Impact of Risk Perception on Trust in Government and Self-Efficiency During COVID-19 pandemic: Does Social Media Content Help Users Adopt Preventative Measures?

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Abstract

The public's actions will likely have a significant effect on the course of the coronavirus disease (COVID-19) pandemic. Human behavior is conditioned and shaped by information and perceptions of people. This study investigated the impact of risk perception on trust in government and self-efficacy. It examined whether the use of social media helps people adopt preventative actions during the pandemic. To test this hypothesis, data were gathered from 512 individuals (students and academicians) who were based in Malaysia during COVID-19. Our results suggested that risk perception had a significant effect on trust in government and self-efficacy. Moreover, these correlations were stronger when social media was used as a source for gathering information on COVID-19, and in some cases it even helped the user avoid being exposed to the virus. This study assessed the relationship between risk perception and the awareness gained from using social media during the pandemic and also highlighted how social media usage influences trust in government and self-efficacy.

Introduction

The current pandemic is caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV–2). As of mid-April 2020, 2,074,529 confirmed cases and 139,378 deaths had been recorded worldwide, including 5,182 confirmed cases in Malaysia. Moreover, as no treatment or vaccine has been developed, preventive and quarantine measures are considered the best methods to avoid infection (WHO, 2020). Therefore, at the individual level, necessary preventive measures have been promoted: regular hand washing, avoiding touching the face, and maintaining an appropriate distance from any individual showing possible symptoms. Moreover, many countries have promoted social distancing to contain the outbreak (WHO, 2020).

In Malaysia, the government decided to implement social distancing by enforcing a movement control order composed of regulations to control the spread of the disease. These measures included the immediate suspension of cross-border movements, as well as schools and universities, and closure of non-essential businesses (PMO, 2020). However, the ability to limit the spread of COVID–19 fundamentally depends on how people react; hence, collecting data on people's perception and their behavioral response during a pandemic is vital to provide this information to policymakers and help them understand how people respond to public health issues (Slovic, 2000).

During a pandemic, it is critical to understand and explore behavioral responses to the risk of infection, especially how people assert their risk perception, how these perceptions shape self-efficacy beliefs and most importantly, how exposure to information on social media affects the relation between risk perception and self-efficacy (Bandura 1990b; Chew & Eysenbach 2010; Isa et al. 2013). Furthermore, it is essential to provide information to people when public health issues arise so that they can understand the risks and respond effectively. Hence, public risk perception and self-efficacy can assist individuals in understanding and managing their responses (Reynolds & Seeger 2005; Vos & Buckner 2016).

Media sources have played a critical role in providing information to the public during crises. Sources such as television and newspapers, have shaped people's risk perception and self-efficacy during public health issues, as was seen during the H1N1 outbreak (Lin & Lagoe 2013; Shim & You 2015). In the information age, social media plays a primary role in how the public acquires information and communicates about crises and catastrophes (Schultz et al. 2011). Notably, the number of people using social media platforms to gather information, especially during a crisis, has dramatically increased (Faustino, Liu, and Jin 2012). Hence, social media platforms (e.g., Facebook, Twitter, Instagram, YouTube, and WhatsApp) have become the primary source of information for many people. Social media is considered the primary source of health information as well, influencing people's risk perception and self-efficacy in preventive behavior (Barman-Adhikari et al. 2016; Young & Rice 2011). Therefore, the importance of social media in helping people make sense of the news during public crises needs to be examined. Regarding this, it is crucial to understand whether using social media as a primary source of information shapes the relationship between risk perception and self-efficacy during COVID–19.

Theory

Risk perception

Paek and Hove (2017) defined the concept of 'risk perception' as "people's subjective assessment of the possibility that negative outcomes or diseases may occur" (p. 1). This perception is governed by two main dimensions: the perceived susceptibility dimension, which refers to how people perceive risk and the likelihood of contracting diseases, and the severity dimension, which refers to people's ability to process information about risks and understand the seriousness and aggressiveness of diseases (El-Toukhy 2015; Pask & Rawlins 2016; Dryhurst, et al., 2020; Balog-Way, & McComas, 2020). Susceptibility and severity play important roles in shedding light on risk perception, according to protection motivation theory (Rogers, 1983). The two constitute the main dimensions of information processing when individuals consider the threats from a hazard. The theory assumes that individuals will feel a sense of pressure to adopt health recommendations to protect themselves from any harm. It further concludes that a high level of perceived risk is needed to adapt healthy behaviors during a crisis. Meanwhile, the extended parallel process model (Witte, 1992) highlights that risk perception is a pivotal element that influences behavioral response during a crisis (Rimal & Real 2003b).

When people evaluate the susceptibility of the harm they might endure during a crisis, they may make assumptions using a heuristic process. When individuals in society are more aware of the risk, they are likely to assume that risks occur more frequently than they do. This is known as availability heuristics (Kahneman et al. 1982). For instance, when individuals are heavily exposed to media coverage of a disease, such as the H1N1 virus, they tend to have a higher perceived risk of contracting the virus compared to others (Paek & Hove, 2017). Risk perception is mainly an interpretation and subjective judgment about a current risk (Slovic, 2000). Hence, it is an essential element of a risk-based decision, such as adopting healthy behavior during a crisis. Therefore, risk perception is explicitly associated with

natural disasters, such as hurricanes or pandemics, as well as human-made disasters, such as nuclear radiation exposure (El-Toukhy 2015; Rimal & Real 2003).

Risk perception has a profound impact on society, as it influences individual behavior during a crisis, which profoundly affects the success of policies and regulations that are implemented to address a crisis. Considering the current outbreak of COVID–19, risk perception can have a substantial impact on the precautionary measures that individuals undertake to reduce their exposure to disease transmission. It shapes people's decision-making in promoting preventive measures during a pandemic (Choi et al. 2017). Another element of risk perception is optimistic bias; this concept states that individuals tend to believe that the risks posed by a disaster are less severe for them than for other people. This tendency to underestimate the harm of a disaster, as they underestimate the probability and severity of that harm inflicted on them, is mainly dependent on the information disseminated regarding a hazard (Weinstein, 1980).Specifically, while analyzing risk perception, the focus is on individual cognitive judgment regarding their susceptibility to a risk; however, such analysis ignores the effect of heuristics and the role of the information sources in shaping perception. Slovic (2000) argued that risk perception should focus on how individuals tend to be influenced by their emotions while making a decision or perceiving risk. It is argued that human beings may perceive risk as more threatening when they feel intense dread about it. Nonetheless, cognitive assessment and emotional judgments are often strong, determining people's risk prospects and behavior (Loewenstein et al. 2001).

Generally, research regarding the factors influencing risk perception has focused on how individual perception is affected by media exposure and the social, cultural, institutional, and political processes. This widely accepted view highlights that the understanding of people's risk perception is not only determined by the scientific information they obtain or their physical experiences with a hazard. McCarthy et al. (2008) argued that a critical factor that affect risk perception is how the media shape public risk perception; they also indicated various types of media factors that affect the risk perception of the public, such as the type of media, amount and tone of coverage, and trustworthiness of the source. When a public issue arises, people tend to perceive the risks to themselves (Pask & Rawlins 2016). The manifestation of infectious diseases, such as COVID–19, which was not anticipated in a specific time or region, tends to lead to immediate public risk perception (Oh, Eom, and Rao 2015). Thus, examining risk perception is essential to understanding how it shapes self-efficacy beliefs.

Trust in government

Citizen's trust in government as a whole is a fundamental topic in the study of social phycology (Hetherington 1998; Houston et al. 2016; Miller 1974; Van der Meer 2010; Vigoda-Gadot and Talmud 2010). Gamson (1968) defined trust in government as "the probability […] that the political system (or some part of it) will produce preferred outcomes even if left untended." (p. 54). Coleman and Iso-Ahola (1993) described trust as a subcategory of risk: the expectation of gain or loss, which determines whether or not citizens will trust the government. Therefore, trust is never absolute, but always conditional and contextual (Ruscio, 1996). According to Braithwaite and Levi (1998), and citizens may differ widely in their

perception. They also identified the two possible ways citizens can trust their government. First, people will trust everyone in the government as an institution, and second, people trust that the decisions taken by the government are in the best interest of the citizens. This definition is based on the conceptual framework of game theory, which provides a specific understanding of trust in government. It is based on the idea that granting trust to the government is based on individual interest, and that trusting the government depends on the individual's strategy to maximize utility. Thus, individuals' trust in the government is based on the idea of self-interest (Braithwaite & Levi 1998; Levi & Stoker 2000).

Trust in government is an important factor that determines the success of any policy. Historically, during crises, trust in government played a crucial role in shaping public behavior, specifically, people's willingness to comply; it also influences their support for government policies during a crisis, specifically health policies (Tomes 2000; Sankar et al. 2003; Tilney 2004). Chanley et al. (2000) highlighted that public trust in the government is one of the most important factors that influences public risk perception and which untimely shapes public policymaking. Therefore, trust in government highlights the importance of public support during a crisis, which will minimize the conflict between the public and the government officials enforcing the rules (Metlay, 2013). For example, if the public does not trust their government during a disaster, specifically a health crisis, a high degree of non-compliance and conflict could be anticipated from the public towards government institutes and their policies. This relation occurs as the negative risk perception will influence public will and the increase public opposition to government activities during a crisis (Pijawka & Mushkatel 1991).

Empirical evidence on epidemics has highlighted that trust in government is vital to the success of any policy during a crisis. For instance, Slovic et al. (1991) concluded that trust in government would decrease if the public viewed their government as abusing its power and being dishonest. During the smallpox outbreak in Milwaukee, Wisconsin, in 1894, the government forcibly isolated poor immigrants in hospitals while allowing wealthy families to stay at home, and as a result, trust in government declined and deteriorated, leading to a month-long riot that allowed the acceleration in the spread of smallpox (Leavitt, 2003). At the core of trust in government during a crisis are the questions of how people trust government agencies and how risk perception shapes public behavior (Smith and Mayer 2018). Specifically, the effect of risk perception on trust in government has been studied, although the literature that discusses this relation is limited. Earlier works have examined how risk perception influences trust in government, which is crucial to understanding how people deal with a public threat or epidemic (Smith & Mayer 2018).

In the context of the COVID–19 pandemic, if information regarding health issues is vast and people are gathering information from different sources, their trust in the government will be based on their determination of the risks and benefits associated with the pandemic. In turn, this determination may influence their acceptance of government health measures to combat COVID–19 (Siegrist & Cvetkovich 2000). Hence, if citizens trust the government, which is responsible for responding to a hazard, their risk perception will be positively influenced and trust will help ensure public acceptance of and cooperation with government agencies (Siegrist & Cvetkovich 2000; Tumlison, Moyer, & Song 2017; Vainio, Paloniemi, & Varho 2017). Thus, studies that have focused on understanding the risk perception of different hazards

have found a strong correlation between risk perception and trust in government (Bronfman and Vázquez 2011; Keller, Visschers, and Siegrist 2012; Vainio et al. 2017).

Self-Efficacy

Self-efficacy helps shape individuals' ability to overcome a social difficulty (Bandura, 1990). This can be understood as an individual's belief in their ability in managing a difficult task they face (Bandura, 1997). Bandura (1997) also added that the primary understanding of self-efficacy theory is 'people's beliefs in their capabilities to produce desired effects by their actions.' (p. 7), The theory argues that efficacy belief is a part of psychological adjustments during a crisis. Self-efficacy can be seen when a public health crisis occurs, such as the COVID–19 pandemic. It plays an imperative role in motivating a person during hazards, which leads to specific changes in the person's behavior and attitudes (Dorsey, Miller, and Scherer 1999). Studies have examined how self-efficacy is shaped by risk perception (Cameron et al. 1996; Coleman and Iso-Ahola 1993; Mishra & Fiddick 2012).

However, the ability of self-efficacy beliefs to encourage a sense of competence and control over the perceived outcomes of a specific unwanted situation is seen as a higher level of self-efficacy, which leads to a greater probability of enacting and adopting health measures during a public health threat (Reid & Aiken 2011). Thus, self-efficacy can also be highlighted as a form of social construct. Although these types of constructs may differ depending on culture, the need for individuals to control seems universal, and studies have also examined how individuals in different cultures practice self-efficacy (Young et al. 1991). For example, the self-efficacy concept has been widely studied in regard to how it changes behavior when dealing with health threats, such as smoking (Carey et al. 1989). Therefore, it is an exciting topic that reflects people's perception of behavioral responses through prevention measures that they should undertake during a health crisis (Isa et al. 2013; Giritli Nygren, & Olofsson, 2020). In particular, self-efficacy is highlighted as a motive and need for control which can also be viewed as a drive to alter behavior. However, this drive is not a permanent personality trait. Self-efficacy is the ability to direct skills to accomplish a desired goal in a practical circumstance that is mostly a domain that arises owing to a threat (Chen et al. 2001; Sherer et al. 1982; Smart et al. 1984). According to social cognitive theory, self-efficacy is an action motivated from within rather than enforced by the environment. Two of the central ideas of the theory are, first, that individuals' cognitive capabilities are powerful tools that allow a person to develop a course of action based on experience; the testing of hypothetical actions using one's mental capabilities will predict the outcome (Bandura 2001; Barone et al. 1997). Second, humans are capable of self-regulation; that is, to achieve a goal, individuals will regulate and change their behavior. Self-regulation will assist in anticipating expectancies and tapping past knowledge and experiences to form beliefs about future events (Molden & Dweck 2006).

Therefore, self-efficacy is a construct that needs to be studied further. The present study aimed to provide a unique understanding of the relation between risk perception and self-efficacy during a pandemic. Risk perception and self-efficacy are affected by information regarding a hazard. People gather information

regarding a public health issue, and this tendency shapes their reaction and behavior during a crisis (McCarthy et al. 2008; Song 2015).

Social Media Content

Traditional media, such as newspapers and television, used to be the primary sources of information for most people (Dudo et al. 2007; Paek et al. 2016), these sources of media are a crucial source of information for the public regarding public health crises (Lin and Lagoe 2013; Oh et al. 2015). Chang (2012) demonstrated the association between risk perception during the H1N1 outbreak and the information produced by television channels.

However, in today's world, social media has transformed the way individuals obtain information, and given the continuous change in the communication industry, people around the world have shown an increasing inclination toward obtaining information through social media platforms, such as Facebook, Twitter, and WhatsApp. Thus, as observed by Lin et al. (2016), health information during crises is mainly obtained from social media platforms as it is more convenient. Unlike with traditional media, users of social media can acquire, generate, and share critical health information. For example, people used social media as a central public platform to discuss and exchange information during the H1N1 outbreak (Davies, 2014). These platforms are a primary contributor to people's risk perception about a public health crisis and also provide information that influences their protective health measures (Chung, 2016). Social media has become the primary platform for people to express their emotional responses, such as worry and fear of health issues and virus outbreaks since the H1N1 outbreak (Chew & Eysenbach 2010; Signorini et al. 2011). During the MERS outbreak, social media platforms played a significant role in the dissemination of factual information, as reflected in a study by Song (2015) that used big data. Such information included news on the systems in place and prevention methods. However, popular and easy-to-access platforms are associated with negative emotional responses to public health issues and are considered a primary contributor to fear and anxiety among the public (Paek & Hove 2017; Signorini et al. 2011; Fu, & Zhu 2020).

Aladwani (2017) highlighted that perceived quality of social media content encompassed Four dimensions: reflective quality which reflects the personal belief of how the content on social media supports ones need, the second dimension is practiced quality which can be understood as how the content on social media meets one need and shape their behavior, thirdly, advocated quality reflects how a person behavior to support and advocate the information on social media and lastly, stimulated quality which reflects individual feelings regarding social media content and how its serves one need in the time of need.

As risk perception incorporates susceptibility and severity of public hazards (El-Toukhy, 2015), social media shapes perceived susceptibility by providing information about the increasing number of patients affected by public health hazards, whereas perceived severity in social media is related to the focus on information that has adverse impacts such as death or severe injury (McWhirter & Hoffman-Goetz 2016).

Hence, exposure to negative information, such as pain concerning the MERS and H1N1 outbreaks, is positively associated with the perceived severity of the disease, whereas the information regarding the increasing number of deaths and infected patients could also be associated with perceived susceptibility. Social media content is assumed to contribute to an increase in people's risk perception during a public health crisis (Choi et al. 2017). Vos and Buckner (2016) asserted that social media content plays a critical role in the spread of information about a crisis and helps the public in making sense of public health issues. However, researchers concluded that limited information regarding self-efficacy is also disseminated.

Another perspective states that risk perception and self-efficiency are constructs that mainly depend on the information obtained about a crisis (Agha, 2003). During the early stages of the COVID–19 outbreak in China, conspiracy theories spread around the globe. Racism, panic buying, and inaccurate information have been linked to the dissemination of information on social media. The widespread misinformation generated panic among the public (Depoux et al. 2020). Subsequently, social media platforms, such as Facebook, have directed users to the World Health Organization website as well as myth-busters and fact-checker websites to combat misinformation about COVID–19 (Merchant and Lurie 2020). Twitter has been highlighting consistent information about COVID–19 (Josephson & Lambe 2020), as the worldwide public panic can be fought with fact-based content (Lancet, 2020).Moreover, social media, as a primary source of information, influences public health responses by providing accurate content, as seen in China during the quarantine. Social media platforms were used to provide advice and reassurance to the public regarding quarantine as well as to convey the ability of the government to manage the outbreak. Hence, social media can provide awareness regarding a disease, specifically on how to prevent an infection by highlighting protective measures (Depoux et al. 2020). At present, 2.9 billion people around the world rely on social media to gather information regarding COVID–19. Thus, information shared will impact the decisions made by the public during the pandemic and will influence their trust in government and self-efficacy beliefs (Depoux et al. 2020; Jin 2020; Merchant & Lurie 2020).

Based on the above arguments, we have formulated the following research hypotheses.

H1: Risk perception has a positive effect on trust in government.

H2: Risk perception has a positive effect on self-efficacy.

H3a: Social media content moderates the relationship between risk perception and trust in government, such that the relation is stronger when perceived quality social media quality is higher.

H3b: Social media content moderates the relationship between risk perception and self-efficacy, such that the relation is stronger when perceived quality social media quality is higher.

Method

Sample and procedure

For data collection, an online survey, designed using Google Forms, was distributed to students and academicians from the University of Malaya (UM) in Kuala Lumpur, Malaysia. This survey was conducted during the movement control order (MCR), which began on March 18, 2020. The cover letter explained the purpose of the study and assured the confidentiality of the participants' responses.

Variable measurement

All variables were measured using a self-report measure of multi-item scales derived from previous studies. All the measures were assessed using a seven-point Likert-type scale, where 1 = *strongly disagree* and 7 = *strongly agree.* All of the items are presented in Appendix 1. When measures are used to examine a latent construct, a choice between reflective or formative indicators must be carefully made (Becker et al. 2012; Sarstedt et al. 2019). Reflective measurements, commonly recommended when personality and attitudinal variables are modeled, are highly correlated indicators (interchangeable) thought to be caused by a targeted latent construct. The formative measures involve indicators that may determine the construct without necessarily being highly correlated (not interchangeable) such that traditional reliability and validity criteria may be inappropriate and irrelevant (Cheah et al. 2019; Sarstedt et al. 2019). The aforementioned criteria may be applied for distinguishing between reflective and formative constructs (i.e., the direction of causality, interchangeability, covariation, and antecedents/consequences of indicators or dimensions) (Sarstedt et al. 2019). Our study encompassed the two types of reflective and formative variables, including multiple first-order constructs that represented important aspects of the targeted construct, and second-order constructs. Specifically, given their complexity, we modeled social media as a second-order formative construct. Determining the type of formative construct is important because excluding any of the dimensions would alter the conceptual domain (e.g., Becker et al. 2012; Cheah et al. 2019; Sarstedt et al. 2019).

To measure risk perception, four items were adapted from Witte (1996) and Zimmerman et al. (2003). The risk perception was measured reflectively as a first-order construct. Trust in government was also positioned as a dependent variable, which was measured reflectively with three items as a first-order construct borrowed from Grimmelikhuijsen (2012). Self-efficacy, as a first-order construct, was measured reflectively with five items adopted from a prior study (Rimal & Real 2003). Finally, social media content was measured with nine items that were slightly modified and adapted from Aladwani (2017). Perceived quality of social media content encompassed Four dimensions: reflective quality (two items), practiced quality (two items), advocated quality (three items) and stimulated quality (three items). These four dimensions were measured reflectively as first-order constructs, and later, they established social media formatively, where high scores indicated a stronger perceived benefit of social media content.

Data Analysis And Results

To examine the proposed hypotheses, we utilized structural equation modeling (SEM) with partial least squares (PLS), using Smart PLS 3.2.8 (Ringle et al. 2015). As this is a powerful and robust statistical procedure (Henseler et al. 2009), it does not require strict assumptions on the distribution of the variables and is appropriate for complex causal analyses with both first- and second-order constructs (Hair et al. 2017). To test the statistical significance of the path coefficients, the PLS analysis used 5,000 subsamples to generate bootstrap t-statistics with n - 1 degrees of freedom, where (n) is the number of subsamples.

Demographic analysis

We collected participants' sex, age, education, and job experience. As presented in Table 1, the majority of the participants were under 35 years and female, and almost half of them had a bachelor's degree.

Common method bias assessment

Common method bias (CMB) refers to the difference between the trait and measured scores attributed to the use of a common method to take more than one measurement of the same or different traits (Podsakoff et al. 2003). CMB could imply a risk in social science research, given that bias may affect findings due to systematic errors. Thus, in the current research, we attempted to prevent CMB during the research design phase by applying the procedural remedies proposed by Podsakoff et al. (2012). Moreover, a statistical technique was used to detect potential CMB situations, namely, a full collinearity test based on variance inflation factors (VIFs) (Kock, 2015). The guidelines followed were those described by Kock and Lynn (2012), who proposed such a test to assess both vertical and lateral collinearities, who indicated that a VIF achieving a value greater than 3.3 would be an indication of pathological collinearity, which in turn is a warning that a model may have CMB. In our model, as shown in Table 2, the maximum VIF was 2.112.

Measurement model assessment

To achieve a reflective measurement model, individual item reliability, internal consistency reliability, convergent validity, and discriminant validity must meet certain criteria. In terms of item reliability, the results shown in Table 3 reveal no serious problems. Most items exceeded the recommended level of 0.707 (Hair et al. 2017). To evaluate the constructs' internal consistency, we used composite reliability which ranged from 0.847 to 0.916, higher than the suggested cutoff threshold of 0.70 (Hair et al. 2017). In support of convergent validity, the average variance extracted (AVE) for the constructs ranged from 0.658 to 0.809, more than the recommended threshold of 0.5 (Hair et al. 2017). For discriminant validity, shown in Table 4, we uncovered no issues, as the AVE for each construct was greater than the variance that each construct shared with the other latent variables (Fornell & Larcker 1981; Hair et al. 2017).

The formative variables revealed minimal collinearity, as the respective VIFs ranged between 1.264 and 2.932 (see Table 3), far below the common cutoff threshold of 5 (Hair et al. 2017). Therefore, collinearity did not reach critical levels in any of our formative constructs. Moreover, the significance and relevance of the outer weights t-value and p-value of the formative constructs were examined. As shown in Table 3, all formative indicators were significant (Hair et al. 2017). Thus, we successfully created a formative measurement model.

Structural model assessment

Table 5 presents the findings related to H1–H3, which involved the direct and interaction effects. In support of H1, the direct effect of risk perception was significantly and positively related to self-efficacy (β = 0.533, t = 4.104, p <0.001); thus, H1 was supported. H2 also showed a significant direct effect of risk perception on trust in government (β = 0.283, t = 2.832, p <0.002); therefore, H2 was supported as well.

Regarding the interaction effect, H3a assumed the interaction effect of risk perception and social media usage on trust in government, for which we found a significant interaction (β = 0.210, t = 2.289, p <0.011). Thus, H3a was supported. Finally, H3b also showed a significant interaction between risk perception and social media on self-efficacy (β = 0.506, t = 3.571, p <0.000). Hence, the second interaction was also supported. To interpret this interaction, we followed Dawson (2014) and plotted high versus low social media usage regression lines (+1 and –1 standard deviation from the mean). This step indicated that the positive relation between risk perception and trust in government was stronger (slope more pronounced) when social media usage was high rather than low (Fig. 3). Moreover, the positive relationship between risk perception and self-efficacy was stronger when the use of social media was high rather than low (see Fig. 4).

Regarding its explanatory power, our model revealed moderate to substantial R^2 values of 0.491 for trust in government and 0.513 for self-efficacy (Hair et al. 2017). We used the Stone-Geisser blindfolding sample reuse technique to determine the predictive relevance of our model, which revealed Q-squarevalues greater than 0. Thus, our research model effectively predicted both trust in government (Q^2 = 0.220) and self-efficacy (Q^2 = 0.241) (Hair et al. 2017).

Discussion And Conclusion

This study aimed to investigate the impact of risk perception on trust in government and self-efficacy during the COVID–19 pandemic. Significantly, this study introduced the contingent role of social media usage as a critical element during the crisis. In particular, risk perception, trust in the government, and self-efficacy during a public health threat were fundamentally dependent on information regarding the hazard (Vos and Buckner 2016). Other scholars have highlighted the importance of empirically investigating the potential effects of social media, such as on behavioral responses (Agha, 2003). Hence, the present study provided new information on how social media helps shape the relation between these constructs during COVID–19. Meanwhile, most governments worldwide and international agencies, such as the WHO, are

adopting social media as the main conduit of the distribution of information to the public (Mejia et al. 2020).

Our investigation derived several significant findings. First, risk perception positively influenced trust in the government. This relation can be understood as follows: people who perceive the risk of public health hazards are likely to increase their trust in the government during a public crisis (Vaughan and Tinker 2009). We also found that individuals demonstrated compliance with government policies to combat the public threat of COVID–19. This finding contributes to the current knowledge of how people would trust the government during a pandemic, highlighting that people's perceived risk will increase their trust in the government during any health crisis, such as the COVID–19 pandemic (Slovic, 2000). In particular, taking into account the trust and confidence model, the public judgment of risk affected trust in government and the indirect acceptance of government measures to combat a public hazard. The model also emphasized that people with high trust in the government, in this case, the government, were more likely to comply with government measures during a crisis (Siegrist, Earle, and Gutscher 2003). Meanwhile, risk perception influenced how the public trusted the government during a pandemic, confirming previous findings (Paek et al. 2008; Vaughan & Tinker 2009). Hence, this study concluded the existence of a significant link between risk perception and trust in the government.

Second, this study also revealed that risk perception significantly influenced individuals' self-efficacy, in line with previous findings. This relation highlighted that people's risk perception of COVID–19 positively impacted their self-efficacy, as people who perceived higher risk of susceptibility and severity of the outbreak subsequently adopted behavioral changes that would help them implement protective measures against the virus (El-Toukhy, 2015). Based on the extended parallel process model, individuals who have high perceived risk and high efficacy are called responsive individuals (Witte, 1992). These individuals are aware of the severity of and their susceptibility to the disease and are highly motivated to implement preventive measures (Flora et al. 1997). Moreover, according to protection motivation theory, during a crisis, public risk perception will be high, which can influence the public to adopt protective measures (van der Weerd 2011; Voeten et al. 2009). Meanwhile, earlier research regarding this relation has shown mixed results. Weinstein (1983) and Weinstein et al. (1990) found that risk perception and self-efficacy have a positive relation, whereas Van der Velde et al. (1992) stated that risk perception has a negative correlation with self-efficacy. Rimal and Real (2003) highlighted that these results were anticipated, as all the findings concern different public health issues. Hence, our study contributes to the literature by reflecting that the relationship between risk perception of COVID–19 and self-efficacy is significant.

Third, we found that risk perception was significantly related to trust in the government. However, in this era of rapid technological advances, this relation may vary, especially when the government have no control over or no social network sources in social media. Therefore, this result indicated that the positive relationship between risk perception and trust in government would be stronger when social media usage is high to acquire information on COVID–19. Specifically, risk perception and trust in the government fundamentally depend on information regarding a hazard, especially when the government's disseminated information is consistent with that on social media, for example, in terms of accurate

numbers of infection and recovery cases of COVID–19 (Braun & Gillespie 2011). Moreover, Braithwaite and Levi (1998) argued that risk perception and trust in government are contingent on the information acquired by people during a public threat; that is, the source of information plays a critical role in this relation. In our study, social media usage strengthened the relationship between risk perception and self-efficacy. However, this relation can be understood as more people becoming aware of the consequences of this virus from information gathered from social media, leading to their increased risk perception of COVID–19 and their adoption of protective measures to ensure self-protection against the virus. Thus, this finding supports the argument that social media can promote healthier behaviors. The results of our study are relevant as they highlight the process through which social media can influence behavior during a pandemic. We confirmed how the usage of social media can exert a significant influence on risk perception and self-efficacy (Agha, 2003).

Limitations and future research

The findings of this study should be interpreted with caution in light of several limitations. The first limitation is the cross-sectional data design, which makes it difficult to provide definitive conclusions regarding causality. However, as this study had to measure sensitive issues, such as the respondents' ethical behavior (Randall & Gibson 1990), complete anonymity was needed (Randall & Fernandes 1991), which makes it difficult to run a longitudinal analysis (e.g., Podsakoff, 2003). Second, all of the respondents were chosen from one institute, the University of Malaya; this shortcoming was due to the limited number of respondents. Future work should focus on expanding to include different organizations. A clear advantage of this approach is that data collected from companies in distinct sectors are more reflective of the broader population than data collected in more restricted settings (one organization) (Randall & Fernandes 1991). Finally, this study was conducted in Malaysia and may be limited to the Malaysian population. The results may not be generalizable to other Asian countries owing to geographic, political, cultural, and other differences.

Declarations

Informed consent: Informed consent was obtained from all individual participants included in the study and the Research Ethics Committee of University of Malaya.

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Tables

Table 1. Profile of participants

Demographic item	Categories	Frequency	Percentage
	18–24	168	32.8
	25–34	154	30.1
Age (years)	35–44	129	25.1
	45–54	47	9.2
	55 and above	14	2.8
	Total	**512**	**100.0**
	Female	302	59.0
Sex	Male	210	41.0
	Total	**512**	**100.0**
	Pre-university	32	6.3
	Bachelor’s degree	227	44.4
Education level	Master's degree	151	29.5
	Doctoral degree	62	12.1
	Academician	40	7.7
	Total	**512**	**100.0**

Note: Sample size = 512

Table 2. Common method bias assessment using full collinearity estimates criteria

Variables	Risk perception	Social media usage	Trust in government	Self-efficacy
VIF	1.419	1.201	1.496	2.112

Note: VIF = Variance inflation factor

Table 3. Measurement model: item loading/weight, construct reliability, and convergent validity

First-order constructs	Second-order constructs	Items	Scale	Loading/weight	CR/VIF	AVE/t-value	p-value
Risk perception		RSP1	Reflective	0.882	0.916	0.732	NA.
		RSP2		0.900			
		RSP3		0.878			
		RSP4		0.756			
Reflective quality		REQ1	Reflective	0.685	0.898	0.718	NA
		REQ2		0.696			
Practiced quality		PRQ1	Reflective	0.853	0.847	0.711	NA.
		PRQ2		0.770			
Advocated quality		ADQ1	Reflective	0.807	0.883	0.715	NA
		ADQ2		0.855			
		ADQ3		0.838			
Stimulated quality		STQ1	Reflective	0.859	0.896	0.715	NA
		STQ2		0.864			
		STQ3		0.735			
	Social media content	Reflective Quality	Formative	0.315	1.461	3.793	0.000
		Practiced Quality		0.322	2.932	3.313	0.000
		Advocated Quality		0.411	1.264	4.739	0.000
		Stimulated Quality		0.402	1.462	4.280	0.000
Trust in government		TRA1	Reflective	0.863	0.851	0.658	NA.
		TRA2		0.686			

	TRA3	0.872			
Self-efficacy	SEF1	0.898	0.911	0.809	NA
	SEF2	0.906			
	SEF3	0.921			
	SEF4	0.893			
	SEF5	0.877			

Note: CR = composite reliability, VIF = variance inflation factor, AVE = average variance extracted, NA. = not applicable.

Table 4. Descriptive statistics, correlation matrix, and discriminant validity

Variables	Mean	SD	1	2	3	4	5	6	7
1. Risk perception	5.885	1.190	**0.856**						
2. Self-efficacy	6.072	1.060	0.386	**0.899**					
3. Social media use	5.746	1.473	0.523	0.588	**0.901**				
4. Trust in government	4.322	0.677	0.539	0.470	0.480	**0.969**			
5. Age	2.280	1.092	0.405	0.307	0.253	0.030	NA.		
6. Sex	1.498	0.606	-0.119	-0.005	-0.134	-0.037	-0.028	NA	
7. Education	2.705	1.022	0.149	0.184	0.161	0.168	0.618	-0.060	NA

Note: SD = standard deviation; NA. = not applicable. Bold values on the diagonal are the square root values of the extracted average variance, shared between the constructs and their respective measures. Off-diagonal elements below the diagonal are correlations among the constructs, where values between 0.12 and 0.15 are significant at $p < 0.05$, and values of 0.16 or higher are significant at $p < 0.01$ (two-tailed test).

Table 5. Structural path analysis: direct, indirect, and interaction effects

						Bias and corrected bootstrap (95% CI)		
Hypothesis	**Direct effect**	**Std beta**	**Std error**	**t-value**	**p-value**	**LL 95% CI**	**UL 95% CI**	**Decision**
H-1	Risk Perception® Self-Efficacy	0.533	0.130	4.104	0.000	0.286	0.723	Supported
H-2	Risk Perception®Trust in Government	0.283	0.100	2.832	0.002	0.121	0.441	Supported
						Bias and corrected bootstrap (95% CI)		
	Interaction Effect	**Std Beta**	**Std Error**	**t-value**	**p-value**	**LL 95% CI**	**UL 95% CI**	**Decision**
H-3a	RIP*SMU®Trust in Government	0.210	0.092	2.289	0.001	0.030	0.342	Supported
H-3b	RIP*SMU®Self-Efficacy	0.506	0.142	3.571	0.000	0.257	0.714	Supported

Note: N = 512. Bootstrap sample size = 5,000. SE = standard error, LL = lower limit, CI = confidence interval, UL = upper limit 95% bias-correlated CI.

Keys: RIP*SMU®Trust in Government = Risk Perception*Social Media Usage®Trust in Government, RIP*SMU®Self-Efficacy = Risk Perception*Social Media Usage®Self-Efficacy

Figures

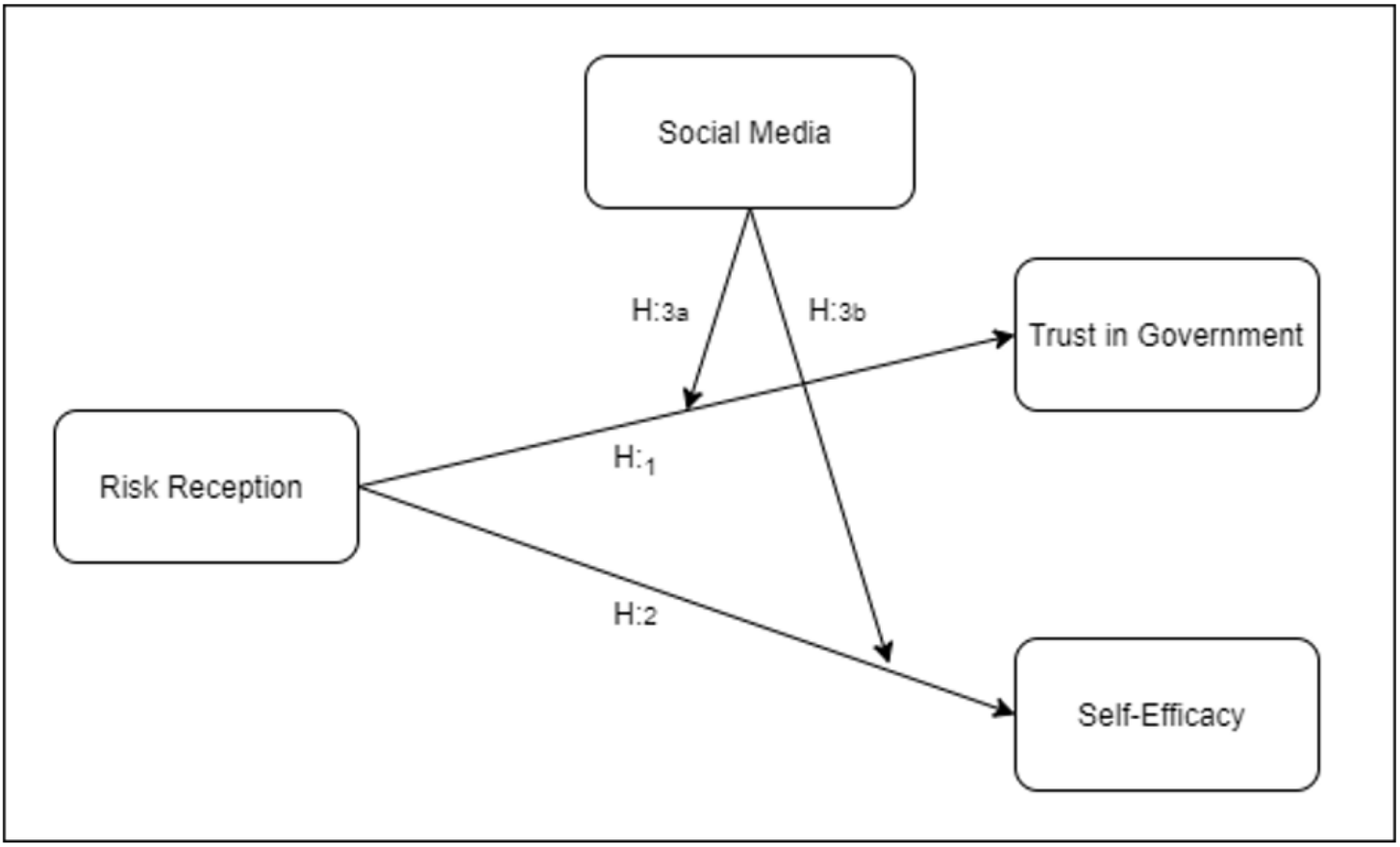

Figure 1

Research framework

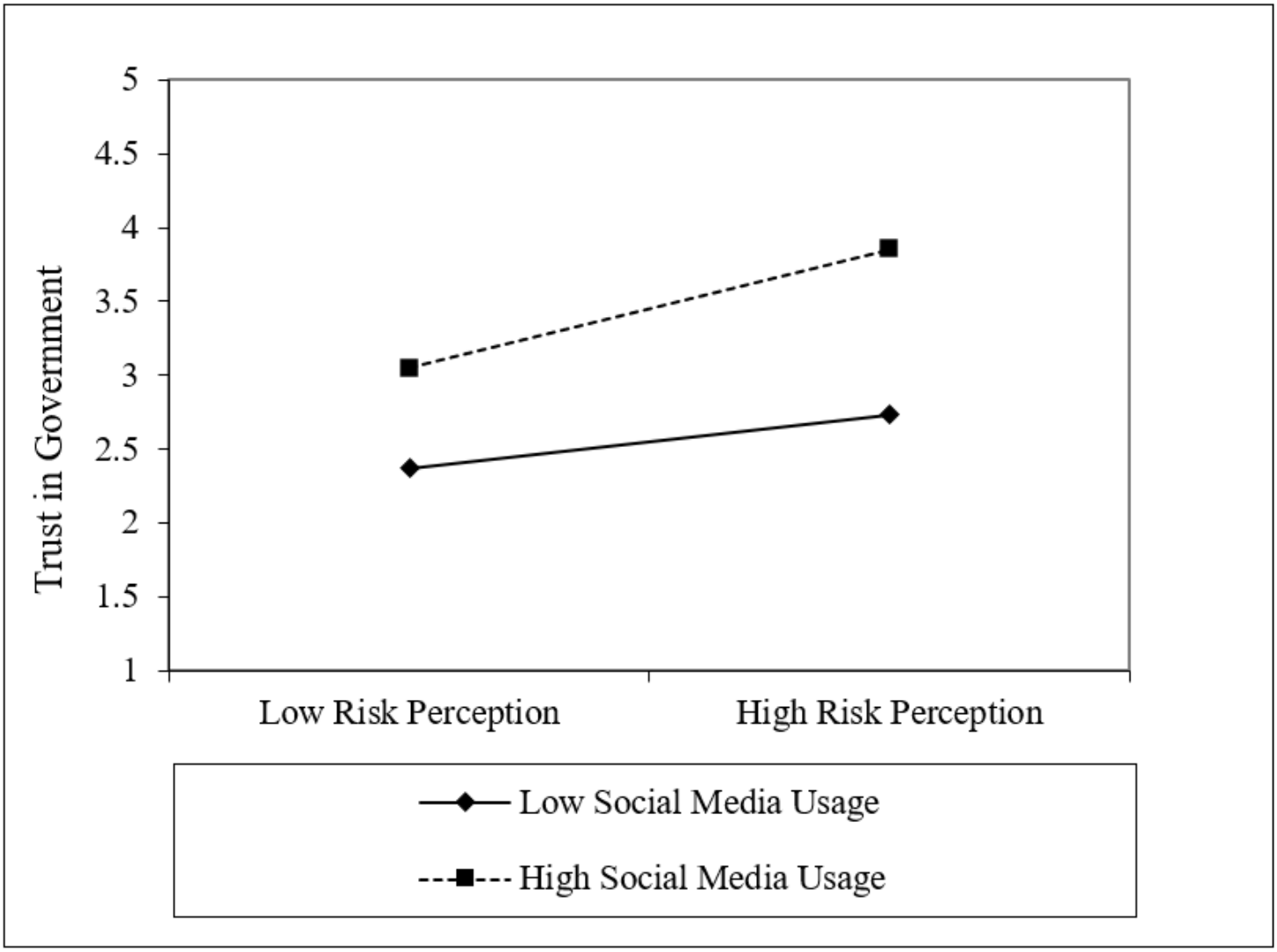

Figure 2

Interaction plot of risk perception effect of social media usage on trust in government

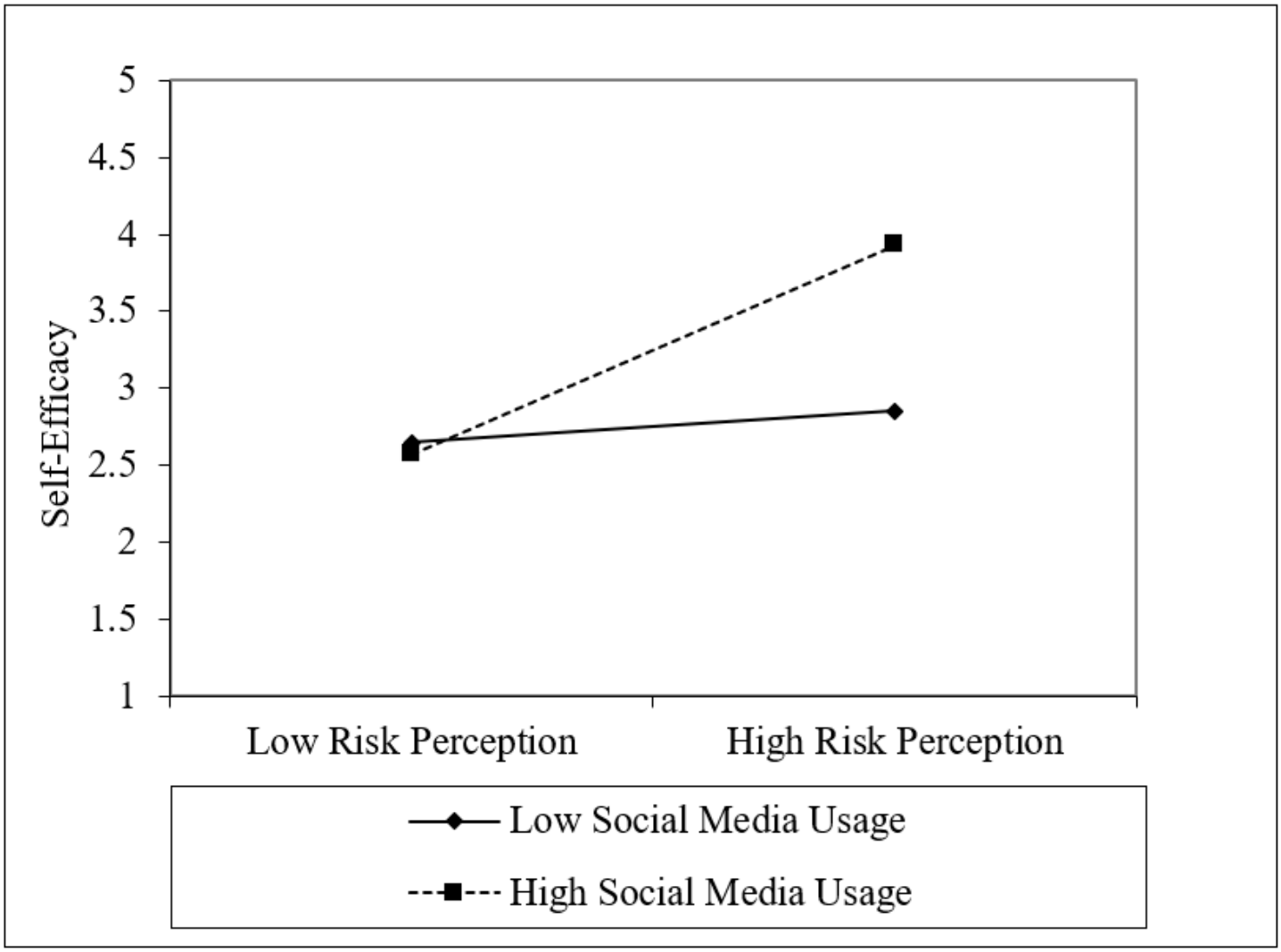

Figure 3

Interaction plot of risk perception × social media usage on self-efficacy