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A Multistage Analysis of Predicting Public Resilience of Impactful Social Media Crisis Communication in Flooding Emergencies

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ABSTRACT The desire of people affected by crises or disasters is to return to their normal lives quickly and easily. Social media provides a platform for crisis response which helps recovery and resilience building. Therefore, this study aims to investigate how social media crisis response and information shaped people's resilience-building, either affected by the flooding or not. Data collected in Malaysia after flooding consist of 375 observations. A multi-stage analysis which consists of partial least square structural equation modeling (PLS-SEM), partial least square predictions algorithm (PLS-predict), and artificial neural networks (ANN), are employed to examine the outcome of social media crisis communications. The result shows support for the significance of crisis, crisis response, social media interaction, and information seeking and sharing are not. Furthermore, the predictive relevance of the model is strong, and the root mean square error (RMSE) obtained from ANN analysis indicated a predictive model capacity. Hence, the findings demonstrated the impact of social media crisis responses that crisis management and communication may use in decision-making.

INDEX TERMS Social media, crisis communication, resilience, crisis response, flooding.

I. INTRODUCTION

Flooding is a crisis or disaster that frequently occurs in various countries worldwide. Specifically, Malaysia is one of the countries commonly impacted by flooding. As a result, several researchers have applied advanced prediction models, especially in hydrological science, to forecast rainfall or stream flow that causes flooding in Malaysia [1]–[12]. The ability to predict rainfall or stream flow is crucial since it can help mitigate flood risks [12]. Therefore, the forecasting models help crisis managers prevent, reduce, or mitigate the impact of the crisis. These models are instrumental since “crisis prevention is the ‘alpha’ or starting point of crisis

management and crisis communication” [13]. Moreover, if a crisis is avoided, nobody suffers any consequences [14].

The flooding can force thousands of people from their homes, impacting individuals, businesses, and the government. In addition, the crisis could affect every sector and introduce adverse psychological effects for all stakeholders and create numerous concerns about food, housing, job security, and mental health [15]. Due to the uncertainties, people may feel emotionally drained, resulting in a drop in motivation and performance. As a result, many could utilize social media to communicate with or inquire about family members trapped in the afflicted areas. Social media enabled individuals to stay connected with family and friends. For example, a Facebook platform includes a safety feature to inform family and friends about individual safety.

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Communication is critical in alleviating stakeholders' fears during a crisis, but little is known about the role of social media in crisis responses, information seeking and sharing, and social media interaction, which may cause individuals to rely less on formal communication to alleviate crisis-related uncertainties. However, an earlier study has examined the public's information seeking and sharing behaviors in the aftermath of terrorist attacks [16]–[18], with a particular emphasis on two social media platforms (i.e., Facebook and Twitter) and a health-related disaster such Covid-19 [14]. Regrettably, these studies do not provide a clear picture of how the public benefits from communication channels such as social media and how these activities may aid in the recovery process following natural catastrophes such as flooding. Therefore, it is necessary to research and investigate numerous social media crisis communication variables that may aid in disaster recovery.

For instance, numerous studies have examined technology adoption or the degree to which consumers are satisfied with technologies such as computers, e-commerce, e-learning, and social media [19]–[25]. In addition, numerous experts have established the value of technology in crisis management and communication [26]–[29]. Nonetheless, the function of social media in crisis communication and management has been researched via the lens of crisis informatics, a term that refers to the use of social media in times of crisis or disaster [26]–[28]. Social media, in particular, has proven to be beneficial for both formal and informal communication during and following crises. Consequently, what is important to people is recovering following a crisis, including resilience building. Thus, studies must begin to connect how technology (social media) is assisting people in recovering from crises and what social media tasks assist individuals during times of crisis.

This study intends to prove the crucial function of social media activities in providing a platform for crisis response and information dissemination to the public during a Malaysian flooding disaster. However, the question remains as to why people participated in the flooding crisis response via social media channels and how their knowledge changed their resilience-building efforts, regardless of whether they were directly affected by the flooding. Therefore, this study examines the factors that contribute to resilience. Thus, the study intends to answer the following research questions (RQ);

- RQ1: Does crisis communication factors influence people's ability to recover from flooding disasters?
- RQ2: To what extent does crisis information seeking and sharing influence people's ability to recover from flooding disasters?

This study makes three contributions to the current body of knowledge. First, even though purposeful use of social media in times of emergencies or crises has garnered considerable attention from academia and practitioners, there is a lack of studies on the factors underlying the mechanism of

resilience-building from an information systems perspective. Second, as social media becomes more prevalent, this research may aid in understanding how people's growing reliance on social media alters their ability to recover during emergencies and disasters. This study examines the effect of elements of crisis communication and crisis information seeking and sharing on resilience. Third, the research model is based on social media crisis communication and resilience (SMCCR) and crisis information seeking and sharing (CISS), which help in understanding how social media can be used in emergencies holistically. Hence, the study is organized as follows: section 2 discussed the existing works, section 3 discussed the model development and hypothesis, section 4 discussed the research methodology, section 5 presented the results of the study, section 6 discussed the findings of the study that comprises research implications and limitations, and section 7 conclude the study.

II. RELATED WORK

The scope of social media crisis communication research has considerably expanded due to Covid-19. A crisis or disaster generates conditions that jeopardize people's well-being. For instance, public health situations such as disease epidemics (e.g., Covid-19) imposed gathering restrictions. These unfortunate circumstances encouraged people to engage with family and friends via modern means such as social media [14], which can apply to natural disasters that destroy the transportation system. Numerous research has been conducted to determine how social media activities assist people during times of disaster [15], [16], [30]–[32]. Reference [30] examine how audiences get information via social and conventional media, as well as the factors that influence media consumption during times of crisis. When audiences utilize social media to gain insider knowledge and check in with family/friends during emergencies, the social-mediated crisis communication (SMCC) model reveals that they use it to obtain insider information and check in with family/friends. Social media usage is influenced by convenience, involvement, and personal recommendations; information overload is not.

Furthermore, to address the nagging question of whether the Web reduces or increases information availability and uses gaps for decision-making, the work by [33] examined the factors that influence health information seeking from the internet, traditional media, and healthcare practitioners among the diverse population of US citizens. While the Web is a convenient source of health information, the findings indicated that it might also lead to inequities in health information. In addition, [16] expand the conceptual framework for public communication during socially mediated health crises. Using a nationally representative sample in the United States, the study developed and validated two multiple-item measures for assessing public health crisis information seeking and sharing. The data indicate that

several information-seeking and information-sharing behaviors exist across platforms, channels, and information sources during times of crisis.

During emergencies, social media is becoming increasingly popular. People's attitudes toward social media information sharing in emergencies were extensively investigated [29], [34], [35]. The state-oriented risk culture and strict censorship were discovered to encourage mobile social media users to seek and share information concerning pandemics during public health emergencies [35]. Moreover, information sharing behavior during an emergency were investigated through behavioral models. For example, [36] proposed an integrated theory of planned behavior (TPB), use and gratification theory (UGT), and prosocial behavior theory (PBT) to examine users' social crisis information sharing behavior. The study found significant support for obtaining information, socializing, social media routines, habits, status seeking, and reciprocity; entertainment is not.

Moreover, [17] formulated an integrative model, combining mobile dependency theory (MDT), UGT, and task-technology fit (TTF) to explain mobile social media use intention in emergencies. The finding revealed that the gratifications (information seeking, information sharing, communication, and solitary play) and task-technology features (mobility and task features) are all significant. Similarly, the TPB and UGT were combined to investigate the information sharing behavior of Facebook users' during COVID-19 [38], which revealed that socializing, entertainment, and status-seeking as significant predictors of information sharing behavior. In addition, [39] explored the factors impacting health information sharing intention and behavior through the integration of TPB, UGT, and social cognitive theory (SCT). The study shows support for status seeking, reciprocity, and social interaction. However, critical mass and entertainment were not significant.

Furthermore, [32] explored the significance of community resilience following a disaster, which has become crucial for averting panic. The study explores the effect of the crisis, crisis response, and social media interaction on people's ability to recover (resilience). By evaluating data collected from individuals who have been isolated, quarantined, or locked down due to Covid-19. The study highlights the critical role of crisis response and social media interaction in predicting resilience and the need to develop efficient crisis management and communication techniques. Similarly, the significance of social media in infectious disease outbreaks has increased; little is known about the underlying mechanisms by which social media use affects risk perception and prevention efforts during epidemics. Finally, reference [31] analyze the relationships between social media use, risk perception, and preventative activities by examining the mediating role of two self-relevant emotions; anger and fear. The data reveal a considerable association between social media use and these emotions, which are also strongly associated with risk perception in the general population. Thus, the study shows that social media use can significantly improve preventative

actions through the use of self-relevant emotions and public perceptions of risk.

Table 1 summarises the related studies for social media crisis communication. Critical evaluation of these studies has shown that 1) Most of the existing studies focused on factors of information sharing behavior, information seeking, crisis communication behavior, and perception of social media, which focuses on addressing information exchange, 2) Only a few studies investigated resilience as an outcome of social media crisis communication, 3) Most of the work focuses on health emergencies such as disease outbreak, which may not apply to crises such as natural disasters, and 4) Most of the studies participants are users of WeChat, popularly known in China. These outcomes revealed that studies on disaster scenarios such as flooding are lacking in countries affected by such calamities. Moreover, because resilience is the hope of any crisis community, more studies are needed to show how social media crisis communication factors influence resilience-building.

Additionally, the vital role of third-party influence in crisis communication and the importance of crisis response via social media demonstrated why crisis response is an important component of social interaction and resilience [30]. Second, [16] develop a feasible and reliable instrument for crisis communication academics and practitioners to evaluate the public's information-seeking and sharing behaviors during social-mediated public health crisis communication. As a result, the informal communication skills acquired by employees through social support may serve as a supplement to their formal communication to ease uncertainty during a crisis [15]. Moreover, informal communication is related to collecting and transmitting knowledge, and social support can be gained through social media interaction or socializing [14], [36], [38]. Nevertheless, interaction and coordination is one of the key dimensions of resilience in emergency management [40], and there is broad consensus that community resilience should be maintained and enhanced [41]. Regardless, preventive behaviors contribute to people recovering from crises [31], a concept referred to as resilience in a SMCCR [14], [32], [37], [42], which can be acquired through crisis response, information seeking, information sharing, and social media interaction.

III. MODEL DEVELOPMENT AND HYPOTHESES

The situational crisis communication theory (SCCT) connects crisis and response strategies, as well as crisis types, from the attribution theory perspective [43]. Individuals seek to understand why a crisis arose through crisis response. The SCCT emphasized the significance of attributions, stating that they affect how people feel and react to bad experiences. The concepts of information seeking and sharing are drawn from CISS concept, which is associated with SMCC model [16]. The study [16] developed a more comprehensive theoretical framework for CISS in public health crises. Additionally, the theoretical framework of social media crisis response and its consequence, dubbed the social media crisis

TABLE 1. Related works.

SN	Ref	Theory	Critical component	Outcome Variable	Social media platform	Crisis scenario
1	[33]		Information seeking	Information seeking behaviour	Internet	Health emergencies
2	[29]		Searching information, information sharing	Citizens attitudes social resilience	Facebook, Twitter, Instagram, and YouTube	Emergencies
3	[36]	TPB, UGT, PBT	Information seeking, entertainment, socializing, social media routines, habit, status seeking, and reciprocity	Information sharing behavior	WeChat	General
4	[16]	CISS	Information seeking, information sharing	Scale development	Twitter, Instagram, Pinterest, and Snapchat	Health emergencies
5	[34]		Information sharing	Citizens perception of social media	Facebook, Twitter, and Instagram	Emergencies
6	[17]	UGT, TTF, and MDT	Information seeking, information sharing, communication, solitary play, mobility, and task features	Social media use intention	WeChat	Emergencies
7	[32]	SMCCR	Crisis, crisis response, social media interaction	Resilience	General	Covid-19
8	[37]	SMCCR	Crisis, crisis response, and social media interaction	Resilience	General	Covid-19
9	[38]	TPB and UGT	Information seeking, entertainment, socializing, and status seeking	Information sharing behavior	Facebook	Covid-19
10	[31]	ATF	Risk information exposure	Preventive behaviour	Blogs, Facebook, Twitter, and YouTube	MERS disease out-breaks
11	[39]	TPB, UGT, SCT	status seeking, social interaction, and norm of reciprocity, social support, critical mass, and entertainment	information sharing behavior	WeChat	Health emergencies
12	[35]		risk culture, strict censorship	Crisis communication behaviours	General	Covid-19

communication and resilience model (SMCCR), was tested to advance social media crisis communication research [14], [32]. The SMCCR model is considered a new theoretical direction in social media crisis communication [44].

Social media usage has been shown to be beneficial for enhancing public resilience [45], as evidenced by an empirical study and a hybrid analysis [32], [37], [42]. However, research on the resilience-building effects of social media crisis response, information seeking, information sharing, and social interaction in a flooding disaster scenario are still insufficient [32]. The CISS acknowledged the need for effective evaluation of crisis information seeking and sharing behaviors as critical communicative behavior outcomes of crisis communication. This is because it considers one of the many communication activities of the public in order to provide a comprehensive picture of CISS public actions. Thus, to assess the critical variables necessary for comprehending communicative behavior during social media-mediated crises response, this study formulated a model by integrating SMCCR and CISS to determine how information seeking and sharing across social media platforms aid people in recovering from flooding disasters, as illustrated in Figure 1.

A. CRISIS

According to SCCT, crises are adverse situations that prompt people to hold crisis management stakeholders accountable for their actions during the crisis. As a result, rapid response protects the crisis management profession’s reputation [43], [46]. However, the information and communication

landscapes have shifted dramatically in the digital age [33]. There is a substantial literature on using social media to identify and document catastrophic events [47], to send or receive help and support [48], to fundraise and volunteerism [48], [49], and to spread disaster warnings [50]. Thus, the robustness of social media has enabled the public to participate in debates about crisis communication, establishing them as strong resources because they do not require inhabitants of afflicted areas or firsthand knowledge of crisis damage [51]. The information can be promptly and widely disseminated via social media crisis response and information seeking and sharing activities.

Similarly, during flooding, crisis management organizations frequently distribute flooding crisis information and recovery action recommendations via a variety of communication channels to reach a diverse audience that can assist in spreading the word about the flooding to additional individuals and groups [52]. While resistance is the desirable outcome immediately following a catastrophe, robustness, rapid, and redundancy (3Rs) are critical components of post-crisis resilience [45]. Therefore, it is vital to evaluate the impact of crisis management actions prior to the crisis’s onset. In addition, crisis management aims to strengthen bonds among people and boost a community’s resilience [45], [53]. As indicated by the following hypotheses, there is a relationship between crisis, crisis response, social media interaction, and resilience building [32], [37], as illustrated in Figure 1.

- Hypothesis 1 (H1): The relationship between crisis and crisis response is positive and significant.

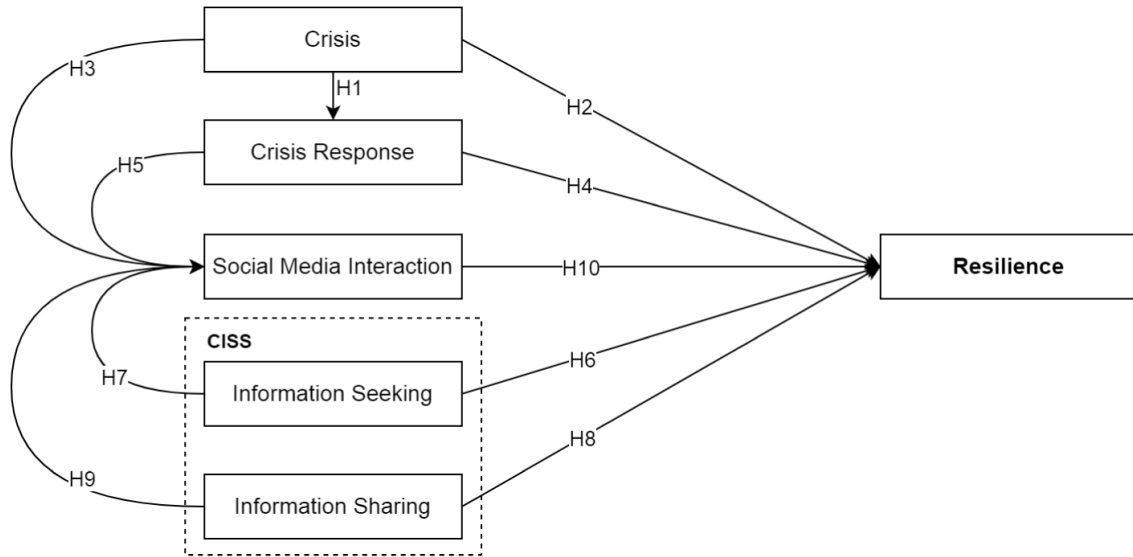


FIGURE 1. The research model for social media crisis communication and resilience.

- Hypothesis 2 (H2): The relationship between crisis and resilience is positive and significant.
- Hypothesis 3 (H3) The relationship between crisis and social media interaction is positive and significant.

B. CRISIS RESPONSE

On social media, public engagement during a crisis is referred to as crisis response. The phrase “crisis response” refers to the way stakeholders (both public and management) react in the aftermath of a crisis or disaster. The crisis response enables stakeholders to create content expressing their views on/about the issue or the body responsible for its resolution. Understanding the full range of public emotions enhances the effectiveness of crisis response methods [53]–[55], as it affects the public’s capacity to recover. The crisis response activity is used to assist individuals in their recovery process. Through controlled media, the digital world, particularly social media platforms, enables crisis management to meet specific concerns [43]. Moreover, the advent of a crisis facilitated the establishment and leadership of a crisis response via social media. Thus, crisis response and social media engagement are used to address the situation when a crisis develops. This demonstrates the value of crisis response and social media involvement in assisting individuals in recovering from a natural disaster such as flooding.

Furthermore, although research has repeatedly demonstrated that both the form and source of information can influence the public’s CISS behaviors [30], [56]–[61], the current literature on crises is deficient in terms of experimenting with catastrophe communication. The major findings demonstrated that respondents, regardless of the type or source of crisis information, had a strong desire to transmit knowledge about the disaster through offline interpersonal channels rather than online organizational and personal media. Reference [62] identified two distinct public segments that behave

differently regarding spreading crisis information. Information seeking and sharing are two constructs constituted of multiple public-made components that require behavioral study [58], [62]. Thus, to fully capture the public’s seeking and sharing of crisis information, the SMCC model requires researchers to include not only the channels and platforms for crisis information but also the ownership or source of various online channels and platforms [58], [62]. As indicated by the following hypotheses, there is a relationship between crisis response, social media interaction, and resilience building [32], [37].

- Hypothesis 4 (H4): The relationship between crisis response and resilience is positive and significant.
- Hypothesis 5 (H5): The relationship between crisis response and social media interaction is positive and significant.

C. CRISIS INFORMATION SEEKING

Information seeking, as a vigilant and proactive strategy of public communication [63], refers to the “planned searching of social media environment for information about a particular problem” [64]. Certain researchers have operationalized crisis information seeking on cognitive and affective levels, with an emphasis on perceived channel importance for crisis information seeking [65] and an interest in obtaining crisis information [66]. Others have taken a behavioral approach to crisis information, defining information seeking as the frequency with which various channels are used for information seeking [30], [62], [67] and the likelihood of channel utilization for information seeking [68].

The process of finding and receiving signals that assist in “lowering confusion about the individual’s state” and “constructing a social and personal (cognitive) understanding of the crisis” is defined as crisis information seeking [69]. The extant literature on how the public acquires

information is mostly concerned with information gained from traditional mainstream media, professional practitioners, and interpersonal communication during times of crisis [65], [67]. Existing research has examined where the public seeks crisis-related information on a range of subjects, including the effects of information content in routine and emergencies, damage, health-related risk, and food-related risk [66], [68]. Moreover, there are various literature that shows the significant of information seeking as a predictor of information sharing behaviour [17], [36], [38]. These findings emphasize the importance of thoroughly evaluating the benefits of social media crisis communication across several social media platforms, particularly during irregular and acute flooding situations. As indicated by the following hypotheses, there is a relationship between information seeking, social media interaction, and resilience building.

- Hypothesis 6 (H6): The relationship between information seeking and resilience is positive and significant.
- Hypothesis 7 (H7): The relationship between information seeking and social media interaction is positive and significant.

D. CRISIS INFORMATION SHARING

The researchers examined the role of social media in information sharing, which is defined by [70] as “online behaviors that utilize technologies and enable distributing of information, ideas, perspectives, thoughts, and media spontaneously.” Despite a lack of agreement across disciplines on how to define social media, public relations scholars have endorsed the following definition: “social media encompass a diverse range of online word-of-mouth forums, including discussion boards, blogs, and chat rooms, consumer-to-consumer e-mail, consumer product or service ratings websites and forums, internet discussion boards and forums, and moblogs” [71], [72]. During a crisis, the public can interact with organizations by providing “comments, views, likes, and shares” in response to crisis information supplied by organizations and other sources on social media platforms [73]. Previous empirical research indicates that crisis information is shared via a single social media platform, such as Twitter [19], [74].

Although, existing research considered information sharing behaviour as the outcome variable [36], [38], [39]. This could be because when a crisis occurs, the first step was to spread crisis information via social media, which included posting on Facebook or retweeting at least one tweet, and propagating government posts about the crisis. This demonstrates the critical need for additional research into why the public distributes crisis information across several social media sites, such as Facebook, Instagram, Twitter, Pinterest, etc., given each platform’s distinct characteristics. As indicated by the following hypotheses, there is a relationship between information sharing, social media interaction, and resilience building.

- Hypothesis 8 (H8): The relationship between information sharing and resilience is positive and significant.
- Hypothesis 9 (H9): The relationship between information sharing and social media interaction is positive and significant.

E. SOCIAL MEDIA INTERACTION

The interactive aspect of social media crisis communication underlines the critical importance of social contact in social media crisis communication. According to the interactive crisis communication model (ICCM), social media is a product or environment that enables groups and individuals to collaborate. The content of the interaction can be textual, visual, audio, or a combination of these [45], [53], [54], [75]. The social media discussion contains information on two independent groups: crisis management and public response.

Nonetheless, the crisis informatics’ objective is to comprehend the interaction of stakeholders involved in crisis response [76]. The study by [62] discovered multiple clusters for the public’s crisis information-seeking behavior across a variety of information sources, including local and national media, local government, and federal government. One of the important clusters is seeking crisis information via social media, including online video, Facebook page updates, Twitter, other people’s blogs, and image sharing sites [75]. Moreover, existing studies have established the positive impact of social media interaction on public resilience, which shows both direct and indirect effects [32]. Similarly, there are various literature that shows the significant of socializing as a predictor of information sharing behaviour [36], [38], [39]. As indicated by the following hypothesis, there is a relationship between social media interaction, and resilience building [32], [37].

- Hypothesis 10 (H10): The relationship between social media interaction and resilience is positive and significant.

IV. RESEARCH METHODOLOGY

This research is being carried out in Malaysia, and the flooding disaster is being utilized as an example of a crisis that shattered public resilience. Simple random sampling technique was used in this study to collect data. This technique is unbiased, allows the likelihood of each member of the population to be selected, and is simple [77]. Furthermore, the study is cross-sectional, and the sample size was computed using G*Power statistics, with 138 being determined to be the bare minimum number of participants required for the research [78], [79]. A five-point Likert scale was used to assess all of the measuring items (reflective). The data collection was performed online through a Google Form. The consent for voluntary involvement was explicitly specified in the questionnaire, which provided the participants with the option to participate or not at their discretion. Table 2 shows the demographic information and response rate for the survey participants. An overall number of three hundred and

TABLE 2. Characteristics of the sample.

Characteristics	Category	Frequency	Percent
Gender	Female	194	51.73
	Male	179	47.73
	Prefer not to say	2	0.53
Age	Under 18 years	17	4.53
	18-24 years	156	41.60
	25-34 years	95	25.33
	35-44 years	82	21.87
	45 and above	25	6.67
Level of Education	Postgraduate	45	12
	Graduate	102	27.2
	Undergraduate	147	39.2
	Diploma and others	81	21.6
Social Media Usage	Yes	371	98.93
	No	3	0.8
	May be	1	0.27
If yes in above, select which is/ are applicable (you can tick as many as you want)	Facebook	313	83.47
	WhatsApp	352	93.87
	Twitter	217	57.87
	Instagram	265	70.67
	SnapChat	102	27.2
	Skype	59	15.73
	WeChat	56	14.93
	Quora	32	8.53
	Tumblr	17	4.53
	Viber	17	4.53
	Weibo	14	3.73
	Line	8	2.13
	QQ	6	1.6
	Tiktok	4	1.07
	Linkedin	4	1.07
	Telegram	8	2.13
	Others (Reddit, Pinterest, Zoom, Youtube, Imo)	9	2.4

seventy-five (375) replies were received and documented as valid data after flooding disasters in Malaysia. Gender, age, degree of education, social media usage, and the current social media platforms are some of the demographic aspects considered.

Furthermore, the study employed Excel to store the data, SPSS 26.0 for data cleaning and neural networks analysis, and SmartPLS 3 for the measurement and structural model assessment. The researchers specifically used SPSS 26.0 to check the normality distribution of the data through common method bias (CMB) and KMO test and multilayer perceptron for the neural networks. In addition, the SmartPLS was utilized for confirmatory composite analysis (CCA), which was used to demonstrate the reliability and validity of the variables, test the hypotheses, and define the structural model of the datasets. Furthermore, the PLS Predict algorithms were used to test the predictive capability of the proposed model.

V. RESULTS

The model was estimated with the support of the SmartPLS 3.3.3 program, which employed the partial least squares regression method [80], [81]. With 10000 samples, confidence intervals were computed using the bootstrapping method [82]. When looking for a straightforward explanation

of the application of partial least squares in information systems research, [23] suggested that researchers consult the work of [24]. This approach proved to be really useful in this research. The proceeding section discussed how the analysis was tested by determining the significance and consequences of the hypothesized relationships between the variables.

A. NORMALITY TEST

Firstly, Harman’s single factor test was utilized to investigate the common method bias [83]. After rotating all of the research items, the results revealed that a single factor explained less than 19.85% of the variation in the measures, which is well below the 50% threshold [83], [84]. Therefore, the common method bias is not a source of concern for this investigation. Secondly, the Bartlett Sphericity test also checks whether two or more independent sources generated a correlation matrix. Consequently, the significance level for this study was determined to be 0.00, which indicates that the data is suitable for resilience building from social media crisis communication. Moreover, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy metric was also used, and the result of the total correlation matrix is 0.825, which is considered satisfactory. This signifies that the term is “marvelous.” Therefore, these normality indexes revealed that the normality distribution is not an issue in this study.

B. MEASUREMENT MODEL ASSESSMENT

The construct reliability of the measures was assessed originally by examining their convergent validity. As illustrated in Table 3, all item loadings exceed 0.500, more precisely between 0.555 and 0.845, showing that the items and their constructs exhibit an appropriate degree of variation [85], [86]. The items (CRI1, CRE1, ISE2, ISE3, ISE4, ISH2, and RES2) below 0.700 are considered for further analysis because the average variance extracted (AVE) values are satisfactory [86]. Likewise, the reliability measures for the model’s latent variables are summarised in Table 3. The Cronbach’s alpha readings range from 0.703 to 0.866 and are greater than 0.70. Additionally, the Rho_A index must be greater than 0.7 to demonstrate composite dependability, which is between 0.704 to 0.983 in this study. The composite reliability (CR) values are greater than 0.80, ranging from 0.805 to 0.897. All AVE metrics are greater than 0.50, ranging from 0.512 to 0.586 [81], [85], [86]. Conclusively, these statistical measurement indices indicate that the measurement model fits the data well.

A comparison of the indicator loadings on the measures’ respective constructs to their indicator loadings on other constructs was used to estimate their discriminant validity. The results show that all indicators loaded at or above the loading of the corresponding constructs, as indicated in Table 4. The loadings of each indicator on its construct were considerably bigger and higher than the loadings of the indicators on the other variables in the sample. Additionally, the discriminant validity of the constructs has been established using the Fornell-Larcker criterion (Table 5). According to this index,

TABLE 3. Item loadings and reliability measures.

Constructs	Items Code	Standardized Loading	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Crisis	CRI1	0.699	0.765	0.776	0.849	0.586
	CRI2	0.790				
	CRI3	0.816				
	CRI4	0.752				
Crisis response	CRE1	0.697	0.703	0.704	0.818	0.529
	CRE2	0.719				
	CRE3	0.716				
	CRE4	0.776				
Information seeking	ISE1	0.845	0.758	0.983	0.809	0.517
	ISE2	0.696				
	ISE3	0.661				
	ISE4	0.657				
Information sharing	ISH1	0.722	0.717	0.75	0.805	0.512
	ISH2	0.555				
	ISH3	0.716				
	ISH4	0.841				
Resilience	RES1	0.706	0.866	0.869	0.897	0.554
	RES2	0.687				
	RES3	0.760				
	RES4	0.789				
	RES5	0.794				
	RES6	0.717				
	RES7	0.752				
Social media interaction	SMI1	0.791	0.760	0.765	0.848	0.582
	SMI2	0.716				
	SMI3	0.754				
	SMI4	0.788				

TABLE 4. Crossloadings of measurement items.

Items	Crisis	Crisis response	Information seeking	Information sharing	Resilience	Social media interaction
CRI1	0.699	0.308	-0.005	0.018	0.184	0.221
CRI2	0.790	0.347	0.030	0.017	0.320	0.280
CRI3	0.816	0.340	0.026	-0.064	0.356	0.335
CRI4	0.752	0.309	-0.019	-0.014	0.283	0.310
CRE1	0.265	0.697	0.091	-0.006	0.425	0.421
CRE2	0.275	0.719	0.081	-0.015	0.297	0.392
CRE3	0.388	0.716	0.033	-0.008	0.318	0.325
CRE4	0.315	0.776	0.139	-0.005	0.409	0.377
ISE1	0.070	0.162	0.845	0.277	0.119	0.087
ISE2	-0.079	0.014	0.696	0.390	0.048	0.034
ISE3	-0.078	-0.021	0.661	0.368	0.050	0.006
ISE4	0.015	0.070	0.657	0.416	0.023	0.050
ISH1	-0.032	0.024	0.346	0.722	-0.038	-0.074
ISH2	0.003	0.090	0.330	0.555	0.057	0.004
ISH3	-0.007	-0.042	0.421	0.716	0.017	-0.046
ISH4	-0.006	-0.025	0.281	0.841	0.053	-0.074
RES1	0.265	0.262	0.080	0.031	0.706	0.411
RES2	0.302	0.344	0.141	0.004	0.687	0.375
RES3	0.269	0.347	0.058	-0.009	0.760	0.370
RES4	0.332	0.436	0.063	-0.018	0.789	0.407
RES5	0.258	0.378	0.065	0.010	0.794	0.383
RES6	0.287	0.357	0.086	0.079	0.717	0.388
RES7	0.272	0.462	0.060	0.025	0.752	0.484
SMI1	0.332	0.412	0.094	-0.007	0.440	0.791
SMI2	0.231	0.358	0.139	-0.006	0.384	0.716
SMI3	0.273	0.372	-0.032	-0.071	0.407	0.754
SMI4	0.311	0.444	0.038	-0.098	0.426	0.788

two criteria must be made to establish discriminant validity: (1) the square root of each construct's AVE is greater than its correlation with another construct, and (2) each item loads the most heavily on the construct with which it is most closely associated [85], [87]. In accordance with Table 5, all values are statistically considerably bigger than the linked construct, suggesting that discriminant validity is acceptable.

C. STRUCTURAL ASSESSMENT MODEL AND HYPOTHESIS TESTING

The findings of the hypothesis testing are illustrated in Figure 2 and discussed in detail in Tables 6, 7, and 8. Generally, the value of R^2 indicates that the endogenous variables have weak to moderate explanatory power in the model. In most cases, the values of Q^2 are compatible with the values

TABLE 5. Fornell-Larcker criterion matrix.

	Crisis	Crisis response	Information seeking	Information sharing	Resilience	Social media interaction
Crisis	0.765					
Crisis response	0.426	0.728				
Information seeking	0.012	0.120	0.719			
Information sharing	-0.018	-0.011	0.442	0.716		
Resilience	0.382	0.503	0.105	0.023	0.745	
Social media interaction	0.379	0.522	0.077	-0.083	0.544	0.763

TABLE 6. PLS explanatory power of model.

Endogenous variables	R^2	R^2 Adjusted	Q^2	Exogenous variables	f^2
Resilience	0.380	0.372	0.204	Crisis	0.024
				Crisis response	0.068
				Information seeking	0.001
				Information sharing	0.003
				Social media interaction	0.146
				Crisis	0.044
Social media interaction	0.311	0.304	0.172	Crisis response	0.215
				Information seeking	0.006
				Information sharing	0.013
				Crisis	0.222
				Crisis response	0.182
				Crisis response	0.179
				0.095	

of R^2 [86]. Resilience had the highest Q^2 values than any other endogenous factor. The research model, in particular, was able to account for some variation in respondents' judgments of social media interaction ($R^2 = 0.311$) and crisis response ($R^2 = 0.182$) related to resilience. The research model also captured significant heterogeneity of resilience ($R^2 = 0.380$). Hence, these findings indicate the structural model explains 38% predictive relevance. The results are presented in Table 6.

The path coefficient statistics reported in Table 7 show that the f^2 (effect size) are consistent with the t values, compatible with the hypothesis. It is noted that the variance inflation factor (VIF) values are less than 5, indicating that collinearity poses a small threat to the results [86], which validates the results of the CMB as well as KMO and Bartlett's test of sphericity conducted previously. Hence, the results of the independent hypothesis are discussed. Specifically, hypothesis 1 was supported, as the crisis had a positive effect on crisis response ($t = 9.095, p = 0.000$). Hypothesis 2 was supported, crisis had a positive effect on resilience ($t = 2.627, p = 0.009$). Similarly, hypothesis 3 was supported; the crisis has a significant effect on social media interaction ($t = 3.825, p = 0.000$). Moreover, hypotheses 4 and 5 were supported, crisis response had a significant effects on resilience and social media interaction ($t = 3.691, p = 0.000$; $t = 8.383, p = 0.000$), respectively.

However, hypothesis 6 and 7 was not supported, information seeking does not have significant effect on either

TABLE 7. PLS structural model results.

Relationships	B	SD	T-Value	P-Value	f^2	VIF
CRI -> CRE	0.426	0.047	9.095	0.000	0.222	1.000
CRI -> RES	0.137	0.052	2.627	0.009	0.024	1.278
CRI -> SMI	0.193	0.050	3.825	0.000	0.044	1.224
CRE -> RES	0.253	0.068	3.691	0.000	0.068	1.516
CRE -> SMI	0.430	0.051	8.383	0.000	0.215	1.248
ISE -> RES	0.024	0.053	0.450	0.653	0.001	1.276
ISE -> SMI	0.070	0.060	1.166	0.243	0.006	1.269
ISH -> RES	0.048	0.069	0.698	0.485	0.003	1.265
ISH -> SMI	-0.105	0.068	1.550	0.121	0.013	1.249
SMI -> RES	0.363	0.052	6.950	0.000	0.146	1.452

resilience nor social media interaction ($t = 0.450, p = 0.653$; $t = 1.166, p = 0.243$). Further, hypothesis 8 was not supported; information sharing had no significant effects on resilience ($t = 0.698, p = 0.485$). Also, hypothesis 9 was not supported; the relationship between information sharing and social media interaction had a negative influence, it was not statistically significant ($t = 0.121, p = 0.013$). However, hypothesis 10 was supported, social media interaction had positive effect on resilience ($t = 6.950, p = 0.000$).

D. PLS PREDICT

Rather than simply reporting model fit, researchers are advised to conduct further analysis of the model by utilizing the PLSpredict technique [88]. The PLSpredict is a collection of processes for the prediction that make use of PLS path models, as well as an evaluation of the predictability of those processes. This is due to the large and rapid development and modifications in the PLS-SEM research field [89]. The PLSpredict technique was used to determine the predictive capability of the model [90], [91]. When using the PLSpredict technique, it is recommended that the measurement models must meet all applicable criteria.

Consequently, the reflecting measurement models have demonstrated satisfactory reliability, convergent validity, and discriminant validity [87], [90], [92]. As a result, the PLSpredict method was initiated, and the predictive relevance of the model was established by comparing the root mean square error (RMSE), mean absolute error (MAE), and $Q^2_{predict}$ values for the PLS-SEM model to those for the naive benchmark model (LM). The $Q^2_{predict}$ is assessed first, according to the PLSpredict interpretation technique [90], before any other predictions measures (RMSE and MAE) are considered; the values of the PLS model must outperform the naive benchmark model [91]. In a similar vein, the RMSE and MAE prediction metrics were evaluated because of the non-normal

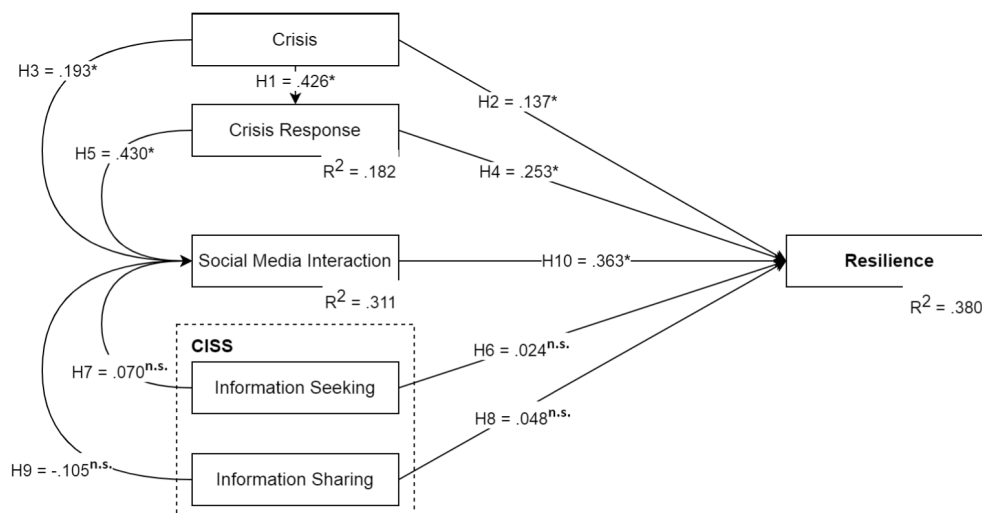


FIGURE 2. Structural model results. Notes: n.s. = non-significant; * $p < 0.05$ = significant.

TABLE 8. Summary of hypotheses tests.

Code	Hypothesis	Verdict
H1	The relationship between crisis and crisis response is positive and significant.	Accepted
H2	The relationship between crisis and resilience is positive and significant.	Accepted
H3	The relationship between crisis and social media interaction is positive and significant.	Accepted
H4	The relationship between crisis response and resilience is positive and significant.	Accepted
H5	The relationship between crisis response and social media interaction is positive and significant.	Accepted
H6	The relationship between information seeking and resilience is positive and significant.	Rejected
H7	The relationship between information seeking and social media interaction is positive and significant.	Rejected
H8	The relationship between information sharing and resilience is positive and significant.	Rejected
H9	The relationship between information sharing and social media interaction is positive and significant.	Rejected
H10	The relationship between social media interaction and resilience is positive and significant.	Accepted

sample (asymmetrically distributed) structure of the data. The PLSpredict is done by running ten (10) k-fold cross-validation on the data. In this example, each fold represents a subgroup of the overall sample, and k denotes the number of subgroups in the overall sample. According to the results of the analysis, $Q62_predict$ is greater than zero, and both RMSE and MAE are negative. Because of this, the errors in the suggested model are less significant than those in the linear model. Notably, if the PLS-SEM result (relative to the LM) yields lower RMSE (or MAE) prediction errors for all the indicators, the model is said to have high predictive ability. Thus, this has resulted in the PLS-SEM forecasts outperforming the linear model. Hence, the findings reveal that the model has a higher predictive capacity, as stated by [90]. Table 9 shows the results of the PLSpredict algorithm.

E. ANN ANALYSIS

According to [22], an artificial neural network (ANN) is a modeling tool capable of simulating human-neutral systems

and learning the agent’s behavior. The learning capabilities of neural networks (NN) can be trained to increase their performance [93], [94]. Because of this advantage, the ANN analysis was carried out in this work using SPSS v24, which was employed following previously published and tested methodologies [17], [95]–[97]. Thus, the ANN with a feed-forward back-propagation algorithm was used to determine the relative importance of exogenous elements to an endogenous variable. A multilayer perceptron (MLP) algorithm was used to accomplish this goal. To avoid overfitting, tenfold cross-validation was performed on the dataset (resulting in ten ANN models), with 70% of the data being used for training and 30% being utilized to determine the projected accuracy of the trained network (also known as testing). Moreover, the scaled conjugate gradient (SCG) algorithm was used as the optimizer for the ANN [98], [99]. In accordance with previous research [25], [97]–[99], the ANN parameters and settings are presented in Table 10.

The ANNs are typically composed of nodes dispersed across three layers: input, hidden, and output. Accordingly, each input node is assigned a synaptic weight, which is then transmitted to the hidden nodes in the hidden layers. Finally, the hidden nodes are turned into an output value using a non-linear activation function such as sigmoid, hyperbolic tang, or arctangent. The synaptic weights are modified iteratively during the learning process (training), and the resulting knowledge is used for decision making [100]. Therefore, this method constructs a specific number of hidden neurons, and the hidden and output layers was triggered using the sigmoid activation function. The RMSE was calculated for each network in the NN model to measure the model’s predictive accuracy [17], [94], [96]. In Table 11, it is demonstrated that the ANN model has an average RMSE of 0.563 for training data and 0.566 for testing data, indicating that the model’s prediction capacity is good. A smaller RMSE value suggests a more precise fit and forecast of the data. Additionally, the number of hidden neurons in an ANN model with non-zero

TABLE 9. PLSpredict assessment of the original model (PLS) vs. Naïve benchmark (LM).

Items	PLS			LM			PLS-LM		
	RMSE	MAE	Q ² _predict	RMSE	MAE	Q ² _predict	RMSE	MAE	Q ² _predict
CRE1	0.637	0.503	0.063	0.641	0.517	0.053	-0.003	-0.013	0.010
CRE2	0.672	0.519	0.070	0.680	0.525	0.046	-0.009	-0.006	0.024
CRE3	0.610	0.468	0.139	0.620	0.481	0.109	-0.011	-0.013	0.030
CRE4	0.653	0.525	0.093	0.659	0.534	0.075	-0.006	-0.009	0.018
RES1	0.814	0.606	0.062	0.822	0.622	0.042	-0.008	-0.016	0.019
RES2	0.808	0.609	0.086	0.818	0.627	0.062	-0.010	-0.018	0.023
RES3	0.747	0.537	0.059	0.761	0.547	0.024	-0.014	-0.009	0.035
RES4	0.630	0.478	0.097	0.63	0.490	0.097	0.000	-0.012	0.000
RES5	0.688	0.498	0.053	0.694	0.510	0.035	-0.006	-0.012	0.018
RES6	0.679	0.495	0.075	0.688	0.512	0.052	-0.009	-0.017	0.024
RES7	0.737	0.55	0.062	0.750	0.563	0.028	-0.013	-0.013	0.034
SMI1	0.587	0.493	0.104	0.600	0.495	0.065	-0.013	-0.002	0.039
SMI2	0.661	0.540	0.043	0.670	0.545	0.017	-0.009	-0.005	0.026
SMI3	0.682	0.535	0.060	0.693	0.547	0.031	-0.011	-0.012	0.030
SMI4	0.638	0.527	0.091	0.653	0.535	0.050	-0.014	-0.009	0.041

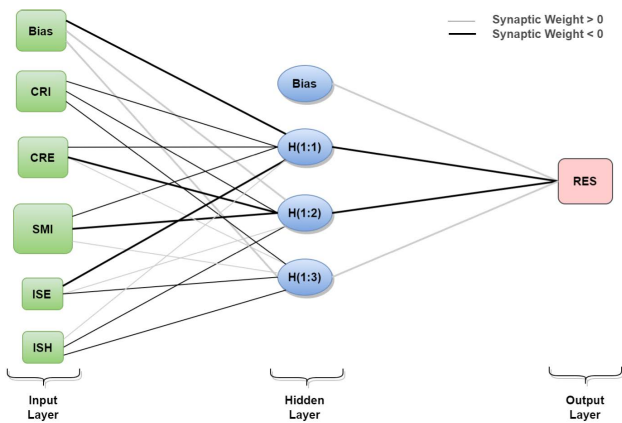


FIGURE 3. ANN model. Notes*: Hidden and output layer activation function: Sigmoid; Input neurons: Crisis (CRI), crisis response (CRE), social media interaction (SMI), information seeking (ISE), and information sharing (ISH); Output neuron: Resilience (RES).

TABLE 10. ANN parameters and settings.

Parameters	Functions
ANN module	Multilayer perceptron with back propagation
Sample	Training: 70% Dataset Testing: 30% Dataset
Resampling	Tenfold cross-validation
Loss function	Sum of square errors (SSE)
Activation functions	Hidden layer: Sigmoid Output layer: Sigmoid
Optimizer	Scaled conjugate gradient (SCG) Lambda value: 0.0000005 Sigma value: 0.00005

synaptic weights was used to determine the significance of external factors. As a result, the models are efficient in capturing the correlations between predictors and outcomes. The ANN is represented in Figure 3.

Following the determination of the ANN model’s expected accuracy and predictive relevance, a sensitivity analysis was carried out to analyze the exogenous variables’ predictive potential concerning the endogenous variables [94], [101]. Thus, this study calculated the relative relevance of each exogenous variable and then computed the normalized relative value of each exogenous variable, as shown in Table 12. The exogenous variables were sorted according to their

TABLE 11. Root Mean Square Error (RMSE) values for training and testing models.

Network	Training	Testing
1	0.521	0.603
2	0.604	0.544
3	0.547	0.582
4	0.584	0.512
5	0.577	0.513
6	0.558	0.581
7	0.563	0.578
8	0.537	0.594
9	0.573	0.590
10	0.566	0.513
Mean	0.563	0.566
SD	0.025	0.034

Note*: Standard Deviation (SD). Network Input Neurons: Crisis, crisis response, social media interaction, information seeking, and information sharing.

normalized relative importance and influence on the outcome variable. Interestingly, when the five variables were evaluated using NN models, social media interaction was the most powerful predictor of resilience, with a normalized relative value of approximately 98%. Furthermore, the results of the relative relevance of crisis responses (67.63%), crisis (42.59%), information seeking (19.07%), and information sharing (15.30%), are significant predictors of resilience, with the crisis response being more significant predictor than crisis as well as information seeking and information sharing. Specifically, social media interaction is the most powerful predictor of resilience, whereas information seeking and information sharing are the weakest predictors.

VI. DISCUSSION

Social media crisis communication is becoming increasingly important in today’s crisis management due to the public involvement in the crisis communication matrix [26], [28], [30], [102]. The purpose of this study was to examine the effect of social media crisis communication factors on public resilience by extending the SMCCR model with CISS constructs; information seeking and sharing. Resilience refers to an individual’s capacity to recover swiftly and successfully from a crisis. Accordingly, this study investigates the influence of initial SMCCR constructs plus the information

TABLE 12. Sensitivity analysis.

N	CRI	CRE	SMI	ISE	ISH
1	0.122	0.274	0.354	0.116	0.135
2	0.262	0.291	0.318	0.056	0.072
3	0.219	0.202	0.486	0.069	0.240
4	0.070	0.431	0.347	0.086	0.067
5	0.122	0.345	0.421	0.050	0.063
6	0.188	0.238	0.427	0.115	0.032
7	0.141	0.292	0.427	0.084	0.056
8	0.132	0.281	0.491	0.050	0.046
9	0.273	0.228	0.366	0.086	0.047
10	0.194	0.193	0.480	0.068	0.066
Average RI	0.172	0.278	0.412	0.078	0.082
Normalized RI (%)	42.59	67.63	98.05	19.07	15.30

Note*: Relative importance (RI). Input Neurons: Crisis (CRI), crisis response (CRE), social media interaction (SMI), information seeking (ISE), and information sharing (ISH).

seeking and sharing to enhance crisis communication and management. A multi-stage analysis was utilized, which is comprised of PLS-SEM, PLS predict, and ANN analysis, to examine how these variables predict resilience to increase global acceptance of social media-based crisis response and communication. Hence, this section presents and discusses the empirical results from three analyses applied to validate and verify the proposed model.

The discussion and developments surrounding the potential for social media to strengthen stakeholder relationships and community resilience during and after crises necessitated an empirical investigation of this research [32]. The study’s fundamental proposition is to extend the SMCCR model that lays the groundwork for effective social media-based crisis communication and management. This confirms the earlier finding of effective social media crisis communication outcome from the structural model’s evaluation. The results confirmed six of the research hypotheses, and four were rejected. This revealed that by engaging meaningfully in crisis response and social interaction on social media, the public’s ability to recover from a flooding catastrophe could be enhanced. However, the information seeking and sharing did not significantly influence resilience. Precisely, the result indicated that crisis, crisis response, social media interaction are statistically significant, while information seeking and information sharing are not.

Further, the predictive power analysis validates the path coefficient finding by indicating that the suggested model’s overall predictive power is strong. Moreover, the ANN data suggested that the value of RMSE is small, meaning that the model has predictive capacity. Also, the ANN sensitivity analysis revealed that social media interaction is the most critical factor for resilience, followed by crisis response, crisis, information seeking, and information sharing, in this order. Hence, the multi-analysis findings correspond to each other. These findings contribute to a novel view about social media-based crisis communication, which has received little attention in the past. The study’s findings emphasize the crucial necessity of social media-based crisis communication for effective crisis communication and management. Thus, crisis management organizations and stakeholders interested in successful social media crisis communication for the purpose

of developing a resilient community should consider enabling or strengthening social media crisis response and social interaction as part of their disaster or crisis management strategies.

Similarly, the findings of this study advance existing works [54], [75], whose conceptualizations of a social media-based crisis communication model underlined the critical role of crisis response and social interaction via social media use in crisis communication. Moreover, the finding of this study supports the SMCCR model, which laid the groundwork for the paradigm extended in this study. However, the information seeking and information sharing variables which are used to supplement SMCCR were not significant. This study is an early attempt that tested the CISS constructs empirically through the items proposed by [16]. Reasonably, this study could respond that the purpose of crisis informatics is to comprehend the interaction of stakeholders involved in crisis communication [76]. Thus, this study paves the way for the advancement of crisis management authorities and the public’s usage of social media for crisis communication.

A. NOVELTY OF THE PROPOSED MODEL

The popular model in crisis communication is the SCCT coined in 2002 [46], [103] and it is still being empirically tested in various settings. The SCCT focuses on response strategies to avoid reputation centered on the organization. Integrated crisis mapping (ICM) is one of the fundamental models in the crisis communication field [104]. The ICM focused on public emotions, highlighting that understanding public emotions to derive effective crisis response strategies. The weakness of SCCT and ICM motivates researchers to propose the SMCC model, which has helped crisis communication researchers in understanding the following;

- Effective crisis communication cannot be accomplished without social media,
- The social media enables people to be actors in crisis communication, and
- The public is classified into influencers, followers, and inactive. The model insists that the crisis managers should identify influencers (first public) to help them make effective social media crisis communication.

Similarly, researchers such as Hagar, Reuter, Palen, Kaufhold, Ludwig, Etc., who studied social media crisis communication under the banner of crisis informatics, proposed the crisis communication matrix, which established that the communication takes place among various entities. The matrix classified the communication between stakeholders into citizen to citizen (C2C), citizen to authorities (C2A), authorities to authorities (A2A), and authorities to citizen (A2C). Consequently, based on the popular models such as SCCT, ICM, and SMCC, researchers made a significant contribution by introducing STREMI [54], ICCM [75], social media crisis management matrix and framework (SMCMMF) [55], and social media disaster resilience model (SMDR). The ICCM is based on SCCT, SMCC, and

traditional crisis communication strategies (CCS), while the SMCMMF is based on SCCT, SMCC and ICM. Most of these models either focus on response strategy, public emotions, type of public, and the interactive feature of social media as claimed by STREMI and ICCM.

Nevertheless, the SMDR is simply the model that introduced the concept of resilience through qualitative and content analysis of disaster-related keywords. Although, descriptive investigations have established how social resilience can be derived from social media crisis communication [29], [34], [35]. As a result, an SMCCR was conceptualized since crisis management and communication aim to improve people's ability to recover from a crisis. The SMCCR has been cited by [44] as one of the new theoretical directions in social media crisis communication. Thus, to extend SMCCR and reevaluate the model in other crisis scenarios different from Covid-19, this study supplements CISS in SMCCR. This is one of the earlier works that demonstrate social media crisis communication factors as influencers of resilience-building into the spotlight of academic research about social media crisis communication.

B. RESEARCH IMPLICATIONS

This research adds to the literature by extending the SMCCR with CISS framework to examine the social media crisis communication elements influencing the public ability to recover from flooding quickly. This is an emergent theoretical approach in social media crisis communication research, as most recent work has focused on SCCT and SMCC [16], [54], [55], [75]. Similarly, another theoretical contribution is the use of CISS items to the research on flooding disasters, which is exclusively emergent [16]. This huge contribution has significant ramifications to advance effective crisis communication and management because the public relies on crisis management and communications institutions to help them recover from crisis effectively.

Notwithstanding existing studies on resilience building through social media crisis communication models, this study is an early empirical study investigating resilience building from social media crisis communication activities. Prior research has primarily concentrated on proposing a framework [16], [45], [54], [55], [75]. However, most of this research proposes a crisis communication framework without validation with primary data. Thus, theory development research emphasizes the importance of measuring ideas and models in various circumstances [105]. Second, this study highlights the crucial role of social media response and social interaction, emphasizing the need to enhance public resilience. In this instance, crisis management and communication activities should be directed toward cognitively portraying social media crisis communication as a crucial technology that saves human lives and increases resilient community. Simultaneously with these efforts, practitioners should expand the breadth of social media crisis communication services while ensuring their quality,

reliability, and sustainability, thereby increasing the resilience and perceived usefulness of social media.

More crucially, public resilience has sparked an interest which is the main desire of any crisis management effort, whether they used traditional media or predisposition to use social media. The fundamental desire of people in a crisis is to return to their normal lives; crisis communication should be bolstered to boost public resilience. For instance, social media crisis communication strategies should be well-designed to offer higher levels of reliability and sustainability. These strategies must be sufficiently implemented in order to safeguard the people from the devastating impact of a crisis. Additionally, crisis management and people with social positions should be cautious when addressing crises online. This enables people to acquire a more favorable opinion of stakeholders' honesty and, as a result, a higher level of resilience. Moreover, crisis management organizations must ensure that public opinion and information should be harvested and kept for decision-making.

VII. CONCLUSION

The purpose of this study is to evaluate the impact of crisis communication delivered through social media on the ability of people to recover from crises swiftly, which is referred to as public resilience in this context. In particular, the study empirically investigated how crisis response, information seeking and sharing, and social media interaction influence public resilience. The research allows members of the public who have been affected by flooding disasters to express their opinions on social media-based crisis responses. This study investigated a model incorporating CISS and SMCCR for assessing the impact of the public's communicative behavior during flooding catastrophes. Furthermore, it discusses how the public responds to crises, information seeking, and information sharing. According to the study, social media crisis communication reflects the public's diverse information-seeking and information-sharing activities. The findings show that six hypotheses were supported, and four were not. As a result, this study allows exploring the impact of crisis communication on crisis management authorities as well as the general public as stakeholders affected by the crisis. Thus, organizations responsible for crisis management and communication must comprehend, enable, and efficiently respond to the flooding calamity. This will provide critical insights for organizations looking to strengthen community resilience, garner public support, and leverage the opportunity to collaborate with influential social media followers on social media platforms to disseminate timely and accurate crisis information to communities and individuals in need.

A. LIMITATION AND FUTURE DIRECTIONS

Numerous restrictions apply to this investigation. First, the respondents in this survey were from a particular country (Malaysia), where people have a greater chance of being affected by flooding. The study's conclusions may vary

dramatically between countries with varying crisis types such as political uprising, gun violence, or public health crisis. Second, this study assessed the information seeking and sharing constructs as the first to do so from items developed by [16]. This may impose some constraints on the research findings, most notably on reliability and validity. Future research should focus on circumnavigating the limits imposed by a homogeneous population and items validity. Additional studies may be conducted to evaluate the prospect of enhancing the CISS constructs by adding more appropriate items.

Additionally, some studies in the literature have identified age as a moderator [105]. This implied that age might alleviate some of the more severe impacts of social media crisis communication. However, this study does not include a comparison of different age groups because it was not within the scope of the study. As a result, future research can concentrate on the well-established moderating effect of age. As a result, an additional study should be conducted to determine whether age is a significant moderator and whether information seeking and sharing characteristics influence resilience in other crisis scenarios. Thus, it is necessary to conduct similar research with respondents of all ages to determine whether distinct outcomes prevail.

Moreover, the lack of addressing technical problem is highlighted as limitation of this work for future research. Future studies could develop a system for crisis management and communication based on the conclusion made by this investigation. Moreover, since this study applied a multi-stage analysis by combining SEM, ANN, and PLSpredict, to address the research problem. Future studies could mine social media crisis content using application programming interface (API). Examining the sentiment of the content through machine learning will help crisis managers applied effective response strategy and recovery plan.

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