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Factors Affecting Prosocial Sharing Health-related Information on Social Media During a Health Crisis

Long Hoang Le
RMIT University, Vietnam, s3829436@rmit.edu.vn

Ai-Phuong Hoang
RMIT University, Vietnam, phuong.hoangai@rmit.edu.vn

Hiep Cong Pham
RMIT University, Vietnam, hiep.pham@rmit.edu.vn

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Full research paper

Long Hoang Le
School of Business and Management
RMIT Vietnam
Ho Chi Minh City, Vietnam
Email: s3829436@rmit.edu.vn

Ai-Phuong Hoang
School of Business and Management
RMIT Vietnam
Ho Chi Minh City, Vietnam
Email: phuong.hoangai@rmit.edu.vn

Hiep Cong Pham
School of Business and Management
RMIT Vietnam
Ho Chi Minh City, Vietnam
Email: hiep.pham@rmit.edu.vn

Abstract

During a health crisis, prosocial sharing of health-related information (HRI) on social media can help to 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 research aims to investigate factors that influence online users' prosocial sharing of HRI during a health crisis. To obtain the objective, this study developed a dual helping-protecting motivation model from the fear appeal model and social exchange theory. The partial least squares analysis, carried out on the surveyed data of 326 participants, revealed that Prosocial sharing is affected by protecting factors (i.e., sharing efficacy, response efficacy) and helping factors (i.e., reciprocity expectation). Additionally, both perceived health risk and perceived information quality risk were found to influence the sharing intention via motivational factors.

Keywords Prosocial sharing, health-related information, health problems, information quality problems, health crisis.

1 Introduction

A health crisis has normally been accompanied by two types of problems, including health-related problems (e.g., physical illness and mental health issues) and information-related problems (e.g., information overload, information uncertainty, and misinformation), in correspondence with the statement of the Director-General of the World Health Organisation, Tedros Adhanom Ghebreyesus: "We're not just fighting an epidemic; we're fighting an infodemic" (World Health Organization 2020). Sharing health-related information (HRI) on social media can either reduce or inflame the problems. 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, and connect people with similar health concerns (Berry et al. 2017; Kye et al. 2019). Besides the direct effects on users' health treatment and health literacy, sharing HRI on social media can provide further merits, for example, creating discussion and maintaining social relationships (Kaufmann and Buckner 2014). Especially, during the recent health crisis (i.e., Covid-19) when forced social isolation policy was implemented in many countries, social media become the popular way to keep communication and address psychological issues.

However, given the above undeniable advantages, sharing HRI on social media can cause several problems. Specifically, sharing misinformation about health might cause negative effects on both individuals and society. For example, the transmission of health treatment misinformation could lead to the wrong decision of parents and even children's deaths, and a financial loss for society (Chen et al. 2018). During a health crisis, when demand for information increases significantly, sharing HRI on social media also soars. Social media and Internet usage can translate a health crisis into a hot social crisis, which is spread publicly and rapidly across communities (Kilgo et al. 2018). In a worsening situation, social media and other interactive online can fuel the information problems by transmitting misinformation and negative emotion (e.g., Chen et al. 2018). Sharing misinformation, or even sharing information "without much thought" (Marin 2021) might cause problems of a health crisis to be more serious. Meanwhile, only prosocial sharing HRI, or sharing with information verification and for community benefits, can help to reduce the problems.

Several knowledge gaps can be identified from the current literature on the online sharing of HRI. First, current literature did not differentiate the domains of sharing behavior, for example, "sharing without much thought" (Marin 2021) with "prosocial sharing" behavior. This non-differentiation leads to a consequence of little research attempt on prosocial sharing behavior. Second, during a health crisis, both disease problems (or health-related problems) and information problems emerged dramatically, which typically cause fear among the community (Usher et al. 2020). With the belief that prosocial sharing can help to reduce these issues, online users are likely to share extensive information on social media. Nevertheless, current literature did not consider fear-aroused motivational factors when examining the motivations for sharing HRI. Finally, there is a lack of a coherent theoretical framework that helps to justify this behavior during a health crisis. Specifically, the majority of past studies focused on the HRI sharing under the lens of social exchange theory, which can be appropriate to justify the sharing behavior in the normal routines but less effective in explaining the sharing behavior during a health crisis.

This research dedicates to fulfill the above knowledge gaps by identifying the relationships between health- and information-related risks, motivational factors, and Prosocial sharing of HRI on social media in the health crisis context. Specifically, this study addresses two research questions as follows: (1) What factors motivate online users' Prosocial sharing of HRI on social media during a health crisis?, and (2) How are the relationships between health- and information-related risks, motivational factors, and prosocial sharing?

2 Literature review

2.1 Prosocial sharing of health-related information on social media

Sharing health information refers to "a voluntary action whereby individuals exchange unvarnished health-related news or their own experiences with others who have information needs" (Kye et al. 2019, p. 183). Information sharing can be considered as one of several main activities in information behavior, which includes information seeking, information use, information exchange, and information transfer (Wilson 1999). Since the establishment of Web 2.0 technology, HRI exchange on social media (i.e., seeking and sharing activities) has evolved rapidly and attracted considerable interest among researchers (Lin and Chang 2018). Sharing of HRI can be a prosocial sharing behavior, which relates to a sharing action with information verifying effort from senders. In other words, online users will add their value and judgment, and be responsible for the information provided during the sharing process.

Online users might prosocially share HRI via social media for community benefits, which included raising awareness about health issues (Berry et al. 2017; Chung 2017), starting communication, and providing support (Berry et al. 2017; Kaufmann and Buckner 2014). While sharing of health-related misinformation and/or rumors has been investigated in the literature, responsible sharing, which can provide merits to the online community and reduce the likelihood of misinformation, has not been understood comprehensively yet.

This study focuses on responsible sharing of HRI, as an activity of online social behavior – which covered three main domains as online donation, online sharing, and online comfort (Leng et al. 2020; Sproull 2011). Online prosocial behavior, extended from face-to-face prosocial behavior (Wright and Li 2011), refers to voluntary activities which aim to help others online than oneself and without reward anticipation (Leng et al. 2020). Leng et al. (2020) also pointed out that online prosocial behavior differs from prosocial behavior in terms of lower cost, anonymity, and less social pressure. Prosocial HRI sharing also requires further efforts of information verification before sharing. Information verification, or validating information quality before sharing (Flanagin and Metzger 2000) becomes crucial during a crisis because it can help to reduce the likelihood of sharing misinformation, which normally emerged significantly during health crises (Laato et al. 2020). Information verification was referred to as information accuracy validation (Flanagin and Metzger 2000). Specifically, in the modern media decade, information verification relates to the actions that “separate reliable content from wrong information” (Khan and Idris 2019, p. 1199).

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

In general, 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”. 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.

In a health crisis, health risk perceptions become the dominant factor that influences human behavior strongly. The past studies indicated that the majority of health crises were typically accompanied by serious harms for both physical and mental health (Bonanno et al. 2010). Besides the health risk, information problems also soar during a health crisis. In the early stage of the crisis, the lack of information might cause information uncertainty, whereas, in the later stage of the crisis, people typically deal with information overload and problems of information quality. The information during a health crisis might be overloaded when the amount of information is large and surpasses the cognitive capacity of individuals (Bawden and 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). The characteristics of information quality include accuracy, completeness, currency, and transparency (Liang et al. 2017). In general, the quality of HRI receiving from Internet sources was of mixed negative quality, i.e., inadequate, incomplete, and source ambiguity (Sudau et al. 2014).

3 Research framework and hypothesis development

3.1 Social exchange theory

Social exchange theory (SET) has been used widely to understand the behavior of information and knowledge exchange on virtual platforms. Originally, SET states that human behavior can be considered as the outcome of a cost/benefit calculation, or maximizing the benefits and minimizing 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). In the context of the online environment, an online user typically calculates the benefits and costs of the information-sharing activities before carrying out the sharing action (Yan et al. 2016). Literature on online HRI sharing highlighted the benefits of sharing, i.e. reciprocity, and sharing cost, i.e. information verification cost.

Reciprocity, grounded from 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). Sproull (2011) indicated that “volunteers reported wanting to help others because ‘it is the right thing to do’ because they had been helped in the past or anticipated they might need help in the future.” The SET indicated that people sharing information online with the expectation of mutual reciprocity (Chiu et al.

2006). Abundant prior empirical studies also pointed out that reciprocity was one of the drivers of sharing information and knowledge online (Singh et al. 2018; Yan and Tan 2014). During a health crisis, people share HRI over social media with the goals of informing and helping others, and also expect to receive reciprocal information from the recipients. Therefore, it is hypothesized that the expected reciprocity will have a positive effect on sharing behavior.

Hypothesis 1: Reciprocity positively influences the intention to share HRI responsibly on social media during a health crisis.

Online users typically compare the sharing benefits and costs before carrying out sharing activities. Derived from face-to-face prosocial behavior, online prosocial behavior might be popular on the small scale with a lower cost (Leng et al. 2020). Indeed, the cost of sharing HRI over social media is certainly low since social media platforms have been designed optimally for sharing goals. However, prosocial sharing of HRI might require a cost of information verification, which is higher than the cost of sharing itself. SET indicates that online users will analyze the benefits and costs before taking the action, or if the verification cost becomes higher, or even impossible in some situations, the intention to share information for the community will decrease accordingly. Hypothesis 2 is posited.

Hypothesis 2: Online users who perceive higher information verification costs will have lower intention to share HRI responsibly on social media during a health crisis.

3.2 Fear appeal model

The fear appeal model describes the mechanism and changes in people's behavior under the fear stimulus. Johnston and Warkentin (2010) recently developed a fear appeal model (FAM) in the information management context. Mainly based on protection motivation theory, FAM suggested more sophisticated relationships among the cognitive process of the users. Specifically, while protection motivation theory did not specify how threat appraisal and coping appraisal jointly influence the change in human behavior (Witte 1992). FAM suggested a sequential impact among this process: "Only if a threat is perceived to be relevant and potentially harmful will an appraisal of efficacy occur." (Johnston and Warkentin 2010, p. 552). Specifically, the change in users' behavior is influenced by two sequential processes, threat appraisal and then, coping appraisal. Threat appraisal includes perceived threat severity and perceived threat vulnerability (Johnston and 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". FAM indicated that both threat severity and threat vulnerability might influence behavioral change but in distant relationships rather than direct relationships (Johnston and Warkentin 2010). Coping appraisal, or evaluation of the ability of adaptive response (i.e., sharing behavior), 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 to perform the response (Bandura 1977; Rogers 1983). FAM suggests that response efficacy and self-efficacy have positive effects on adaptive behavior, whereas response costs (i.e., information verification cost) negatively affect adaptive behavior (Rogers 1983). Bandura (1977) emphasized that adaptive behavior 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 intention.

In this study, online users might perceive threats from two main sources: from the disease (i.e., health risk) and the information risk. As mentioned above, a health crisis typically has a low probability of occurrence but can cause severe negative damages and loss in the healthcare system, people's lives, and psychological stress. Within the fear aroused from a health crisis, people can perceive the health risk (i.e., the disease severity and vulnerability) and information quality risk (i.e., misinformation, lack of current information, information incompleteness, information irrelevance, and information unreliability). This study, therefore, conceptualizes two main perceived threats including *perceived health risk* and *perceived information quality risk*, both of which can cause problems to the community. Whatever types of problems they have, the much more severity people perceive, they tend to carry out responses (i.e., sharing of information that they perceived being of good quality) to protect themselves and other people from the damages and losses. When online users perceive higher risks from health and information, they will perceive higher capability to sharing more HRI in their responsibility and higher expectation that the sharing will help to reduce the risks. These hypotheses are stated as follows:

Hypothesis 3a,b: Online users who perceive higher health risks to others will perceive (a) higher response efficacy, (b) higher sharing self-efficacy.

Hypothesis 4a: Online users who perceive higher information quality risk to others will perceive higher response efficacy.

Information quality risk might have a different impact on self-efficacy. The model of information behavior by Wilson (1999) suggested that the information quality risk can influence online users' self-efficacy, or their conviction to successfully sharing information to help others. Hypothesis 4b, accordingly, was postulated as:

Hypothesis 4b: Online users who perceive higher information quality risk to others will perceive lower sharing self-efficacy.

Another worthy argument is that when online users perceive high health risks and information quality risks to other people, the motivations of helping others and reciprocity will improve. Specifically, the past study indicated that under high-risk conditions such as a health crisis, systematic processing becomes more salient compared to the heuristic system (Yang 2016). 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 the higher expectation of receiving quality information in the future as the reciprocity. These arguments can be hypothesized as follows:

Hypothesis 3c, 4c: Online users who perceive (3c) higher health risks to others, and (4c) higher information quality risk to others will perceive higher reciprocity expectations.

Information verification requires online users to invest their time and effort. Since there are extensive ways to verify online information (Flanagin and Metzger 2000), this cost highly depends on the verifying skill of online users. Literature on information verification behavior indicated that information verification behavior was highly associated with personal information literacy (Jones-Jang et al. 2021), and perceived self-efficacy (Khan and 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 effort in the verification process. The hypothesis relates the relationship between self-efficacy and verification cost is presented as follows:

Hypothesis 5: Online users who perceive higher sharing self-efficacy will have a lower cost of information verification.

In the moral behavior manner, Marin (2021, p. 7) mentioned three conditions of moral responsibility, including "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". In this study, prosocial sharing of HRI over social media is considered as the adaptive response to the fear aroused from a health crisis. Online users tend to share HRI as their moral responsibility when they perceive the effectiveness of sharing, their knowledge and value via the information-verifying process and consider the cost of sharing. Before sharing HRI over social media, people evaluate the efficacy of the sharing, their capability of sharing, compare with the costs of sharing. As argued above, sharing "accuracy" information over social media can be one of the good 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 intention will increase. Therefore, the related hypotheses are presented as follows:

Hypothesis 6,7: Online users who perceive (6) higher response efficacy, and (7) higher sharing self-efficacy will have a higher intention to share HRI responsibly on social media during a health crisis.

Figure 1 presents the research framework.

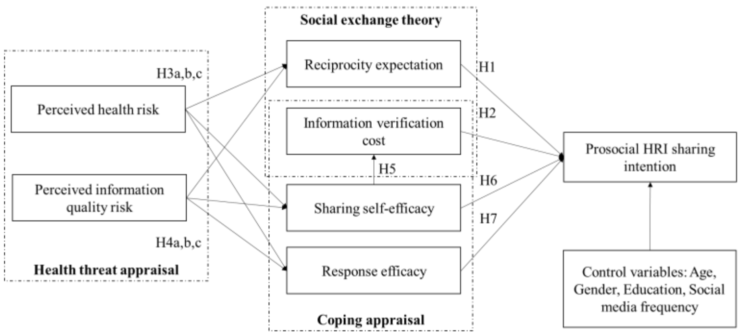

Figure 1: Dual-motivation model of sharing HRI on social media during a health crisis

4 Method

This study followed the positivism position and the deductive reasoning. Specifically, the conceptual framework and hypotheses were deducted from two theoretical bases (SET and FAM). The hypothesis testing was carried out via an online survey instrument and quantitative data analysis.

4.1 Measures

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"), perceived severity, perceived vulnerability, response efficacy, sharing self-efficacy, and response costs from Johnston and Warkentin (2010), perceived information quality risk from Nicolaou and McKnight (2006). Perceived health risk was formative measured 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 intention 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").

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 carried out in English native 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 was at least 300 respondents to warrant the "good quality" for both factor analysis and structural equation modelling (Hair et al. 2016).

4.3 Data analysis

For the measurement model, confirmatory factor analysis was adopted to assess the construct reliability and validity. For the path analysis, partial least squares analysis (PLS-SEM) was favorable for three reasons: (i) the goal of this study was to develop a conceptual model to explain/predict the intention behavior, which is appropriate to the use of PLS-SEM, (ii) PLS-SEM can help to incorporate reflective and formative between construct measurement model, and (iii) PLS-SEM can relax the normality assumption, which was not reasonable in a health crisis (Hair et al. 2016).

5 Research findings

5.1 Measurement model

The data descriptions were presented in Table 1.

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 1. Data descriptions

The measurement model was evaluated via reliability and validity assessments (Table 1). The findings from Table 2 showed that all the Cronbach's Alpha (Cron. Alpha) and Composite Reliability (C.R.) were larger than 0.7, and factor loadings were larger than 0.708, indicating good reliability and convergent validity (Hair et al. 2016). Table 3 and Table 4 indicated that the squared roots of the Average Variance Extracted (AVE) were larger than construct correlations, and factor loadings for each construct were larger than cross-loadings for other constructs. The discriminant validity, therefore, was acceptable.

	Items	Cron. Alpha	C. R.	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 2. 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**

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

Table 3. Construct correlation

	Prosocial sharing	Reciprocity	Info. ver. cost	Sharing self-efficacy	Response efficacy	Perceived info. qual. risk	Severity	Vulnerability
PSI1	**0.908**	0.523	0.177	0.310	0.613	0.098	0.282	0.289
PSI2	**0.928**	0.582	0.229	0.287	0.621	0.135	0.285	0.276
PSI3	**0.904**	0.617	0.332	0.189	0.614	0.271	0.212	0.260
PSI4	**0.905**	0.610	0.305	0.192	0.608	0.223	0.249	0.258
RECIP1	0.488	**0.808**	0.353	0.160	0.453	0.307	0.193	0.245
RECIP2	0.492	**0.832**	0.368	0.214	0.506	0.277	0.217	0.277
RECIP3	0.598	**0.838**	0.437	0.086	0.592	0.289	0.174	0.258
RECIP4	0.512	**0.806**	0.366	0.107	0.565	0.322	0.209	0.209
COST2	0.136	0.308	**0.742**	-0.015	0.145	0.477	0.106	0.192

COST3	0.340	0.499	**0.914**	-0.175	0.346	0.514	0.007	0.251
COST4	0.219	0.378	**0.873**	-0.101	0.232	0.456	0.036	0.194
COST5	0.180	0.321	**0.833**	-0.174	0.147	0.461	-0.015	0.190
SELEF1	0.179	0.095	-0.166	**0.815**	0.212	-0.097	0.246	0.211
SELEF2	0.188	0.182	-0.104	**0.761**	0.251	-0.089	0.255	0.234
SELEF3	0.277	0.136	-0.114	**0.841**	0.282	-0.127	0.253	0.209
REFF1	0.588	0.481	0.175	0.299	**0.843**	0.062	0.163	0.260
REFF2	0.565	0.552	0.225	0.272	**0.832**	0.088	0.225	0.236
REFF3	0.563	0.544	0.203	0.308	**0.864**	0.106	0.191	0.230
REFF4	0.519	0.573	0.341	0.145	**0.780**	0.160	0.186	0.289
INFR1	0.240	0.383	0.476	-0.116	0.150	**0.873**	-0.004	0.090
INFR3	0.133	0.225	0.430	-0.081	0.101	**0.804**	0.013	0.164
INFR5	0.067	0.242	0.483	-0.125	0.026	**0.790**	-0.058	0.134
SEVE1	0.263	0.193	0.018	0.225	0.227	-0.033	**0.851**	0.403
SEVE2	0.224	0.197	0.040	0.304	0.211	-0.013	**0.828**	0.417
SEVE3	0.213	0.209	0.003	0.244	0.133	0.005	**0.806**	0.382
VULN1	0.231	0.223	0.191	0.201	0.234	0.091	0.421	**0.829**
VULN2	0.338	0.372	0.353	0.133	0.306	0.234	0.319	**0.762**
VULN3	0.144	0.130	0.057	0.301	0.190	0.032	0.401	**0.778**

Table 4. Factor loadings and cross-loadings

5.2 Structural model

The R-squared value equals 0.56, indicating that 56% of the variance of Prosocial sharing can be explained by the research model. All the Variance Inflation Factors were less than 5, representing no multicollinearity issue. Table 5 provided the structural findings, where most of the hypotheses, except H2, were 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 demographics variables such as age, gender, and country did not influence the prosocial sharing behavior.

Hypotheses		Beta	T-value	P-value	Conclusions
H1	Reciprocity → Prosocial sharing	0.319	3.917	0.000	Supported
H2	Info. verification cost → Prosocial sharing	-0.016	0.345	0.730	Not supported
H3a	Perceived health risk → Response efficacy	0.303	4.801	0.000	Supported
H3b	Perceived health risk → Sharing self-efficacy	0.349	5.360	0.000	Supported
H3d	Perceived health risk → Reciprocity	0.290	4.603	0.000	Supported
H4a	Perceived info. qual. risk → Response efficacy	0.101	2.012	0.045	Supported
H4b	Perceived info. qual. risk → Sharing self-efficacy	-0.156	3.058	0.002	Supported
H4c	Perceived info. qual. risk → Reciprocity	0.341	6.986	0.000	Supported
H5	Sharing self-efficacy → Info. verification cost	-0.158	2.583	0.010	Supported
H6	Sharing self-efficacy → Prosocial sharing	0.102	2.067	0.039	Supported
H7	Response efficacy → Prosocial sharing	0.405	5.415	0.000	Supported

Control	Age → Prosocial sharing	0.026	0.662	0.508	*Not sig.*
Control	Country → Prosocial sharing	-0.066	0.974	0.331	*Not sig.*
Control	Education → Prosocial sharing	0.142	3.039	0.002	***
Control	Gender → Prosocial sharing	0.044	1.203	0.230	*Not sig.*
Control	Social media freq. → Prosocial sharing	0.099	2.208	0.028	**

Table 5. Structural model results

6 Discussions

6.1 Discussions on findings

This study aims to identify factors affecting the prosocial sharing of HRI during a health crisis by integrating the SET and FAM. While past studies have focused on either health concerns (e.g., Kar et al. 2021; Sritharan and Sritharan 2020) or information problems (e.g., Tully et al. 2020), the findings highlighted that both health- and information-related problems have positive impacts on prosocial sharing via motivational factors. Regarding the motivational factors, during a health crisis, online users were found to 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 intention was also affected by the fear-aroused factors, which means online users appeared to evaluate the crisis risks, following 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 intention can be explained in two ways. First, the information verification might have been low-cost so that online users did not take it into their consideration. Second, online users might not care to verify online information before consuming it. Past studies found that online users shared online information on social media without verifying effort during a health crisis (Laato et al. 2020).

6.2 Research contributions

Theoretically and perhaps most critically, the significance can be originated from the development of a conceptual framework from two theoretical bases, the SET and FAM. The literature review indicated that although the SET was commonly applicable and effective in justifying the online sharing of HRI during the normal routine (Lin and Chang 2018; Yan and Tan 2014; Yan et al. 2016), it was not sufficient to justify this behavior during a health crisis when the fear was spread among the community (Li 2021). The integration of the SET and FAM in the so-called dual-motivation model can better explain the prosocial sharing during a health crisis, as well as make contributions to both theories. Another theoretical contribution includes the differentiation between online sharing domains. The differentiation of prosocial sharing, sharing "without much thought", and sharing misinformation can pave the way to future research since each type of sharing domain accompanies different motivations and derives different consequences. While current studies on health crisis communication focused on sharing misinformation (Tully et al. 2020), this study highlighted the importance of prosocial sharing.

Practically, 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 policy to harmonize the information volume across the crisis stages, and reduce the problems of misinformation and information overload (OECD 2015). In other words, prosocial sharing can be an effective strategy to address the problem of misinformation spreading, which has emerged seriously in recent years.

6.3 Limitations and future research

This study suffered several limitations. First, using the survey instrument, this study only captured the impacts of health and information risks and motivational factors on sharing intention in a longitudinal period, which might be necessary since a health crisis typically prolongs and users' behavior would change continually during the health crisis. Future research can track the sharing behavior of online users for a longer time to better understand their motivation. Second, online behavior might differ across personal traits and cultural values (e.g., Le and Duong 2020). Future research can extend this argument to understand the differences in online sharing engagement of online users from different cultural backgrounds. Finally, this study's findings indicated the significant impacts of education and social media use frequency on Prosocial sharing. Future research can explore further these impacts, especially the roles of health literacy and social media literacy (Jones-Jang et al. 2021).

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