhance risk and crisis communication in several ways: (1) they are collaborative and participatory and thus can improve situation awareness, (2) they are decentralized, thus, information can circulate quickly, and (3) they are geographically traceable and thus allow for the monitoring of a crisis" (OECD, 2015, p. 78). OECD also classified five types of social media used in health communication during a health crisis, including (1) social network sites, (2) content-sharing platforms, (3) collaborating knowledge-sharing platforms, (4) blogs and micro-blogs, and (5) crisis management platforms (OECD, 2015, p. 78). These platforms can be used differently in managing crisis communication. For example, social network sites are used for sharing information across site communities, whereas, crisis management platforms are employed to map and update emergency responses.

However, the actual use of social media in dealing with health communication problems remains unclear. Theoretically, online discussions and social media engagement can be among several effective measures that mitigate the impacts of mental and psychological issues (Sritharan & Sritharan, 2020; Torales et al., 2020). However, social media and online information sharing can turn a health crisis into a severe social crisis since the crisis can spread quickly without proper verification across communities (Kilgo et al., 2018). Albarracin and Jung (2021) pointed out that studies on information dissemination during COVID-19 need to be specific because different online contents can change the attitude and behaviour of online users accordingly.

2.3 Prosocial sharing of health-related information on social media

Staub (1978, p. 89) referred to prosocial as "behaviour that benefits the self as well as others, such as cooperation, and positive acts that are part of a person's attempts to initiate a relationship with another person or are aspects of an ongoing relationship" and "demands some form of self-sacrifice from the actor". Another relevant term, altruism, was used for a more restrictive situation when people carry out activities with the apparent goal of benefiting others more than themselves (Underwood & Moore, 1982, p. 27). Other studies also recognised prosocial behaviour as voluntary behaviour intended to benefit others (Eisenberg, 2014; Eisenberg et al., 2006), while altruism is considered a subtype of prosocial behaviour (Eisenberg, 1982; Eisenberg, 2014).

Online prosocial sharing of HRI is an extension of face-to-face prosocial behaviour (Wright & Li, 2011). It is part of the three main domains of online prosocial behaviour: online donation, online sharing, and online comfort (Leng et al., 2020; Sproull, 2011). Leng et al. (2020) pointed out that online prosocial behaviour differs from face-to-face prosocial behaviour in terms of lower cost, anonymity, and less social pressure. Prosocial HRI sharing might require further efforts of information verification before sharing. Information verification, or validating information quality before sharing (Flanagin & Metzger, 2000) becomes crucial when people share information to help the community.

Even though understanding the underlying mechanisms of prosocial behaviour can offer profound implications (Donald et al., 2019), we have yet to understand the factors motivating prosocial action. There are several possible reasons leading to this under-researched situation. The extensive types of prosocial sharing and diverse contexts can be one of the reasons that the motivations of prosocial sharing are difficult to investigate (Eisenberg, 2014; Eisenberg & Spinrad, 2014). For example, spontaneously prosocial behaviours (e.g., prosocial sharing) are costly, whereas response prosocial behaviours such as cheering others are at low cost. Prior studies suggest that prosocial behaviour is motivated by altruism rather than personal self-reward (Eisenberg et al., 2006); however, in many situations, prosocial behaviour can be non-altruism motivated but following norms, and/or because of expectation of self-reputation (Donald et al., 2019). The development of prosocial behaviour can be an outcome of cognitive development or socialisation, affective motivations (e.g., empathy), and moral reasoning (Eisenberg, 1982). Additionally, the evaluation of motivations for prosocial behaviour is difficult because the development of prosocial behaviour can be influenced by either individual traits or universal aspects (Dunfield, 2014; Eisenberg & Spinrad, 2014).

We thus discover several research gaps through our literature review. First, as stated above, although the motivations for performing prosocial behaviour are crucial, there is still a lack of understanding of those motivations (Eisenberg & Spinrad, 2014). The various types of prosocial behaviour and contextual dependence on the behaviour have challenged researchers to put their effort into this topic. Second, given health- and information-related risks emerge during health crises, how they can affect online users' sharing behaviour is still an uncovered question. Finally, online prosocial sharing of HRI during a health crisis requires knowledge in several research areas such as prosocial behaviour, online information sharing, and health crisis communication. The use of a single theory (e.g., social exchange theory, altruism theory) is not sufficient to explain the mechanisms underlying the behaviour.

To fill these gaps, this study develops a model by integrating social exchange theory (SET) and the fear appeal model (FAM) to justify the antecedent factors of prosocial sharing of HRI on social media during a health crisis. The following sections present the our theoretical foundation of our research.

2.4 Social exchange theory

SET has been used widely to understand the behaviour of information and knowledge exchange on virtual platforms (Yan et al., 2016). Originally, SET stated that human behaviour can be considered as the outcome of a cost/benefit calculation, or maximising the benefits and minimising the costs (Emerson, 1976). Under the assumption of rationality, SET can be applied in various contexts, from the market base to the social base (Blau, 1964). Additionally, the straightforward approach to the reciprocity process, e.g. provide help and expect to receive back, can be used widely to develop conceptual frameworks (Cropanzano et al., 2017;

Cropanzano & Mitchell, 2005). For example, extensive past studies adopted SET in the research on online knowledge and information sharing in a normal routine (Jin et al., 2010; Lin & Chang, 2018; Yan & Tan, 2014; Yan et al., 2016). However, given its broad conceptual framework, SET showed limitations when being applied to justify individuals' behaviour during a critical situation (Cook et al., 2013; Cropanzano et al., 2017). First, as a broad framework, SET did not specify the factors that affect the behaviour, and additionally, the subsequent explanations of behaviourd offered by SET might be too general and imprecise (Cropanzano et al., 2017). Second, the rationality assumption of SET suggested that people would make "conscious choices based upon self-interest deliberation before taking action" (Cook et al., 2013, page 340). However, in the context of human interaction, the assumption might not be valid as people might not always perform prior calculations of returns before acting (Cook et al., 2013). Rationality would not hold when examining prosocial behaviour, which is a voluntary action motivated by the benefit for others. Finally, given the great increase in information demand during a health crisis (Dreisiebner et al., 2020), SET might be not sufficient to explain the sharing behaviour in such a critical event. In other words, SET in its original was not developed to explain sharing behaviour in crises.

Maslow's basic need theory specifies four levels of basic needs, including physiological, safety, love and belongingness, esteem, and self-actualisation (Maslow, 1954). During a health crisis, the need for physiological, safety, and love and belonging become more salient than the top two higher levels of need (i.e., esteem and self-actualisation) (Ryan et al., 2020; Yuen et al., 2021). In this situation, prosocial sharing behaviour might be motivated by protecting factors and community benefit expectations. SET is limited in addressing what motivational factors are incorporated to explain prosocial sharing during a health crisis and how they influence an individual's behaviour. We thus included Maslow's complementary theory of basic needs in our application of SET as the foundation for exploring the impacts of fear-aroused motivations on prosocial sharing.

2.5 The Fear appeal model

Fear appeal models describes the mechanism and changes in people's behaviour under a fear stimulus (Witte, 1992). Johnston and Warkentin (2010) recently developed a fear appeal model (FAM) in the information security and management context. Mainly based on protection motivation theory, their FAM suggests a sophisticated relationships among the cognitive processes of the users of information technologies, in particular in information management and security contexts. Specifically, while protection motivation theory did not specify how threat appraisal and coping appraisal jointly influence the change in human behaviour (Witte, 1992), the FAM suggests a sequential impact amounts process, as "only if a threat is perceived to be relevant and potentially harmful will an appraisal of efficacy occur." (Johnston & Warkentin, 2010, p. 552). In other words, the change in online and information technologies users' behaviour is influenced by two sequential processes, threat appraisal and coping appraisal.

Threat appraisal includes perceived threat severity and perceived threat vulnerability (Johnston & Warkentin, 2010; Rogers, 1983). Witte (1992, p. 332) defined perceived severity as "an individual's beliefs about the seriousness of the threat", whereas perceived vulnerability, or perceived susceptibility, is "an individual's beliefs about his or her chances of experiencing the threat". The FAM indicates that both threat severity and threat vulnerability might influence behavioural change but in distant relationships rather than direct relationships

(Johnston & Warkentin, 2010). Coping appraisal, or evaluation of the ability of adaptive response (i.e., sharing behaviour), includes the cognitive calculus between response efficacy and self-efficacy (Floyd et al., 2000; Rogers, 1983). Response efficacy refers to "the belief that the adaptive response will work, that taking the protective action will be effective in protecting the self or others" (Floyd et al., 2000, p. 411). Self-efficacy refers to the belief of an individual to be capable or not performing the response (Bandura, 1977; Rogers, 1983). The FAM suggests that response efficacy and self-efficacy have positive effects on adaptive behaviour, whereas response costs (i.e., information verification cost) negatively affect adaptive behaviour (Rogers, 1983). Bandura (1977) emphasised that adaptive behaviour can be enabled once people perceive its coping effectiveness and their ability to implement it. Therefore, sharing efficacy and self-efficacy possibly have direct impacts on sharing activity.

The next section presents the research model and hypotheses.

3 Research model and hypotheses

3.1 The threat appraisal process: impacts of health risk and information quality risk

Online users might perceive threats in a crisis from two main sources: health risk (i.e., from a disease) and information risk. A health crisis typically has a low probability of occurrence but can cause severe outcomes and overload in the healthcare system, people's lives, and psychological stress. Within the fear aroused from a health crisis, people can perceive health risk and information quality risk. This study, therefore, conceptualises two main perceived threats including *perceived health risk* and *perceived information quality risk*, which can jointly cause problems for the community.

During a crisis, people perceive a higher risk for their and others' health, especially in terms of severity and vulnerability. Perceived severity relates to the perception of the degree of damage and loss caused by the health crisis, whereas perceived vulnerability involves the high probability of being infected. Compared to a regular disease (e.g., seasonal flu), a health crisis is typically accompanied by a new, serious, and infectious disease, which causes perceived severity and perceived vulnerability to people's health.

Information quality risk is another threat to people during a health crisis. Information quality risk might include multiple dimensions, for example, (information) shortage, inaccuracy, incompleteness, irrelevance, and unreliability (Nicolaou & McKnight, 2006). These problems can be rooted in newly discovered diseases (e.g., new variants, new symptoms, and new treatment methods) or spreading unverified information. Numerous past studies investigated the occurrence of information quality problems during past health crises, for example, misinformation, information uncertainty, and information overload during the global Zika outbreak (Bode & Vraga, 2018; Kilgo et al., 2018), and the COVID-19 pandemic (Apuke & Omar, 2021; Cuan-Baltazar et al., 2020; Laato et al., 2020). User perception of information quality risk was found to have significant impacts on users' mental health, attitudes toward health campaigns, and information-sharing behaviour. Specifically, Laato et al. (2020) investigated the positive effects of this perception on cyberchondria and unverified information-sharing behaviours. Additionally, Soroya et al. (2021) discovered that information overload and excessive information can cause information anxiety, and consequent information avoidance activities. Featherstone and Zhang (2020) discovered that perceived information quality risk can facilitate users' negative emotions and attitudes towards vaccination.

Whatever types of problems they have, the more severe threats people perceive, the more they carry out responses (i.e., sharing of information that they perceive to be of good quality) to protect themselves and other people. When online users perceive higher risks from health and information, they will more likely expect that their information sharing will help to reduce the risks. The following hypotheses are put forward:

H1a. Online users who perceive higher health risk will perceive higher response efficacy.

H2a. Online users who perceive higher information quality risk will perceive higher response efficacy.

Regarding the impacts of risk perceptions on sharing self-efficacy, different types of risk might have different effects. The emergency of a health crisis can force people to update disease information and acquire knowledge to protect themselves and others (Laato et al., 2020). Social media provides an interactive environment, which not only helps online users to update new information but also to share personal experiences and health conditions (OECD, 2015). During a health crisis, when other face-to-face communication types might be limited, online users tend to use social media more frequently to connect with others, which also helps them to improve their social media sharing capability. However, the use of social media for information sharing might lead to information overload and quality issues because of a large volume of unstructured information pushed on social media in a short time. Consequently, information quality risk might have a different impact on self-efficacy. The model of information behaviour by Wilson (1999) suggested that the information quality risk can influence online users' self-efficacy, or their conviction to successfully share information to help others. Accordingly, the next two hypotheses, postulate:

H1b. Online users who perceive higher health risk to others will perceive higher sharing self-efficacy.

H2b. Online users who perceive higher information quality risk to others will perceive lower sharing self-efficacy.

Reciprocity, grounded in SET, refers to "actions that are contingent on rewarding reactions from others and that cease when these expected reactions are not forthcoming" (Blau, 1964, p. 6). Another worthy argument is that when online users perceive high health risk and information quality risk, expectations of reciprocity will increase. Yang, (2016) \ found that under high-risk conditions such as a health crisis, systematic processing becomes more salient compared to the heuristic system. Consequently, when people perceive higher risks, they are willing to provide prosocial activities to help other people (Yang, 2016). The risks under a health crisis are significantly greater than those during the normal routine, which means, online users might perceive a higher threat from health risk and information quality risk to both them and others. When they consider online sharing of HRI over social media as a coping method to reduce the risks, they are likely to interact more frequently on social media to exchange information. In other words, online users share quality information with a higher expectation of receiving quality information in the future as reciprocity. These arguments can be hypothesised as follows:

H1c. Online users who perceive higher health risk to others will perceive higher reciprocity expectations.

H2c. Online users who perceive higher information quality risk to others will perceive higher reciprocity expectations.

3.2 Exchanging motivations for online prosocial sharing

Online users typically assess benefits (i.e., reciprocity) and costs (i.e., information verification effort and operational costs) before the actual sharing activity (Yan et al., 2016). Sproull (2011) indicated that people are willing to help others once they receive support in the past, or anticipate support in the future. SET explains that people share information online with an expectation of mutual reciprocity (Chiu et al., 2006). Reciprocity was identified as a driver of sharing information and knowledge online (Singh et al., 2018; Yan & Tan, 2014). During the uncertain situation of a health crisis, people share HRI over social media to inform and help others. Moreover, they typically also expect to receive reciprocal information from others. Therefore, it is hypothesised that the expected reciprocity will have a positive effect on sharing behaviour.

H3. Perceived reciprocity positively influences the likelihood of prosocial sharing HRI on social media during a health crisis.

The costs of prosocial sharing of HRI can include operational cost (i.e., cost of the sharing process) and cognitive cost (i.e., verification cost) (Yan et al., 2016). As stated above, online prosocial sharing can be done at low operational costs (Leng et al., 2020). Since social media performs explicit functions for users to share information conveniently (Le et al., 2022), the sharing execution might be less costly. However, information verification effort, including time and energy spent on checking information accuracy (Fallis, 2004), might be costly during a health crisis when online users have to process overwhelming information from extensive sources. The verification cost can differ across situational conditions and users' capabilities (Fallis, 2004). Information verification is complex and uncertain, i.e., being at risk of accepting false information even after checking it (Lazer et al., 2018). However, whether the verification is successful or not, the effort of information verification can imply the responsibility of the information senders, accompanied by their prosocial sharing goals. SET indicates that online users analyse the benefits and costs before taking the action, or specifically, if the verification cost becomes higher, or even impossible in some situations, the likelihood of information sharing will decrease. Hypothesis 4 is posited as follows:

H4. Perceived information verification costs negatively influence the likelihood of prosocial sharing HRI on social media during a health crisis.

3.3 Protecting motivations for online prosocial sharing

Since there are extensive ways to verify online information (Flanagin & Metzger, 2000), the verification cost highly depends on the verifying skill of online users. Literature on information verification behaviour indicates that information verification behaviour is highly associated with personal information literacy (Jones-Jang et al., 2021), and perceived self-efficacy (Khan & Idris, 2019). In line with these past studies, this research argues that online users who perceive higher sharing self-efficacy are likely to have higher skills in checking information quality, and therefore, take less time and energy in the verification process. The hypothesis relates to the negative relationship between self-efficacy and verification cost is presented as follows:

H5. Online users who perceive higher sharing self-efficacy will have a lower cost of information verification.

In this study, prosocial sharing of HRI over social media is considered as the adaptive response to the fear aroused by a health crisis. The FAM suggests a two-stage process (i.e., threat appraisal and coping appraisal) to explain why people implement an adaptive response when facing fear (Johnston & Warkentin, 2010; Rogers, 1983; Witte, 1992). In the second phase of coping appraisal, when people think that their behaviour can help to resolve the problem, they are willing to act. In this study, after the first stage of health risk and information quality risk evaluations, online users carry out the second stage of examining their online sharing action. In this stage, online users might make evaluations in three aspects: (i) to assess the effectiveness of their sharing action (i.e., prosocial sharing efficacy); (ii) to assess their ability to share information on social media (i.e., sharing self-efficacy); and (iii) to assess the costs of sharing (i.e., mainly involving the information verification cost). The possible negative impact of information verification costs has been rationalised and proposed in the above hypothesis H4.

This section focuses on the role of prosocial sharing efficacy and sharing self-efficacy on prosocial sharing behaviour. Following the explanation of the FAM, when online users expect that their sharing action can help to reduce the risks aroused by a health crisis, they are likely to share HRI on social media. Regarding sharing self-efficacy, online users also consider their ability to share information, which significantly relies on four sources: mastery experiences, vicarious experience, persuasiveness, and emotion (Bandura, 1977). In general, a social media platform can provide extensive functions for information sharing, for example, Facebook has the 'share', 'like', 'tag', 'hashtag', and 'copy/paste' functions, which are appropriate for different community ranges. Additionally, social media has been considered a public environment (Barak et al., 2008), where people can share HRI across platforms to different targets and even repeatedly look at their sharing experience (e.g., Facebook's 'memories' function), indicating mastery experiences. Online users can observe HRI sharing actions from others on social media, indicating vicarious experiences. Regarding persuasiveness and emotional arousal, social media users are encouraged by the platforms and others to share information. For example, Facebook users who share HRI on social media can receive comments and/or emoticon reactions such as 'like', 'love', and 'care'. Online users might consider these sources of prosocial sharing self-efficacy and their capability to share before taking action. Accordingly, this study proposes that online users who perceive higher prosocial sharing self-efficacy are willing to perform a sharing action.

In addition to the viewpoint of the FAM, the moral behaviour manner can be considered since prosocial sharing is highly associated with altruism and morality (Eisenberg, 2014; Eisenberg et al., 2006; Krebs, 1982). A study by Marin (2021, p. 7) stated three conditions of moral responsibility: "a causal connection between the agent's actions and an outcome, the agent's knowledge of the consequences, and the agent's freedom to act". Accordingly, a prosocial sharing action of HRI can be implemented as a moral responsibility when online users perceive: (i) sharing effectiveness; (ii) their knowledge and value contribution by an information-verifying process; and (iii) sharing cost (i.e., mainly involving information verification cost). Before sharing HRI over social media, people evaluate the efficacy of the sharing and their capability of sharing and compare them with the costs of sharing. As argued above, sharing qualified information over social media can be one of the best measures to reduce information uncertainty and alleviate health illiteracy; therefore, if people are confident about the effectiveness of sharing information and their ability to perform sharing, the likelihood of sharing behaviour will increase. Therefore, the related hypotheses are presented as follows:

H6. Online users who perceive higher response efficacy will have a higher likelihood of prosocial sharing of HRI on social media during a health crisis.

H7. Online users who perceive higher sharing self-efficacy will have a higher likelihood of prosocial sharing of HRI on social media during a health crisis.

Figure 1 presents the conceptual framework for this research.

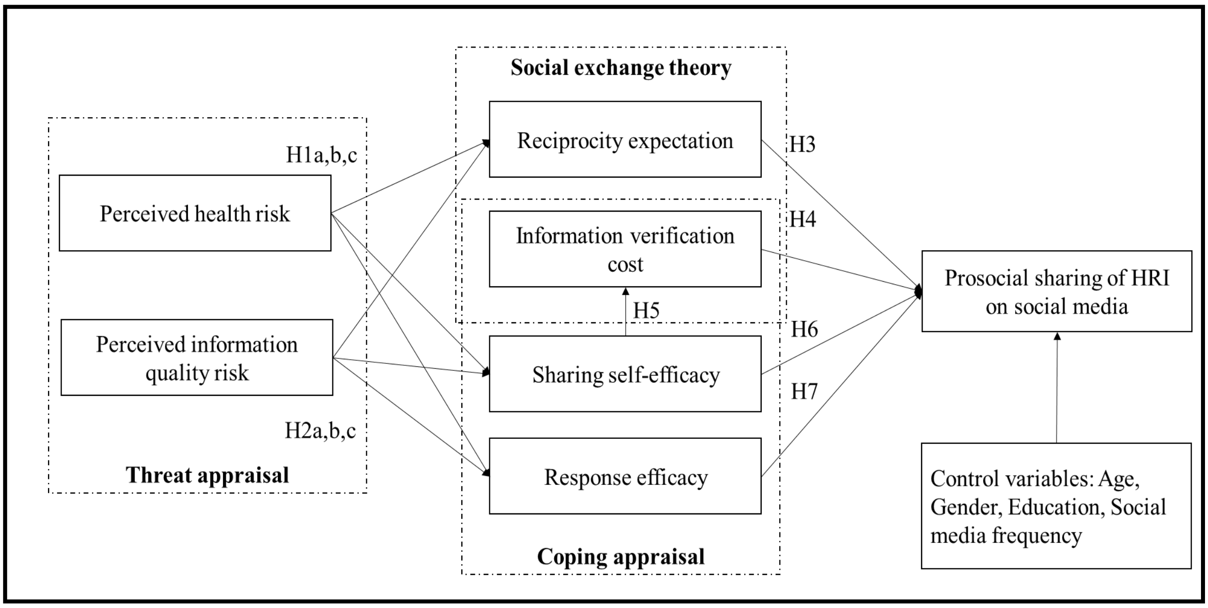

Figure 1. Dual-motivation model of sharing HRI on social media during a health crisis

4 Method

This study follows the positivist paradigm and applies deductive reasoning. The conceptual framework and hypotheses are deducted from two theoretical bases (SET and the FAM). The hypothesis testing was carried out via an online survey instrument and quantitative data analysis.

4.1 Measures

We first reviewed the construct definitions and their measurements in the literature. To warrant the validity of the scale, the question items were adapted from previous studies, i.e., prosocial sharing from Wright and Li (2011) (e.g., “share good information related to health”, “share HRI to help”, “share HRI to cheer someone up”, “share HRI to let someone know I care about them”), reciprocity expectation from Singh et al. (2018), perceived severity, perceived vulnerability, response efficacy, sharing self-efficacy, and response costs from Menard et al. (2017) and Johnston and Warkentin (2010), perceived information quality risk (i.e., measured in five dimensions of timeliness, accuracy, relevance, completeness, and reliability) from Nicolaou and McKnight (2006). The measurements were adapted by adding the social media context and the context of a health crisis. A pilot survey was carried out to examine the face and content validity. Most of the constructs were measured reflectively, whereas perceived health risk was formative with two components of perceived severity (i.e., magnitude) and perceived vulnerability (i.e., likelihood). All items were measured on the Likert scale. Specifically, for the sharing behaviour items, the likelihood scale was adopted (1 = "extremely unlikely" to 7 = "extremely likely"), whereas, for the motivation items, the agreement scale was adopted (1 = "strongly disagree" to 5 = "strongly agree").

Concepts	Measurement items
Prosocial sharing of HRI	Adapted from Wright and Li (2011): 1. During health crises, I share good information related to health on social media. 2. During health crises, I share health-related information on social media to help others. 3. During health crises, I share health-related information on social media to cheer someone up. 4. During health crises, I share health-related information on social media to let someone know I care about them.
Perceived health risk	***Perceived severity*** (Adapted from Menard et al. (2017)): 1. It would be severe if I and people around me were infected. 2. It would be serious if I and people around me were infected. 3. It would be significant if I and people around me were infected. ***Perceived vulnerability*** (Menard et al. 2017; Johnston and Warkentin 2010; Hodgkins and Orbell 1998): 1. I and people around me are at risk of becoming infected with the pandemic disease. 2. It is likely that I and people around me will become infected with the pandemic disease. 3. It is possible that I and people around me will become infected with the pandemic disease. *4. My chances of being infected with the pandemic disease in the future are very low. (* reversed)*
Perceived information quality risk	Adapted from Nicolaou and McKnight (2006): 1. The information exchanged during health crises is currently not enough to meet my needs. (timeliness) 2. There are accuracy problems in the information exchanged during health crises (accuracy) 3. The information exchanged during health crises is not as what I need. (relevance) 4. The information exchanged during health crises is not complete. (completeness) 5. The information exchanged during health crises can hardly be relied upon. (reliability)
Prosocial sharing efficacy	Adapted from Johnston and Warkentin (2010) and Hodgkins and Orbell (1998): 1. Sharing health-related information through social media works for protection. 2. Sharing health-related information through social media is effective for protection. 3. When sharing health-related information through social media, people are more likely to be protected. 4. If I share health-related information through social media, I would ensure the early detection of any abnormalities.
Sharing self-efficacy	Adapted from Johnston and Warkentin (2010): 1. Sharing health-related information through social media is easy. 2. Sharing health-related information through social media is convenient. 3. I am able to share health-related information through social media without much effort.
Information verification cost	Adapted from Menard et al. (2017): 1. Verifying health-related information is time-consuming for me. 2. Verifying health-related information is burdensome for me. 3. Verifying health-related information is financially costly for me. 4. Verifying health-related information would require too much from me. 5. Verifying health-related information is not worth it.
Reciprocity expectation	Adapted from Singh et al. (2018), Bock et al. (2005): 1. Sharing health-related information through social media would make me visible to the world. 2. Sharing health-related information through social media would help me get acquainted with new people. 3. Sharing health-related information through social media will help me meet my future needs. 4. If I share health-related information through social media, I can get back when I need it.

Table 1. Construct measurements

4.2 Sample selection

The online questionnaire was composed by Qualtrics and delivered to respondents via Amazon Mechanical Turk (M-Turk), which has been previously validated as a platform where academics can employ respondents for their rigorous research (Steelman et al., 2014). Several criteria were settled: (i) the survey was to be carried out in English-native (as in officially recognised) speaking countries (i.e., U.S., U.K., Australia, Singapore, and Hong Kong), (ii) respondents must hold social media accounts, (iii) respondents must perceive the Covid-19 occurrence in their place during the survey time. The sample size had to be at least 300 respondents to warrant the "good quality" for both factor analysis and structural equation modelling (Hair et al., 2016). The respondents were paid a one-dollar compensation fee for their time. Several filtering questions were also set to determine whether the respondents understood the context of a health crisis.

In the pilot survey, 38 respondents were included to help refine the questionnaire. After the pilot survey, the content of several questions has been revised to be clearer and more specific. In the main survey, a total of 346 responses were received after two weeks, in the preriod from July 18th, 2021, to August 2nd, 2021. Among them, 20 respondents failed the reversed questions and were eliminated from the data analysis. The final sample included 326 respondents. The data descriptions are presented in Table 2.

Demographic Variables		Frequency (n = 326)	Percentage (%)
Gender	1-male	175	53.7
	2-female	151	46.3
Age	18-25	40	12.3
	26-33	103	31.6
	33-40	59	18.1
	Over 40	124	38.0
Education	Not graduated yet	48	14.7
	Bachelor's degree	202	62.0
	Post-graduate	76	23.3
Frequency of social media usage (hours/day)	Less than 2 hours	100	30.7
	2 - less than 4 hours	136	41.7
	4 - less than 6 hours	71	21.8
	6 hours or more	19	5.8

Table 2. Data descriptions

4.3 Data analysis technique

For the measurement model, confirmatory factor analysis was adopted to assess the construct's reliability and validity. For the path analysis, two types of structural equation models were considered, including covariance-based structural equation modelling (CB-SEM) and partial least squares structural equation modelling (PLS-SEM) (Hair et al., 2019). This study adopted the PLS-SEM because of three main reasons. First, while CB-SEM focuses on theory testing and theory confirmation, PLS-SEM is appropriate for predictive purposes (i.e., maximising the R^2 values) (Hair et al., 2019). The goal of this study is to adopt two theories to develop a conceptual framework including risk perceptions and motivational factors that predict prosocial sharing behaviour. Second, PLS-SEM can easily incorporate reflective and formative construct measurement models, whereas CB-SEM requires construct specification modifications to handle formative constructs (Hair et al., 2019). This study includes both reflective and formative constructs. Specifically, perceived health risk is a formative construct, which includes two dimensions of health severity (i.e., the magnitude of risks) and health vulnerability (i.e., the likelihood of risks). Finally, when CB-SEM requires the normality assumption, the data used in PLS-SEM can be non-normally distributed (Hair et al., 2019). Finally, this study focuses on the behaviour of online users during critical events such as emergencies and crises, therefore, data might hardly satisfy the normality assumption.

5 Research findings

5.1 Measurement model

The measurement model was evaluated via construct reliability and validity. The findings from Table 3 showed that all Cronbach's Alpha and Composite Reliability were larger than 0.7, and factor loadings were larger than 0.708, indicating good reliability and convergent validity (Hair et al., 2019).

To assess discriminant validity, we used Fornell and Larcker's criterion (see Table 4) and the Heterotrait-Monotrait ratio criterion (see Table 5) (Hair et al., 2019). All the square roots of AVEs were larger than the correlation than other inter-construct correlations. Additionally, the HTMT value is below 0.90 (except for the higher-order formative construct), and discriminant validity has been established (Henseler et al., 2015). Therefore the discriminant validity of the measurement was acceptable.

	No. of items	**Cronbach's Alpha**	**Composite Reliability**	**AVE**
Prosocial sharing	4	0.932	0.952	0.831
Reciprocity expectation	4	0.839	0.892	0.674
Info. verification cost	4	0.874	0.900	0.646
Response efficacy	4	0.849	0.899	0.689
Sharing self-efficacy	3	0.731	0.848	0.650
Disease severity	3	0.772	0.868	0.687
Disease vulnerability	3	0.699	0.833	0.624
Perceived info. qual. risk	3	0.775	0.863	0.678

Table 3. Construct reliability

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Disease severity (1)	**0.829**							
Disease vulnerability (2)	0.484	**0.790**						
Info. verification cost (3)	0.031	0.248	**0.804**					
Perceived info. qual. risk (4)	-0.017	0.146	0.566	**0.823**				
Prosocial sharing (5)	0.282	0.297	0.276	0.198	**0.911**			
Reciprocity expectation (6)	0.241	0.301	0.462	0.363	0.639	**0.821**		
Response efficacy (7)	0.231	0.305	0.279	0.124	0.674	0.647	**0.830**	
Sharing self-efficacy (8)	0.311	0.269	-0.154	-0.131	0.269	0.170	0.310	**0.806**

Table 4. Construct correlation

Note. Bold numbers on the diagonal are the square root of the AVE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prosocial sharing (1)								
Reciprocity expectation (2)	0.720							
Info. verification cost (3)	0.287	0.517						
Sharing self-efficacy (4)	0.321	0.225	0.173					
Response efficacy (5)	0.757	0.764	0.300	0.390				
Perceived info. qual. risk (6)	0.212	0.423	0.685	0.170	0.143			
Perceived health risk (7)	0.394	0.390	0.209	0.445	0.381	0.149		
Severity (8)	0.332	0.300	0.067	0.415	0.284	0.046	*1.113**	
Vulnerability (9)	0.372	0.400	0.318	0.376	0.400	0.229	*1.150**	0.656

Table 5. HTMT for discriminant assessment
Note: * severity and vulnerability were the sub-construct of perceived health risk

5.2 Structural model

The structural model was evaluated via instructions of Hair et al. (2019), the structural analysis included collinearity examination, R-squared value assessment for explanatory power, f-squared for the effect size evaluation, Q-squared for predictive accuracy, and path coefficients for hypothesis testing. All the Variance Inflation Factors (VIF) were less than 5, representing no multicollinearity issue. The R-squared value equals 0.56, indicating that 56% of the variance of prosocial sharing can be explained by the research model. The blindfolding procedure from SmartPLS 3.0 performed that the Q2 value of prosocial sharing was 0.460, indicating a medium predictive relevance of the PLS-path model (Hair et al., 2019).

Hypotheses		**f^2**	**Beta**	**T-value**	**Conclusions**
H1a	Perceived health risk → Response efficacy	0.102^{small}	0.303***	4.801	Supported
H1b	Perceived health risk → Sharing self-efficacy	0.140^{small}	0.349***	5.360	Supported
H1c	Perceived health risk → Reciprocity	0.107^{small}	0.290***	4.603	Supported
H2a	Perceived info. qual. risk → Response efficacy	0.011	0.101*	2.012	Supported
H2b	Perceived info. qual. risk → Sharing self-efficacy	0.028^{small}	-0.156**	3.058	Supported
H2c	Perceived info. qual. risk → Reciprocity	0.147^{small}	0.341***	6.986	Supported
H3	Reciprocity → Prosocial sharing	0.113^{small}	0.319***	3.917	Supported
H4	Info. verification cost → Prosocial sharing	0.000	-0.016^{ns}	0.345	Not supported
H5	Sharing self-efficacy → Info. verification cost	0.026^{small}	-0.158**	2.583	Supported
H6	Sharing self-efficacy → Prosocial sharing	0.019	0.102*	2.067	Supported
H7	Response efficacy → Prosocial sharing	0.195^{medium}	0.405***	5.415	Supported
Control	Age → Prosocial sharing	0.001	0.026^{ns}	0.662	*Not sig.*
Control	Education → Prosocial sharing	0.044^{small}	0.142**	3.039	***
Control	Gender → Prosocial sharing	0.004	0.044^{ns}	1.203	*Not sig.*
Control	Social media freq. → Prosocial sharing	0.018	0.099*	2.208	**

Table 6. Structural model results
*Significance level: ***p < 0.001, **p < 0.01, *p < 0.05; effect size f2: small (>0.02), medium (>0.15), large (>0.35)*

Table 6 provides the structural findings, including f^2 analysis and path coefficient results. Most of the hypotheses, except H2, are supported. Specifically, both perceived health risk and perceived information quality risk significantly influence motivational factors, which include both social exchange motivation (i.e., reciprocity) and protection motivations (i.e., self-efficacy and response efficacy). Additionally, these motivational factors were found to have significant impacts on prosocial sharing. Regarding the control variables, education and social media frequency were found to have significant impacts on prosocial sharing of HRI, whereas other demographic variables such as age and gender did not influence the prosocial sharing behaviour.

Figure 2 summarises the sturctural equation findings.

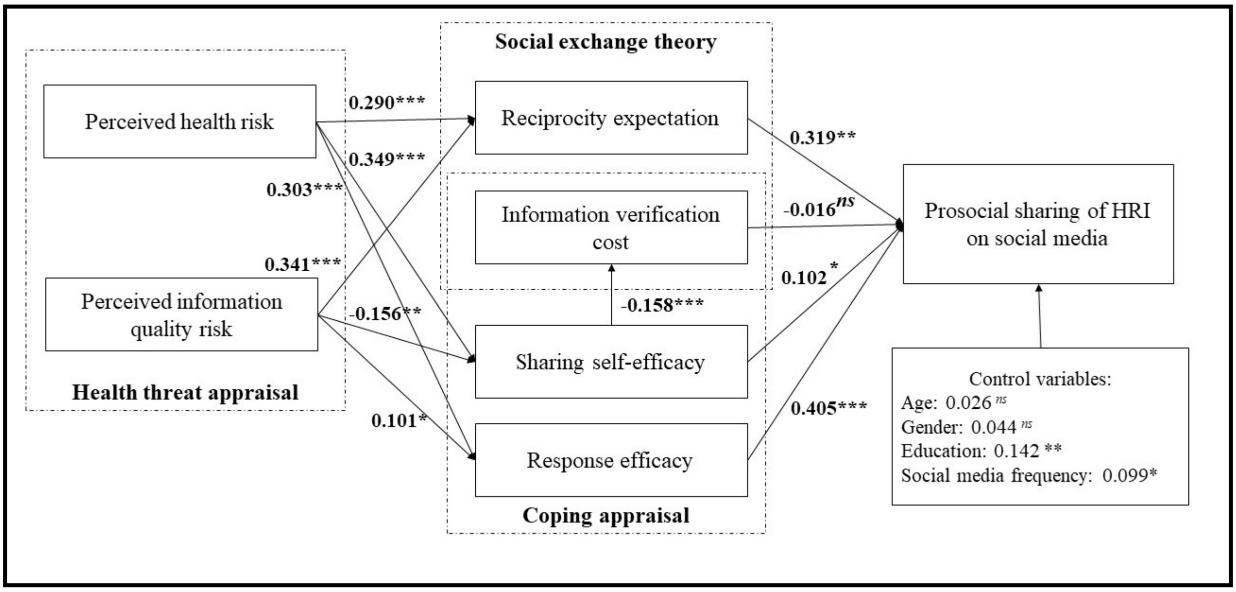

Figure 2. Structural equation findings

6 Discussion

This study aimed to identify factors affecting the prosocial sharing of HRI during a health crisis by integrating the SET and the FAM. While past studies have focused on either health risk (e.g., Kar et al., 2021; Sritharan & Sritharan, 2020) or information risk (e.g., Tully et al., 2020), our findings highlight that both health- and information-related risks have positive impacts on prosocial sharing via motivational factors.

The measurement findings indicate a higher health risk perception across online users in both formative dimensions ($mean_{severity}$ = 4.035, $median_{severity}$ = 4, $mean_{vulnerability}$ = 3.678, $median_{vulnerability}$ = 4, as measured by the 5-point scale). Our findings are in correspondence with past studies that also investigated increased human perceptions of crisis health risk, for example, the COVID-19 risk perception score ranged from 4.78 to 5.45 (over 7) across surveyed participants in ten countries in Dryhurst et al.'s (2020) study. Additionally, the factor analysis revealed that only three dimensions of timeliness, relevance, and reliability were reliable and valid to reflect perceived information quality risk. In other words, the survey participants evaluated that much information in a health crisis was typically outdated, irrelevant, and not reliable.

Regarding the motivational factors, during a health crisis, we found that online users behave both rationally and cognitively. Specifically, online users were likely to share information on social media with the expectation of getting reciprocal information and support from others. The sharing behaviour was also affected by fear-aroused factors, which means online users appeared to evaluate the crisis risks, followed by appraising the effectiveness of online prosocial sharing activities before taking the sharing action. The insignificance of the impact of information verification cost on sharing behaviour can be explained in two ways. First, the information verification might have been low-cost, so online users did not consider it. Second, online users might not care to verify online information before consuming it. This would be in line with past studies that found that online users shared online information on social media without verifying effort during a health crisis (see e.g. Laato et al., 2020).

6.1 Theoretical contributions

This study makes several theoretical contributions. The first contribution is the development of a conceptual framework to explain factors influencing online prosocial sharing of HRI during a health crisis. The research model was developed from two theoretical bases, SET and the FAM. The literature review indicated that although theories of prosocial sharing of HRI on social media theories are commonly applicable and effective in justifying the online sharing of HRI during the normal routine (Le et al., 2022), they are not sufficient to justify this behaviour during a health crisis. Information behaviour during a health crisis becomes greatly different compared to it under the normal routine (Dreisiebner et al., 2020; Soroya et al., 2021); consequently, additional factors need to be considered when explaining the higher frequency of sharing behaviour. This study advances the literature by incorporating the fear-aroused factor of the FAM into a research model (Li, 2021) based on SET. In this way, this study also extends the FAM by incorporating social exchange factors and applying the integrated model to explain prosocial communication during a health crisis. The research model furthermore offers contributions to the literature on health crisis communication. In particular, the findings provide theoretical implications along with the two types of risk perceptions (i.e., health risk and information quality risk), two types of motivational factors (social exchange factors and coping appraisal factors), and the process of prosocial sharing of HRI. The findings of this study will also respond to the call for research on an investigation of the psychological influences that affect users' information behaviour on social media during a health crisis (Mheidly & Fares, 2020).

Another theoretical contribution of significance is the differentiation between online sharing domains. Literature on sharing HRI on social media did not distinguish prosocial sharing from other sharing domains and, consequently, did not differentiate the perceptions and motivations behind HRI sharing. The extant literature focuses on examining factors of sharing misinformation (Alvarez-Galvez et al., 2021; Chen et al., 2018; Khan & Idris, 2019; Wang et al., 2019), and sharing information "without much thought" (Marin, 2021), and scholars have put little effort into identifying the antecedents of online prosocial sharing. The findings of this research can pave the way for further research in the future since each type of sharing domain accompanies different motivations and derives different consequences. With this differentiation, this study contributes to the literature on prosocial behaviour. It also addresses a research call by Eisenberg (2014) by discovering motivations and underlying mechanisms of a dimension of prosocial behaviour (i.e., online prosocial sharing) in a specific context (i.e., a health crisis). Specifically, this study proposes that under the negative impacts of a health crisis, people perform prosocial sharing actions with dual motivations, including information exchange and health protection.

6.2 Practical implications

The practical implications are also profound. First, this study confirms the common use of social media in sharing HRI during a health crisis. Given the wide spreadability of social media information, social media platforms enhance their use in sharing HRI during a health crisis. Specifically, the theoretical model validated in this study suggests that both health- and information risks can urge online users to share more information on social media. Additionally, the main motivations for sharing health information on social media include expectations of returning information and community protection. From these findings, social media companies can put further efforts into the feature of sharing HRI during health crises. For example, current pro-community features "crisis response" and "emotional health" on Facebook can be suggested directly to online users during health crises. Furthermore, Facebook can expand these features with further functions such as providing questions about information quality and sharing objectives, which might help to reduce the efforts of sharing non-validated information.

Second, although information problems during a health crisis have been emphasised recently by the World Health Organisation (World Health Organisation, 2020), this study is among the early studies providing scientific evidence that both health and information problems can jointly affect the evaluations and behaviours of online users. The findings of this research suggest that policymakers should not only focus on health problems but also include instruments to update and clarify information during their campaign to fight against a health crisis.

Finally, the identification of motivational factors can provide suggestions for health communicators to promote online users' prosocial sharing of HRI on social media during a health crisis, which helps to enhance disease awareness and reduce health risks. Regarding information problems during a health crisis, information problems might vary throughout a health crisis, for example, information shortage in the early stage, but information overload in the later stage. Understanding the sharing motivation can help to provide appropriate incentive/restrictive policies to harmonise the information volume across the crisis stages, and reduce the problems of misinformation and information overload (OECD, 2015). For example, to promote a health message (e.g., wearing masks during the COVID-19, drinking more water), health communicators can spread the message by emphasising the expected outcomes (i.e., sharing for receiving further information as exchange, sharing for protecting the community) and the efficacy of sharing (e.g., "sharing this message, a little activity but huge community support").

6.3 Limitations and future research

This study has several limitations. First, using the survey instrument, this study only captured the impacts of health and information risks and motivational factors on sharing behaviour at one particular point in time. Since health crises typically develop over a time period and users' behaviour changes continually during a health crisis, future process research should track the sharing behaviour of online users for a longer time to better understand both the users' motivations and the changes. Second, online behaviour might differ across personal traits and cultural values (e.g., Le & Duong, 2020). Future research should extend this argument by investigating the differences in online sharing engagement of online users from different cultural (including language) backgrounds. Finally, this study's findings indicated the significant impacts of education and social media use frequency on prosocial sharing. Future research should explore further these impacts, especially the roles of health literacy and social media literacy (Jones-Jang et al., 2021).

7 Conclusion

Social media can assist people in effective communication during a health crisis. However, the use of social media in sharing information might inflame the crisis problems when spreading misinformation, rumours, and fake news. This research argued that only prosocial sharing, or responsible sharing for the community's benefit, can help reduce the crisis' problems, especially in terms of health risk and information quality risk. This research introduced a theoretical framework for understanding the process underlying prosocial sharing of HRI on social media during a health crisis. Specifically, the dual exchanging-protecting model, developed from integrating SET and the FAM fear appeal, investigated the relationships between perceived risks (i.e., perceived health risk and perceived information quality risk), motivational factors and online users' prosocial sharing of HRI on social media. To validate the model, this research employed confirmatory factor analysis and PLS-SEM on the surveyed data of 326 participants. The findings revealed that 56.7% of prosocial sharing can be explained by protecting motivations (i.e., prosocial sharing efficacy and sharing self-efficacy), exchanging motivations (i.e., reciprocity expectation), and risk perceptions. The model developed and validated in this research serves as an open framework for future research to explore further factors affecting the online prosocial sharing of HRI. The findings of this study provide scientific evidence and advice for health communicators and social media companies to increase the effective use of social media in health campaigns.

Acknowledgement

The RMIT University's Business and Law College Human Ethics Advisory Network (BL CHEAN) granted ethics approval for this research to be conducted on 7th December 2020.

References

Albarracin, D., & Jung, H. (2021). A Research Agenda for the Post-Covid-19 World: Theory and Research in Social Psychology. *Asian Journal of Social Psychology, 24*(1), 10. doi:10.1111/ajsp.12469

Alvarez-Galvez, J., Suarez-Lledo, V., & Rojas-Garcia, A. (2021). Determinants of Infodemics During Disease Outbreaks: A Systematic Review. *Frontiers in Public Health, 9*(236). doi:10.3389/fpubh.2021.603603

Apuke, O. D., & Omar, B. (2021). Fake News and Covid-19: Modelling the Predictors of Fake News Sharing among Social Media Users. *Telematics and Informatics, 56*, 101475.

Bandura, A. (1977). Self-Efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review, 84*(2), 191-215. doi:10.1037/0033-295X.84.2.191

Barak, A., Boniel-Nissim, M., & Suler, J. (2008). Fostering Empowerment in Online Support Groups. *Computers in Human Behavior, 24*(5), 1867-1883.

Bawden, D., & Robinson, L. (2009). The Dark Side of Information: Overload, Anxiety and Other Paradoxes and Pathologies. *Journal of Information Science, 35*(2), 180-191. doi:10.1177/0165551508095781

Berry, N., Lobban, F., Belousov, M., Emsley, R., Nenadic, G., & Bucci, S. (2017). # Whywetweetmh: Understanding Why People Use Twitter to Discuss Mental Health Problems. *Journal of Medical Internet Research, 19*(4), e107. doi:10.2196/jmir.6173

Blau, P. M. (1964). *Exchange and Power in Social Life.* New Brunswick, NJ, USA: Transaction Publishers.

Bode, L., & Vraga, E. K. (2018). See Something, Say Something: Correction of Global Health Misinformation on Social Media. *Health Communication, 33*(9), 1131-1140.

Bonanno, G. A., Brewin, C. R., Kaniasty, K., & Greca, A. M. L. (2010). Weighing the Costs of Disaster: Consequences, Risks, and Resilience in Individuals, Families, and Communities. *Psychological Science in the Public Interest, 11*(1), 1-49. doi:10.1177/1529100610387086

Campos, P., Saguy, A., Ernsberger, P., Oliver, E., & Gaesser, G. (2006). The Epidemiology of Overweight and Obesity: Public Health Crisis or Moral Panic? *International Journal of Epidemiology, 35*(1), 55-60. doi:10.1093/ije/dyi254

Chen, L., Wang, X., & Peng, T.-Q. (2018). Nature and Diffusion of Gynecologic Cancer–Related Misinformation on Social Media: Analysis of Tweets. *Journal of Medical Internet Research, 20*(10), e11515. doi:10.2196/11515

Chiu, C.-M., Hsu, M.-H., & Wang, E. T. G. (2006). Understanding Knowledge Sharing in Virtual Communities: An Integration of Social Capital and Social Cognitive Theories. *Decision Support Systems, 42*(3), 1872-1888. doi:10.1016/j.dss.2006.04.001

Cook, K. S., Cheshire, C., Rice, E. R., & Nakagawa, S. (2013). Social Exchange Theory. In J. DeLamater, & A. Ward (Eds), *Handbook of Social Psychology (pp.* 61-88). Dordrecht, The Netherlands: Springer Publisher. https://doi.org/10.1007/978-94-007-6772-0_3

Cropanzano, R., Anthony, E. L., Daniels, S. R., & Hall, A. V. (2017). Social Exchange Theory: A Critical Review with Theoretical Remedies. *Academy of Management Annals, 11*(1), 479-516. doi:10.5465/annals.2015.0099

Cropanzano, R., & Mitchell, M. S. (2005). Social Exchange Theory: An Interdisciplinary Review. *Journal of Management, 31*(6), 874-900. doi:10.1177/0149206305279602

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. *JMIR Public Health and Surveillance, 6*(2), e18444.

Donald, J. N., Sahdra, B. K., Van Zanden, B., Duineveld, J. J., Atkins, P. W., Marshall, S. L., & Ciarrochi, J. (2019). Does Your Mindfulness Benefit Others? A Systematic Review and Meta-Analysis of the Link between Mindfulness and Prosocial Behaviour. *British Journal of Psychology, 110*(1), 101-125. doi:10.1111/bjop.12338

Dreisiebner, S., März, S., & Mandl, T. (2020). Information Behavior During the Covid-19 Crisis in German-Speaking Countries. *arXiv preprint arXiv:2007.13833*. doi:10.1108/JD-12-2020-0217

Dryhurst, S., Schneider, C. R., Kerr, J., Freeman, A. L., Recchia, G., Van Der Bles, A. M., . . . Van Der Linden, S. (2020). Risk Perceptions of Covid-19 around the World. *Journal of Risk Research, 23*(7-8), 994-1006.

Dummer, T. J., & Cook, I. G. (2007). Exploring China's Rural Health Crisis: Processes and Policy Implications. *Health Policy, 83*(1), 1-16. doi:10.1016/j.healthpol.2006.12.002

Dunfield, K. A. (2014). A Construct Divided: Prosocial Behavior as Helping, Sharing, and Comforting Subtypes. *Frontiers in Psychology, 5*, 958. doi:10.3389/fpsyg.2014.00958

Eisenberg, N. (1982). *The Development of Prosocial Behavior*.(First Edition. New York, NY USA: Academic Press.

Eisenberg, N. (2014). *Altruistic Emotion, Cognition, and Behavior (Ple: Emotion)*. London, UK: Psychology Press.

Eisenberg, N., Fabes, R., & Sprinrad, T. (2006). Prosocial Behavior. In N. Eisenberg, D. William, & R. M. Lerner (Eds.), *Handbook of Child Psychology, Social, Emotional, and Personality Development* (Vol. 3, pp. 646-718). Hoboken, NJ, USA: John Wiley & Sons.

Eisenberg, N., & Spinrad, T. L. (2014). Multidimensionality of Prosocial Behavior: Rethinking the Conceptualization and Development of Prosocial Behavior. In L. M. Padilla-Walker & G. Carlo (Eds.), *Prosocial Development: A Multidimensional Approach* (pp. 17-39). New York, NY, USA: Oxford University Press.

Emerson, R. M. (1976). Social Exchange Theory. *Annual Review of Sociology, 2*(1), 335-362. doi:10.1146/annurev.so.02.080176.002003

Fallis, D. (2004). On Verifying the Accuracy of Information: Philosophical Perspectives. *Library Trends, 52*(3), 463-487.

Featherstone, J. D., & Zhang, J. (2020). Feeling Angry: The Effects of Vaccine Misinformation and Refutational Messages on Negative Emotions and Vaccination Attitude. *Journal of Health Communication, 25*(9), 692-702.

Flanagin, A. J., & Metzger, M. J. (2000). Perceptions of Internet Information Credibility. *Journalism & Mass Communication Quarterly, 77*(3), 515-540. doi:10.1177/107769900007700304

Floyd, D. L., Prentice-Dunn, S., & Rogers, R. W. (2000). A Meta-Analysis of Research on Protection Motivation Theory. *Journal of Applied Social Psychology, 30*(2), 407-429. doi:10.1111/j.1559-1816.2000.tb02323.x

Gaspar, R., Pedro, C., Panagiotopoulos, P., & Seibt, B. (2016). Beyond Positive or Negative: Qualitative Sentiment Analysis of Social Media Reactions to Unexpected Stressful Events. *Computers in Human Behavior, 56*, 179-191. doi:10.1016/j.chb.2015.11.040

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to Use and How to Report the Results of Pls-Sem. *European Business Review*. doi:10.1108/EBR-11-2018-0203

Hair, J. J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A Primer on Partial Least Squares Structural Equation Modeling (Pls-Sem)*. Thousand Oaks, CA, USA: Sage Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135. doi:10.1007/s11747-014-0403-8

Jin, B., Park, J. Y., & Kim, H.-S. J. B. (2010). What Makes Online Community Members Commit? A Social Exchange Perspective. *Behaviour & Information Technology, 29*(6), 587-599. doi:10.1080/0144929X.2010.497563

Johnston, A. C., & Warkentin, M. (2010). Fear Appeals and Information Security Behaviors: An Empirical Study. *MIS Quarterly*, *34(*2), 549-566. doi:10.2307/25750691

Jones-Jang, S. M., Mortensen, T., & Liu, J. (2021). Does Media Literacy Help Identification of Fake News? Information Literacy Helps, but Other Literacies Don't. *American Behavioral Scientist, 65*(2), 371-388. doi:10.1177/0002764219869406

Kar, N., Kar, B., & Kar, S. (2021). Stress and Coping During Covid-19 Pandemic: Result of an Online Survey. *Psychiatry Research, 295*, 113598. doi:10.1016/j.psychres.2020.113598

Khan, M. L., & Idris, I. K. (2019). Recognise Misinformation and Verify before Sharing: A Reasoned Action and Information Literacy Perspective. *Behaviour & Information Technology, 38*(12), 1194-1212. doi:10.1080/0144929X.2019.1578828

Kilgo, D. K., Yoo, J., & Johnson, T. J. (2018). Spreading Ebola Panic: Newspaper and Social Media Coverage of the 2014 Ebola Health Crisis. *Health Communication, 34*(8), 811-817. doi:10.1080/10410236.2018.1437524

Krebs, D. (1982). Altruismm — a Rational Approach. In N. Eisenberg (Ed.), *The Development of Prosocial Behavior* (pp. 53-76). New York, NY, USA: Academic Press.

Kye, S., Shim, M., Kim, Y., & Park, K. (2019). Sharing Health Information Online in South Korea: Motives, Topics, and Antecedents. *Health Promotion International, 34*(2), 182-192. doi:10.1093/heapro/dax074

Laato, S., Islam, A. N., Islam, M. N., & Whelan, E. (2020). What Drives Unverified Information Sharing and Cyberchondria During the Covid-19 Pandemic? *European Journal of Information Systems, 29*(3), 288-305. doi:10.1080/0960085X.2020.1770632

Lazer, D. M., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., . . . Rothschild, D. (2018). The Science of Fake News. *Science, 359*(6380), 1094-1096. doi:10.1126/science.aao2998

Le, L. H., & Duong, G. H. (2020). Engagement in the Online Brand Community: Impacts of Cultural Traits. *Journal of International Consumer Marketing, 32*(2), 146-158. doi:10.1080/08961530.2019.1649992

Le, L. H., Hoang, P. A., & Pham, H. C. (2022). Sharing Health Information across Online Platforms: A Systematic Review. *Health Communication, 38*(8), 1550-1562. doi:10.1080/10410236.2021.2019920

Leng, J., Guo, Q., Ma, B., Zhang, S., & Sun, P. (2020). Bridging Personality and Online Prosocial Behavior: The Roles of Empathy, Moral Identity, and Social Self-Efficacy. *Frontiers in Psychology, 11*. doi:10.3389/fpsyg.2020.575053

Li, R. (2021). Fear of Covid-19: What Causes Fear and How Individuals Cope with It. *Health Communication*, 1-10. doi:10.1080/10410236.2021.1901423

Liang, H., Xue, Y., & Zhang, Z. (2017). Understanding Online Health Information Use: The Case of People with Physical Disabilities. *Journal of the Association for Information Systems, 18*(6), 433. doi:10.17705/1jais.00461

Lin, H.-C., & Chang, C.-M. (2018). What Motivates Health Information Exchange in Social Media? The Roles of the Social Cognitive Theory and Perceived Interactivity. *Information & Management, 55*(6), 771-780. doi:10.1016/j.im.2018.03.006

Marin, L. (2021). Sharing (Mis) Information on Social Networking Sites. An Exploration of the Norms for Distributing Content Authored by Others. *Ethics and Information Technology*, 1-10. doi:10.1007/s10676-021-09578-y

Maslow, A. H. (1954). The Instinctoid Nature of Basic Needs. *Journal of Personality, 22*, 326-347. doi:10.1111/j.1467-6494.1954.tb01136.x

Menard, P., Bott, G. J., & Crossler, R. E. (2017). User Motivations in Protecting Information Security: Protection Motivation Theory Versus Self-Determination Theory. *Journal of Management Information Systems, 34*(4), 1203-1230. doi:10.1080/07421222.2017.1394083

Mheidly, N., & Fares, J. (2020). Leveraging Media and Health Communication Strategies to Overcome the Covid-19 Infodemic. *Journal of Public Health Policy, 41*, 410-420. doi:10.1057/s41271-020-00247-w

Naslund, J., Aschbrenner, K., Marsch, L., & Bartels, S. (2016). The Future of Mental Health Care: Peer-to-Peer Support and Social Media. *Epidemiology and Psychiatric Sciences, 25*(2), 113-122. doi:10.1017/S2045796015001067

Nicolaou, A. I., & McKnight, D. H. (2006). Perceived Information Quality in Data Exchanges: Effects on Risk, Trust, and Intention to Use. *Information Systems Research, 17*(4), 332-351. doi:10.1287/isre.1060.0103

OECD. (2015). *The Changing Face of Strategic Crisis Management*. Retrieved from Paris: https://www.oecd-ilibrary.org/content/publication/9789264249127-en

Rogers, R. W. (1983). *Cognitive and Psychological Processes in Fear Appeals and Attitude Change: A Revised Theory of Protection Motivation*. New York, NY, USA: Guilford Press.

Ryan, B. J., Coppola, D., Canyon, D. V., Brickhouse, M., & Swienton, R. (2020). Covid-19 Community Stabilization and Sustainability Framework: An Integration of the Maslow Hierarchy of Needs and Social Determinants of Health. *Disaster medicine and public health preparedness, 14*(5), 623-629. doi:10.1017/dmp.2020.109

Seeger, M. W., Sellnow, T. L., & Ulmer, R. R. (2003). Communication and Organizational Crisis. Westport,. CT, USA: Greenwood Publishing Group.

Shanbehzadeh, S., Tavahomi, M., Zanjari, N., Ebrahimi-Takamjani, I., & Amiri-Arimi, S. (2021). Physical and Mental Health Complications Post-Covid-19: Scoping Review. *Journal of Psychosomatic Research*, 110525. doi:10.1016/j.jpsychores.2021.110525

Singh, J. B., Chandwani, R., & Kumar, M. (2018). Factors Affecting Web 2.0 Adoption: Exploring the Knowledge Sharing and Knowledge Seeking Aspects in Health Care Professionals. *Journal of Knowledge Management, 22*(1), 21-43. doi:10.1108/JKM-08-2016-0320

Soroya, S. H., Farooq, A., Mahmood, K., Isoaho, J., & Zara, S.-e. (2021). From Information Seeking to Information Avoidance: Understanding the Health Information Behavior During a Global Health Crisis. *Information Processing & Management, 58*(2), 102440. doi:10.1016/j.ipm.2020.102440

Sproull, L. (2011). Prosocial Behavior on the Net. *Daedalus*, 140-153. doi:10.1162/DAED_a_00120

Sritharan, J., & Sritharan, A. (2020). Emerging Mental Health Issues from the Novel Coronavirus (Covid-19) Pandemic. *Journal of Health and Medical Sciences, 3*(2), 157-162. doi:10.4103/psychiatry.IndianJPsychiatry_372_20

Staub, E. (1978). Predicting Prosocial Behavior: A Model for Specifying the Nature of Personality-Situation Interaction. In L. A. Pervin, & M. Lewis (Eds), Perspectives in Interactional Psychology (pp. 87-110). Boston, MA, USA: Springer Publisher. https://doi.org/10.1007/978-1-4613-3997-7_5

Steelman, Z. R., Hammer, B. I., & Limayem, M. (2014). Data Collection in the Digital Age: Innovative Alternatives to Student Samples. *MIS Quarterly, 38*(2), 355-378. doi:10.25300/MISQ/2014/38.2.02

Sudau, F., Friede, T., Grabowski, J., Koschack, J., Makedonski, P., & Himmel, W. (2014). Sources of Information and Behavioral Patterns in Online Health Forums: Observational Study. *Journal of Medical Internet Research, 16*(1), e10. doi:10.2196/jmir.2875

Thackeray, R., Neiger, B. L., Smith, A. K., & Van Wagenen, S. B. (2012). Adoption and Use of Social Media among Public Health Departments. *BMC Public Health, 12*(1), 1-6. doi:10.1186/1471-2458-12-242

Thompson, R. R., Garfin, D. R., Holman, E. A., & Silver, R. C. (2017). Distress, Worry, and Functioning Following a Global Health Crisis: A National Study of Americans' Responses to Ebola. *Clinical Psychological Science, 5*(3), 513-521. doi:10.1177/2167702617692030

Torales, J., O'Higgins, M., Castaldelli-Maia, J. M., & Ventriglio, A. (2020). The Outbreak of Covid-19 Coronavirus and Its Impact on Global Mental Health. *International Journal of Social Psychiatry, 66*(4), 317-320. doi:10.1177/0020764020915212

Tully, M., Bode, L., & Vraga, E. K. (2020). Mobilizing Users: Does Exposure to Misinformation and Its Correction Affect Users' Responses to a Health Misinformation Post? *Social Media+ Society, 6*(4), 2056305120978377. doi:10.1177/2056305120978377

Underwood, B., & Moore, B. (1982). Perspective-Taking and Altruism. *Psychological Bulletin, 91*(1), 143-173. doi:10.1037/0033-2909.91.1.143

Usher, K., Durkin, J., & Bhullar, N. (2020). The Covid-19 Pandemic and Mental Health Impacts. *International Journal of Mental Health Nursing, 29*(3), 315. doi:10.1111/inm.12726

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. doi:10.1016/j.socscimed.2019.112552

Wilson, T. D. (1999). Models in Information Behaviour Research. *Journal of Documentation, 55*(3), 249-270. doi:10.1108/EUM0000000007145

Witte, K. (1992). Putting the Fear Back into Fear Appeals: The Extended Parallel Process Model. *Communications Monographs, 59*(4), 329-349. doi:10.1080/03637759209376276

World Health Organisation (2020, 15 February 2020). Re: Munich Security Conference. Message posted to https://www.who.int/director-general/speeches/detail/munich-security-conference

Wright, M. F., & Li, Y. (2011). The Associations between Young Adults' Face-to-Face Prosocial Behaviors and Their Online Prosocial Behaviors. *Computers in Human Behavior, 27*(5), 1959-1962. doi:10.1016/j.chb.2011.04.019

Yan, L., & Tan, Y. (2014). Feeling Blue? Go Online: An Empirical Study of Social Support among Patients. *Information Systems Research, 25*(4), 690-709. doi:10.1287/isre.2014.0538

Yan, Z., Wang, T., Chen, Y., & Zhang, H. (2016). Knowledge Sharing in Online Health Communities: A Social Exchange Theory Perspective. *Information & Management, 53*(5), 643-653.

Yang, Z. J. (2016). Altruism During Ebola: Risk Perception, Issue Salience, Cultural Cognition, and Information Processing. *Risk Analysis, 36*(6), 1079-1089. doi:doi.org/10.1111/risa.12526

Yuen, K. F., Leong, J. Z. E., Wong, Y. D., & Wang, X. (2021). Panic Buying During Covid-19: Survival Psychology and Needs Perspectives in Deprived Environments. *International Journal of Disaster Risk Reduction, 62*, 102421. doi:10.1016/j.ijdrr.2021.102421

Zhao, H., Fu, S., & Chen, X. (2020). Promoting Users' Intention to Share Online Health Articles on Social Media: The Role of Confirmation Bias. *Information Processing & Management, 57*(6), 102354. doi:10.1016/j.ipm.2020.102354

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), 102390. doi:10.1016/j.ipm.2020.102390

Copyright: © 2023 authors. This is an open-access article distributed under the terms of the Creative Commons Attribution-NonCommercial 3.0 Australia License, which permits non-commercial use, distribution, and reproduction in any medium, provided the original author and AJIS are credited.

doi: https://doi.org/10.3127/ajis.v27i0.4349