Source and Temporal Patterns in Twitter Risk-Protection Messaging During Cyclone Shaheen in Oman: A Quantitative Content Analysis Guided by the CERC Model

Amira Ali * and Bahiyah Omar

School of Communication, Universiti Sains Malaysia, 11800 USM, Penang, Malaysia

***Corresponding author**

DOI: https://doi.org/10.47772/IJRISS.2026.100701090

Received: 06 August 2026; Accepted: 11 August 2026; Published: 21 August 2026

ABSTRACT

Social media can support rapid warning, information sharing, and public guidance during natural disasters, but communication patterns may vary according to who posts, when messages appear, and what guidance they contain. Guided by the temporal logic of the Crisis and Emergency Risk Communication (CERC) model, this study examined source- and posting-period-based patterns in Twitter communication during Cyclone Shaheen in Oman. A quantitative content analysis was conducted on the final analytic sample of 600 publicly accessible tweets posted between 24 September and 15 October 2021. Stratified random sampling represented five source categories—governmental meteorology, non-meteorological government, media, netizen, and amateur accounts—and three posting periods: before, during, and after the cyclone. Tweets were coded for timeliness, action orientation, format, online attitudinal engagement, and preparedness-, response-, and recovery-related guidance. Intercoder reliability calculated on 50 tweets was 0.82. Overall, 71.0% of tweets were timely, 45.8% were action-oriented, 87.7% combined text and visuals, and 92.0% received at least one like or retweet. Preparedness guidance appeared in 46.8% of tweets, response guidance in 35.7%, and recovery guidance in 45.5%. The three-item composite risk-protection content score differed significantly by posting period, $F(2, 597) = 3.70$, $p = .025$, and by source, Welch's $F(4, 249.89) = 21.74$, $p < .001$. The highest descriptive period mean occurred after the cyclone. Meteorological accounts recorded the highest descriptive source mean, followed by government accounts, with no significant difference between those two sources. The findings are consistent with CERC's phase-sensitive premise and show that risk-protection messaging was distributed across institutional, media, and citizen sources. Likes and retweets are interpreted as online reactions and message amplification, not as evidence of offline protective action.

Keywords: Crisis and Emergency Risk Communication, Cyclone Shaheen, Twitter, quantitative content analysis, risk-protection messaging

INTRODUCTION AND BACKGROUND TO THE STUDY

Communication is central to disaster management because warnings, situation updates, and recovery information shape the protective options available to affected communities. In rapid-onset disasters, communication priorities change quickly: audiences initially require forecasts and preparedness instructions, then immediate safety guidance, and later information about relief, service restoration, and rebuilding. The Crisis and Emergency Risk Communication (CERC) model captures this temporal logic by treating communication as a staged process rather than a single response activity (Reynolds & Seeger, 2005; Veil et al., 2008).

Social media has expanded the range of actors able to participate in this process. Authorities and meteorological agencies can issue warnings directly; media organisations can amplify and interpret official information; and citizens can share local observations, requests, and community support. Twitter, now known as X, has been particularly prominent in disaster research because its public architecture enables short updates, reposting, hashtags, and near-real-time interaction (Kim & Hastak, 2018; Pourebrahim et al., 2019). Research across hurricanes, earthquakes, fires, and floods shows that Twitter can support situational awareness and risk communication, although the accuracy, relevance, and credibility of user-generated information remain persistent challenges (Abedin & Babar, 2018; Seneviratne et al., 2024).

Cyclone Shaheen provides an important context for examining these dynamics. The cyclone made landfall in northern Oman in October 2021 and generated intense rainfall, flooding, infrastructure disruption, and extensive public communication needs (Terry et al., 2022). Official agencies, media outlets, meteorological specialists, and citizen accounts used Twitter before, during, and after the event. This produced a communication environment in which authoritative warnings, visual forecasts, local updates, safety instructions, and recovery information circulated simultaneously.

Prior studies have established that disaster-related Twitter content changes over time (Spence et al., 2015; Wukich, 2016) and that source type influences who receives attention and how information is circulated (Liu & Xu, 2019). Research has also emphasized the importance of timely and actionable messages, especially when audiences must decide whether to prepare, evacuate, avoid hazardous areas, or retransmit warnings to others (Kinsky et al., 2021; Mehta et al., 2022). Multimedia is similarly relevant. Visual material can display a cyclone track, hazard area, road closure, or damage, while accompanying text supplies interpretation and instruction. Analysing both content and format is therefore necessary to understand how disaster messages are constructed (Alam et al., 2018).

This study examines the quantitative component of a wider investigation of Twitter use during Cyclone Shaheen. It focuses on five source categories, two observable message characteristics, three tweet formats, online attitudinal engagement, and risk-protection guidance. Two related but distinct temporal dimensions are maintained throughout the analysis. Posting period identifies when a tweet appeared—before, during, or after the cyclone—whereas message function identifies whether its content contained preparedness-, response-, or recovery-related guidance. Likes and retweets are treated as indicators of online engagement and amplification. Risk-protection messaging refers to protective guidance represented in tweet content; neither measure is interpreted as verified offline behaviour.

Statement of the problem

Existing research establishes that social media is widely used to circulate warnings, situational updates, and public guidance during disasters. Evidence of platform use alone, however, does not explain how risk-protection communication is organised. For Cyclone Shaheen, the central problem is the limited integrated quantitative evidence concerning who communicated, when tweets were posted, how messages were constructed, how they were engaged with online, and what preparedness-, response-, or recovery-related guidance they contained. This limitation is important in Oman, where tropical-cyclone exposure and an established early-warning system create a practical need for communication that is timely, actionable, and responsive to changing information needs (Al-Zaabi & Al-Zadjali, 2022).

First, disaster-related Twitter studies often combine communicators into broad official and public groups, obscuring differences among governmental meteorological accounts, other government institutions, media organisations, specialist netizens, and amateurs. These sources differ in institutional responsibility, technical expertise, access to verified information, media reach, and local knowledge. A source-sensitive analysis is therefore required to describe how activity was distributed across the five source categories before, during, and after Cyclone Shaheen (Mojtahedi & Oo, 2017; Avvenuti et al., 2018).

This source-related gap is connected to message timing and design. Public-information needs change as a rapidly developing cyclone moves from warning to impact and recovery, while communicators use different combinations of timeliness, action orientation, text, and visuals. Studies that aggregate an event into one period or examine content separately from format cannot show how message characteristics and text-only, visual-only, and combined text-and-visual formats are distributed across posting periods. A descriptive analysis that links source activity, posting period, message characteristics, and format is therefore needed (Alam et al., 2018).

Second, online reactions and risk-protection guidance require separate measurement. A like may indicate acknowledgement, approval, concern, or solidarity, while a retweet amplifies a message; neither verifies comprehension, compliance, or an offline protective action. Similarly, a tweet containing preparedness, response, or recovery guidance documents communicated content rather than the recipient's subsequent behaviour. Conflating these measures can overstate Twitter's behavioural effects. The analysis must therefore describe online attitudinal engagement across sources and posting periods while reporting the prevalence of risk-protection guidance as a distinct content measure.

Third, descriptive frequencies alone cannot determine whether the overall concentration of risk-protection content differs systematically by posting period or source. Inferential testing is needed to establish whether a composite score based on preparedness, response, and recovery varies across the periods before, during, and after the cyclone and across amateur, government, media, meteorological, and netizen sources. Recovery was treated as a broad CERC-related function that included both recovery adaptation and future resilience. This three-item structure was adopted to preserve conceptual balance across the main CERC-related functions and to avoid giving disproportionate statistical weight to recovery-related content. These comparisons provide a focused test of CERC's phase-sensitive logic and of source-based variation without asserting a causal effect on audience behaviour (Reynolds & Seeger, 2005; Veil et al., 2008).

These gaps are especially relevant because disaster-related social-media communication in Oman remains comparatively underexamined. Findings from other national and institutional settings cannot automatically explain the Twitter environment surrounding Cyclone Shaheen. Context-specific evidence is needed while maintaining a clear boundary between observable message content, platform engagement, and unobserved offline behaviour.

Accordingly, this study addresses three aligned analytical tasks. It describes tweet-source activity, message characteristics, and tweet formats across posting periods; describes online attitudinal engagement across sources and periods together with the overall prevalence of preparedness-, response-, and recovery-related guidance; and tests whether the three-item composite risk-protection content score differs by posting period and source category. These tasks directly structure the objectives, research questions, hypotheses, analysis, results, and discussion.

Study objectives

The study pursued three objectives:

1. To describe how tweet-source activity, message characteristics (timeliness and action orientation), and tweet formats (text only, visual only, and combined text and visual) were distributed across the posting periods before, during, and after Cyclone Shaheen in Oman.
2. To describe online attitudinal engagement (at least one like or retweet) across the five tweet-source categories and three posting periods, and to report the overall prevalence of preparedness-, response-, and recovery-related guidance.
3. To test whether the three-item composite risk-protection content score differed significantly by posting period and tweet-source category.

Research questions and hypotheses

RQ1: How were tweet-source activity, message characteristics (timeliness and action orientation), and tweet formats (text only, visual only, and combined text and visual) distributed across the posting periods before, during, and after Cyclone Shaheen in Oman?

RQ2: How was online attitudinal engagement (at least one like or retweet) distributed across the five tweet-source categories and three posting periods, and what was the overall prevalence of preparedness-, response-, and recovery-related guidance?

RQ3a: Did the three-item composite risk-protection content score differ significantly across the three posting periods?

H1: The three-item composite risk-protection content score differs significantly across the periods before, during, and after Cyclone Shaheen.

RQ3b: Did the three-item composite risk-protection content score differ significantly across the five tweet-source categories?

H2: The three-item composite risk-protection content score differs significantly across amateur, government, media, meteorological, and netizen Twitter sources.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Crisis and Emergency Risk Communication model

CERC integrates risk communication and crisis communication within a framework organised around changing public needs (Reynolds & Seeger, 2005). Its classic formulation includes pre-crisis, initial event, maintenance, resolution, and evaluation phases. The model emphasises speed, accuracy, credibility, clarity, empathy, and action-oriented guidance while recognising that the relative importance of these principles changes as an emergency develops (Veil et al., 2008). CERC has been applied to social-media communication in health emergencies and natural hazards, including Twitter analyses of hurricane communication (Vos & Buckner, 2016; Jin & Spence, 2021; Kinsky et al., 2021).

For analytical clarity, this study represents CERC's temporal logic through two related but non-equivalent dimensions. Posting period records when a tweet appeared: before, during, or after Cyclone Shaheen. Message function records whether the tweet contained preparedness, response, or recovery guidance. These dimensions are expected to correspond in broad terms, but they are not treated as identical; a tweet posted in any period could contain more than one type of guidance. This distinction allows the study to examine temporal change without assuming that posting time determines message content.

Message characteristics and tweet formats

Timeliness is important when information loses value as conditions change. Before impact, early warnings can support household and institutional readiness. During impact, rapid updates can communicate road closures, shelter instructions, service interruptions, and immediate hazards. Timeliness is therefore examined as an observable message characteristic whose distribution may vary by posting period. Prior research indicates that emergency agencies use Twitter unevenly across disaster stages and that rapid, continuous updates are especially relevant during uncertainty (Wukich, 2016; Kinsky et al., 2021).

Action-oriented communication translates hazard information into practical guidance by indicating what audiences should do, where they should go, what they should avoid, or how they can obtain assistance. Experimental research on bushfire and severe-weather warnings shows that explicit instructing information can improve clarity, self-efficacy, and protective intentions (Mehta et al., 2022; Atwell Seate et al., 2024). These findings justify coding action orientation as a message property; they do not establish that each directive tweet caused a protective action.

Tweet format may shape how information is presented. Text-only tweets can provide explanation, visual-only tweets can display maps or images, and combined text-and-visual tweets can integrate interpretation with graphical information. Multimodal disaster datasets demonstrate the analytical importance of studying these elements together (Alam et al., 2018). In this study, format is treated as a descriptive message feature rather than as evidence of effectiveness.

Sources, engagement, and risk-protection messaging

Source type structures access to and presentation of disaster information. Government agencies typically issue official instructions and operational updates; governmental meteorological accounts provide forecasts and hazard tracking; media organisations report and amplify information; netizens may add specialist or community interpretation; and amateurs may contribute local observations and circulation. These categories are analysed as distinct communication sources, without assuming that source label alone establishes accuracy, credibility, or public trust (Panagiotopoulos et al., 2016; Splendiani & Capriello, 2022).

Online attitudinal engagement records whether a tweet received at least one like or retweet. Likes indicate an observable platform reaction, while retweets also redistribute a message to additional networks. The binary indicator therefore captures reaction and amplification only; it does not establish comprehension, agreement, compliance, or offline behaviour.

Risk-protection messaging is conceptualised as content that supports preparedness, response, or recovery. Preparedness guidance includes advance warnings and preventive steps; response guidance includes immediate safety instructions, emergency information, and actions during impact; recovery guidance includes post-impact adaptation and future resilience. For the final composite measure, recovery adaptation and future resilience were treated as subcomponents of the broader recovery function rather than as separate scoring dimensions. The framework guides the descriptive examination of source activity, message characteristics, formats, engagement, and guidance (RQ1–RQ2). It also supports the non-directional expectation that the three-item composite risk-protection content score will differ by posting period and source category (RQ3a–RQ3b; H1–H2). The study tests patterns and group differences, not causal effects on recipients.

RESEARCH DESIGN AND METHODOLOGY

Research design and unit of analysis

The study used quantitative content analysis to identify recurring and measurable characteristics in Twitter communication. Content analysis enables systematic comparison of public messages across predefined categories (Bruns & Stieglitz, 2012; Neuendorf, 2002). The unit of analysis was one public tweet related to Cyclone Shaheen.

Population, sampling, and screening

The initial collection used the Twitter REST application programming interface and Arabic and English search terms related to Cyclone Shaheen, tropical cyclones, early warning, flooding, storm surge, and strong winds. The collection period was 24 September to 15 October 2021 and yielded approximately 46,000 tweets. Stratified random sampling was used because communication was expected to vary by both source and posting period (Kim et al., 2018). The sample-size calculation yielded an initial screening sample of 655 tweets from the approximately 46,000-tweet population, using a 99% confidence level and a 5% margin of error.

The 655 initially selected tweets were screened for direct relevance to Cyclone Shaheen, consistency with the study period, sufficient textual or visual information for coding, duplication, and correct source classification. Unrelated posts, exact duplicates, and records that could not be reliably coded were excluded. In total, 55 tweets were removed during screening, leaving a final analysed sample of 600 tweets (N = 600). All descriptive and inferential analyses reported in this article were conducted on these 600 tweets. The final sample comprised 190 tweets from the before period (24 September–2 October), 145 from the during period (3–4 October), and 265 from the after period (5–15 October). Five source strata were represented: amateur, government (non-meteorological), media, netizen, and meteorology (governmental meteorological) accounts. Table 1 presents the final distribution.

Arabic and English tweets were identified based on the language of the tweet text and the Arabic and English search terms used during data collection. The same coding instrument was applied to both Arabic and English tweets to maintain consistency across the dataset. Coding decisions were based on the complete meaning of the tweet, including textual and visual elements where relevant. When tweets contained both Arabic and English elements, they were coded according to the overall message meaning rather than language alone. The coders were familiar with Arabic-language social-media content and the Omani disaster context, including local expressions, place names, official warning terminology, and culturally specific references related to Cyclone Shaheen. English tweets were coded using the same conceptual definitions to ensure comparability across languages. No separate coding scheme was created for each language.

Table 1: Final sample distribution by source and posting period (N = 600)

Source	Before, n (%)	During, n (%)	After, n (%)	Total, n (%)
Amateur	50 (26.3)	40 (27.6)	60 (22.6)	150 (25.0)
Government	40 (21.1)	35 (24.1)	75 (28.3)	150 (25.0)
Media	55 (28.9)	30 (20.7)	70 (26.4)	155 (25.8)
Netizen	20 (10.5)	20 (13.8)	30 (11.3)	70 (11.7)
Meteorology	25 (13.2)	20 (13.8)	30 (11.3)	75 (12.5)
Total	190 (100.0)	145 (100.0)	265 (100.0)	600 (100.0)

Operationalization and coding

Message characteristics were coded for presence (1) or absence (0). For this quantitative article, timeliness was represented by the broad binary item identifying urgent, current, or continuing cyclone information, while action orientation was represented by the broad binary item identifying a directive or recommended action. Tweet format was represented by three mutually exclusive binary indicators: text only, visual only, or combined text and visual. The final data file contained exactly one format classification for each of the 600 tweets.

Source was coded into one of the five strata shown in Table 1. Online attitudinal engagement was derived directly from two binary coding items: whether the tweet had at least one like and whether it had at least one retweet. A tweet was classified as engaged when either item was present. This measure identifies observable platform reaction and amplification; it does not demonstrate an offline behavioural outcome.

Risk-protection content was operationalized through three broad CERC-related indicators: preparedness, response, and recovery. Preparedness captured preventive steps, planning, warnings, or resource readiness before the cyclone. Response captured immediate safety guidance, compliance with instructions, emergency services, or actions during impact. Recovery captured post-impact assistance, restoration, adjustment, recovery adaptation, and future resilience. Although recovery adaptation and future resilience were distinguished during coding to capture the richness of post-cyclone communication, they were treated as subcomponents of the broader recovery function rather than as separate dimensions in the final composite score.

Each of the three main indicators was coded as 1 when present and 0 when absent. Recovery was coded as present when either recovery adaptation or future resilience appeared in the tweet. The three indicators were then summed to create a three-item composite risk-protection content score ranging from 0 to 3. A score of 0 indicated that no risk-protection guidance was present, whereas a score of 3 indicated that the tweet contained preparedness, response, and recovery guidance. This structure preserved conceptual alignment with the CERC-related functions of preparedness, response, and recovery and avoided giving disproportionate statistical weight to recovery-related content.

Intercoder reliability

The primary researcher coded the complete dataset. A second coder with media and communication experience and familiarity with Arabic-language social-media content received training on the coding definitions and independently coded 50 tweets, including 10 from each source category. Holsti's coefficient was calculated from 41 agreements and nine disagreements, producing an overall intercoder reliability value of 0.82. This exceeded the study's minimum criterion of 0.70 and indicated acceptable overall agreement for the coding instrument.

Variable-specific intercoder reliability was also assessed for the three components of the risk-protection content score: preparedness, response, and recovery. As shown in Table 2, the reliability coefficients for the three components were all above 0.80, indicating acceptable agreement between the two coders. The overall intercoder reliability coefficient was 0.82, further supporting the reliability of the three-item composite risk-protection measure.

Table 2: Intercoder Reliability for the Three Risk-Protection Components

Risk-protection component	**Intercoder reliability**
Preparedness	0.83
Response	0.81
Recovery	0.82
Overall	0.82

Data analysis

Frequencies and percentages were used to answer RQ1 and RQ2 by describing source activity, message characteristics, formats, online engagement, and guidance prevalence. A one-way analysis of variance (ANOVA) was used to answer RQ3a and test H1 by comparing the three-item composite risk-protection content score across the three posting periods. For RQ3b and H2, source-group differences were assessed using one-way ANOVA procedures, with Welch's ANOVA used when the homogeneity-of-variance assumption was not met.

The three-item composite score was created by summing the presence of preparedness, response, and recovery guidance in each tweet. Although recovery adaptation and future resilience were identified during coding, they were treated as subcomponents of the broader recovery category in the final composite score. This ensured that preparedness, response, and recovery contributed equally to the risk-protection content measure.

Before interpreting the inferential results, the relevant assumptions were assessed separately for the posting-period and tweet-source analyses. Independence was addressed through the study design, as each tweet represented a separate observation and was assigned to only one posting period and one tweet-source category. Normality was assessed using the skewness and kurtosis of the model residuals, while homogeneity of variance was examined using Levene's test. Scheffé-adjusted post-hoc comparisons were used for the posting-period analysis when homogeneity was satisfied. When the homogeneity-of-variance assumption was not met for the source analysis, Welch's ANOVA and Games–Howell post-hoc comparisons were used. The significance threshold was set at $p < .05$. All 600 cases had valid values for the variables used in these analyses.

DATA ANALYSIS AND RESULTS

RQ1: Source activity, message characteristics, and tweet formats across posting periods

Communication volume and message construction varied across the three posting periods. Media and amateur sources contributed the largest shares before the cyclone, while government communication was most prominent after impact. Meteorological accounts maintained a smaller but comparatively steady presence. As shown in Table 3, timeliness was very high before (92.6%) and during (93.8%) the cyclone, then declined to 43.0% after

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

it. Action orientation followed the same pattern, appearing in 73.7% of tweets before and 74.5% during, compared with 10.2% after.

Combined text-and-visual communication dominated every posting period and accounted for 87.7% of the full sample. Text-only posts were more common after the cyclone than before or during it, while visual-only posts remained rare. These results answer RQ1 by documenting how source activity, message characteristics, and tweet formats were distributed over time.

Table 3: Message characteristics and tweet formats by posting period

Variable	Before (n = 190), n (%)	During (n = 145), n (%)	After (n = 265), n (%)	Total (N = 600), n (%)
Timely	176 (92.6)	136 (93.8)	114 (43.0)	426 (71.0)
Action-oriented	140 (73.7)	108 (74.5)	27 (10.2)	275 (45.8)
Text-only	16 (8.4)	9 (6.2)	39 (14.7)	64 (10.7)
Visual-only	2 (1.1)	2 (1.4)	6 (2.3)	10 (1.7)
Text and visual	172 (90.5)	134 (92.4)	220 (83.0)	526 (87.7)

Note: Message characteristics were binary and could co-occur. Tweet-format categories were mutually exclusive.

RQ2: Online attitudinal engagement by source and posting period

Of the 600 tweets, 552 (92.0%) received at least one like or retweet. Meteorological tweets recorded engagement for all 75 posts (100.0%), followed by government tweets (148 of 150; 98.7%), media tweets (145 of 155; 93.5%), netizen tweets (64 of 70; 91.4%), and amateur tweets (120 of 150; 80.0%). By posting period, engagement was highest during the cyclone (138 of 145; 95.2%), followed by the before period (178 of 190; 93.7%) and the after period (236 of 265; 89.1%). The largest absolute number of engaged tweets appeared after the cyclone because that period contained the most observations, although its within-period rate was the lowest of the three periods.

Table 4: Online attitudinal engagement by source and posting period

Source or posting period	Engaged, n (%)	No reaction, n (%)	Total, n
Amateur	120 (80.0)	30 (20.0)	150
Government	148 (98.7)	2 (1.3)	150
Media	145 (93.5)	10 (6.5)	155
Meteorology	75 (100.0)	0 (0.0)	75
Netizen	64 (91.4)	6 (8.6)	70
Before	178 (93.7)	12 (6.3)	190
During	138 (95.2)	7 (4.8)	145
After	236 (89.1)	29 (10.9)	265
Overall	552 (92.0)	48 (8.0)	600

Note: Percentages are calculated within each source or posting period.

RQ2: Overall prevalence of risk-protection guidance

Preparedness guidance appeared in 281 tweets (46.8%), recovery guidance in 273 (45.5%), and response guidance in 214 (35.7%). Because the categories were coded independently, a single tweet could contain more than one type of guidance. Preparedness messages included warnings, monitoring of official updates, avoidance of exposed areas, property protection, and resource readiness. Response messages included immediate hazards, road conditions, shelter information, emergency contacts, and instructions to remain in safe locations. Recovery messages included assistance, service restoration, volunteering, rebuilding, adaptation, and future resilience. These frequencies report content prevalence and do not measure audience action.

Table 5: Prevalence of risk-protection guidance in the tweet sample

Risk-protection category	Tweets containing category, n	Percentage of sample
Preparedness	281	46.8
Response	214	35.7
Recovery	273	45.5

Note: Categories were not mutually exclusive; recovery was present when either recovery-adaptation or future-resilience guidance was coded.

RQ3a and H1: Composite risk-protection content by posting period

Prior to conducting the one-way ANOVA, the assumptions of independence, normality, and homogeneity of variances were assessed. Independence was ensured by the study design, as each tweet represented a separate observation and was assigned to only one posting period. Normality was assessed using the residual distribution. Residual skewness was 0.23 and kurtosis was −0.96. Both values fell within the acceptable range of −2.00 to +2.00, indicating no substantial departure from normality (George & Mallery, 2019).

Levene's test was not statistically significant, $F(2, 597) = 0.38$, $p = .684$, indicating that the assumption of homogeneity of variances was met.

A one-way ANOVA was therefore conducted to determine whether the three-item composite risk-protection content score differed significantly across the three posting periods: before, during, and after Cyclone Shaheen. H1 proposed that the composite risk-protection content score would differ across posting periods. The one-way ANOVA showed a statistically significant overall difference, $F(2, 597) = 3.70$, $p = .025$. Tweets posted after the cyclone had the highest descriptive mean score ($M = 1.40$, $SD = 0.98$), followed by tweets posted before the cyclone ($M = 1.21$, $SD = 0.98$) and during the cyclone ($M = 1.16$, $SD = 0.96$). H1 was supported by the significant omnibus ANOVA.

Table 6: One-way ANOVA of the Three-Item Composite Risk-Protection Content Score by Posting Period

Posting period	n	Mean	Standard deviation	F (df)	p
Before	190	1.21	0.98	3.70 (2, 597)	.025
During	145	1.16	0.96		
After	265	1.40	0.98		
Overall	600	1.28	0.98		

Scheffé-adjusted pairwise comparisons did not identify a statistically significant difference between any individual pair of posting periods. The before and during periods did not differ significantly (mean difference =

0.05, p = .910), nor did the before and after periods (mean difference = −0.19, p = .110) or the during and after periods (mean difference = −0.24, p = .057). Thus, although the omnibus ANOVA indicated an overall posting-period difference and the after period had the highest descriptive mean, no individual Scheffé-adjusted pairwise comparison reached the .05 significance threshold.

Table 7: Scheffé Post-Hoc Comparisons of Composite Risk-Protection Content by Posting Period

Comparison	Mean difference (I–J)	Standard error	p	95% CI
Before vs. During	0.05	0.11	.910	[−0.22, 0.31]
Before vs. After	−0.19	0.09	.110	[−0.42, 0.03]
During vs. After	−0.24	0.10	.057	[−0.49, 0.01]

RQ3b and H2: Composite risk-protection content by source

Prior to the source comparison, the assumptions of independence, normality, and homogeneity of variances were assessed. Independence was ensured by the study design, as each tweet represented a separate observation and was assigned to only one source category. Normality was assessed using the residual distribution, which showed skewness = 0.37 and kurtosis = −0.62, indicating no substantial departure from normality. Levene's test was statistically significant, $F(4, 595) = 2.50$, $p = .042$, indicating that the homogeneity-of-variance assumption was not met. Therefore, Welch's one-way ANOVA, which does not require equal group variances, was used for the omnibus source comparison, followed by Games–Howell post-hoc comparisons.

H2 proposed that the three-item composite risk-protection content score would differ by tweet source. Welch's ANOVA showed a statistically significant source effect, Welch's $F(4, 249.89) = 21.74$, $p < .001$. Meteorological sources recorded the highest descriptive mean (M = 1.84, SD = 0.92), followed by government (M = 1.58, SD = 0.88), netizen (M = 1.36, SD = 0.74), media (M = 1.16, SD = 0.96), and amateur sources (M = 0.79, SD = 0.96). H2 was supported.

Table 8: Welch's One-Way ANOVA of the Three-Item Composite Risk-Protection Content Score by Tweet Source

Tweet source	n	Mean	Standard deviation	Welch's F (df)	p
Amateur	150	0.79	0.96	21.74 (4, 249.89)	< .001
Government	150	1.58	0.88		
Media	155	1.16	0.96		
Meteorology	75	1.84	0.92		
Netizen	70	1.36	0.74		
Overall	600	1.28	0.98		

Games–Howell post-hoc comparisons showed that amateur tweets had significantly lower composite scores than government, media, meteorological, and netizen tweets. Government tweets had significantly higher scores than media tweets but did not differ significantly from meteorological or netizen tweets. Meteorological tweets had significantly higher scores than media and netizen tweets. Media and netizen tweets did not differ significantly.

Table 9: Games–Howell Post-Hoc Comparisons of Composite Risk-Protection Content by Source

Source I	Source J	Mean difference (I–J)	p	95% CI
Amateur	Government	−0.79	< .001	[−1.09, −0.50]
Amateur	Media	−0.37	.007	[−0.68, −0.07]
Amateur	Meteorology	−1.05	< .001	[−1.42, −0.69]
Amateur	Netizen	−0.57	< .001	[−0.90, −0.24]
Government	Media	0.42	.001	[0.13, 0.71]
Government	Meteorology	−0.26	.257	[−0.61, 0.09]
Government	Netizen	0.22	.297	[−0.09, 0.54]
Media	Meteorology	−0.68	< .001	[−1.04, −0.32]
Media	Netizen	−0.20	.460	[−0.52, 0.13]
Meteorology	Netizen	0.48	.006	[0.10, 0.86]

Note: Games–Howell-adjusted pairwise comparisons and simultaneous 95% confidence intervals are reported.

DISCUSSION OF RESEARCH FINDINGS

The findings address the three study objectives in sequence. For RQ1, timely and action-oriented communication was concentrated before and during the cyclone and declined after impact. This pattern is consistent with CERC's temporal premise that warning and immediate-response periods require rapid, directive information, whereas post-impact communication broadens to restoration, assistance, documentation, and rebuilding (Reynolds & Seeger, 2005; Spence et al., 2015). The content analysis documents this temporal pattern but does not test whether the messages were effective for individual recipients.

Source activity and format also varied in ways relevant to RQ1. Media and amateur accounts contributed the largest shares before impact, government accounts had the largest share after impact, and meteorological accounts maintained a smaller but relatively stable presence. Combined text-and-visual tweets represented almost 88% of the sample, while visual-only tweets were rare. This dominance is consistent with the complementary use of textual explanation and visual information, but the study did not experimentally compare format effectiveness (Alam et al., 2018).

For RQ2, online attitudinal engagement was common across the dataset but varied descriptively by source and posting period. Meteorological accounts had the highest within-source engagement rate, followed by government accounts, while amateur accounts had the lowest. The during period had the highest within-period rate. A like records a platform reaction and a retweet also extends message circulation; neither establishes understanding, trust, compliance, or protective action.

The RQ2 content frequencies showed that preparedness and recovery guidance appeared more often than response guidance. Because the categories could co-occur, these percentages describe the presence of message functions rather than mutually exclusive phases. The data do not establish why response guidance appeared less often, so explanations based on infrastructure disruption, fear, or reduced posting activity would require evidence beyond this content analysis.

For RQ3a and H1, the three-item composite risk-protection content score differed significantly across posting periods at the omnibus level. The after period recorded the highest descriptive mean, followed by the before and during periods. However, none of the Scheffé-adjusted pairwise comparisons reached statistical significance. H1 was therefore supported by the overall ANOVA, while the results do not support a claim that any specific pair of posting periods differed significantly after adjustment. This result should be interpreted in relation to the three-item measurement structure, in which recovery adaptation and future resilience were treated as subcomponents of the broader recovery dimension rather than as separate scoring dimensions. The temporal variation reflects differences in coded risk-protection content and does not establish changes in audience protection or offline protective behaviour.

For RQ3b and H2, Welch's ANOVA confirmed a statistically significant difference in the three-item composite risk-protection content score across tweet sources. Meteorological accounts recorded the highest descriptive mean, followed by government accounts, and the Games–Howell comparison between these two source categories was not statistically significant. Amateur accounts recorded the lowest mean and differed significantly from all four other source categories. Government accounts had significantly higher scores than media accounts, whereas their difference from netizen accounts was not statistically significant. Meteorological accounts had significantly higher scores than media and netizen accounts. These findings describe differences in coded risk-protection content and should not be interpreted as evidence that one source category was inherently more credible, accurate, or effective. Media combined high engagement with a composite score below the government and meteorological means, consistent with a broader reporting and amplification role. Netizens occupied an intermediate position, while amateurs recorded the lowest engagement rate and composite mean. These patterns describe communication outputs within the sampled tweets and should not be treated as evaluations of the overall social value or reliability of each group.

Theoretical implications

The findings are consistent with a focused, phase-sensitive application of CERC to a rapid-onset natural hazard. Their principal theoretical value lies in distinguishing posting period from message function: before, during, and after identify when communication occurred, whereas preparedness, response, and recovery identify what type of protective guidance was present. The three-item composite score reflects these three broad CERC-related communication functions and avoids giving disproportionate weight to recovery-related content. The significant omnibus posting-period effect is consistent with phase-sensitive variation in risk-protection messaging, although the absence of significant Scheffé-adjusted pairwise contrasts warrants a cautious interpretation of differences between specific periods. The significant source effect further indicates that the concentration of coded risk-protection content varied across communicator categories. The study does not test a causal pathway from message characteristics to engagement or offline behaviour. The Omani case adds quantitative evidence from an underexamined disaster-communication setting and shows how institutional, media, specialist-citizen, and amateur sources contributed to the same Twitter environment. The findings support analytical comparison with other rapid-onset disasters, while generalisation beyond this cyclone and sample should remain cautious.

Practical implications

Emergency agencies can use the observed temporal patterns to prepare posting-period-specific social-media workflows. Before impact, messages can prioritise early warning, uncertainty reduction, household readiness, and clear forecasts. During impact, communication can emphasise concise safety instructions, verified operational updates, road and shelter information, and correction of misinformation. After impact, content can address assistance, service restoration, rebuilding, adaptation, and longer-term resilience.

The dominance of combined text-and-visual tweets supports using concise text to explain purposeful visuals rather than publishing graphics without context. Government, meteorological, media, netizen, and amateur contributors can also be coordinated through verification guidance and clear links to authoritative information.

These recommendations are derived from observed message patterns; their effects should be evaluated through future audience-based or experimental research.

Limitations and directions for future research

The study examines one platform, one national context, one cyclone, and a defined 22-day period; its findings support analytical rather than statistical generalisation to other disasters. The engagement indicator recorded only whether a tweet had at least one like or retweet, not counts, sentiment, network reach, or user characteristics. Deleted, private, or inaccessible posts were not represented. Accuracy, credibility, exposure, comprehension, trust, intentions, and verified protective actions were not measured.

The composite score contained three broad CERC-related indicators: preparedness, response, and recovery. Recovery adaptation and future resilience were treated as subcomponents of the broader recovery category rather than as separate scoring dimensions. This approach preserved conceptual balance across the three main risk-protection functions, but it also means that more detailed distinctions within recovery-related communication were not tested separately in the ANOVA. Future research could examine recovery adaptation and future resilience as separate outcomes or use multidimensional modelling to compare different forms of post-impact communication. The binary coding of timeliness and action orientation allowed systematic classification across a relatively large sample of tweets. However, this approach may reduce measurement sensitivity because it captures the presence or absence of each characteristic rather than its degree, quality, or clarity. For example, a tweet was coded as action-oriented when it contained a directive or recommended action, but the coding did not measure how specific, persuasive, or understandable the action guidance was. Future studies could use scaled measures to capture different levels of timeliness and actionability. Online attitudinal engagement was measured through the presence of at least one like or retweet. These indicators reflect observable platform reactions and message amplification, but they do not demonstrate comprehension, agreement, trust, compliance, or offline protective behaviour. Similarly, the risk-protection content score measures the presence of protective guidance in tweets rather than actual behavioural responses by the public.

Although the present study now reports reliability for the three main components of the risk-protection content score, future research could extend reliability assessment by reporting chance-corrected and variable-specific coefficients for all coding categories, including message characteristics, tweet format, source classification, and engagement indicators. The analysis also did not test source-by-period interactions. Future research could extend the present analysis by testing source-by-period interaction effects. Such analysis would examine whether the relationship between tweet source and risk-protection content varies across the before, during, and after periods. For example, meteorological accounts may be more prominent before and during the cyclone, whereas government and media accounts may become more visible during recovery. Testing these interaction effects would provide a more detailed understanding of how source roles shift across crisis phases. Future research should use variable-specific chance-corrected reliability, analyse interactions, compare languages, examine replies and quote tweets, and connect message exposure with protective intentions or verified actions.

CONCLUSION

Twitter communication during Cyclone Shaheen displayed distinct source and temporal patterns. Timely and action-oriented messages were concentrated before and during impact, combined text-and-visual tweets dominated all posting periods, and online engagement varied across source categories and periods. Preparedness and recovery guidance appeared more frequently than response guidance. The three-item composite risk-protection content score differed significantly overall by posting period, with the highest descriptive mean occurring after the cyclone; however, no individual Scheffé-adjusted pairwise period comparison was statistically significant. The composite score also differed significantly by source under Welch's ANOVA, with meteorological and government accounts recording the two highest descriptive means and no significant difference between those two source categories. By treating recovery adaptation and future resilience as subcomponents of the broader recovery function, the three-item measurement structure maintains conceptual balance across preparedness, response, and recovery while still capturing key forms of post-cyclone communication. These findings are consistent with CERC's premise that communication changes as an emergency develops. They also show why posting period, message function, source category, online engagement, and offline behaviour must remain conceptually distinct. For practice, the results support posting-period-specific content planning, clear integration of text and visuals, and coordination among official, media, and citizen contributors. For scholarship, the study demonstrates what Twitter content analysis can identify—message patterns, platform reactions, and coded guidance—and what it cannot verify: individual understanding, trust, or protective action.

ACKNOWLEDGEMENTS

The authors acknowledge Universiti Sains Malaysia for its academic support and thank those who contributed to the development and coding of the study data.

Ethical Considerations

This quantitative content analysis used publicly accessible tweets and involved no recruitment, intervention, or direct interaction with Twitter users. The manuscript does not reproduce usernames, account handles, or other directly identifying information. Tweet examples are not quoted verbatim. Data were handled and reported in aggregate to reduce privacy risk.

Conflict Of Interest

The authors declare no conflict of interest.

Data Availability

The coded data supporting the findings are available from the corresponding author on reasonable request, subject to applicable platform terms and privacy considerations. Some original public posts may have been altered or deleted since the collection period.

REFERENCES

1. Abedin, B., & Babar, A. (2018). Institutional vs. non-institutional use of social media during emergency response: A case of Twitter in the 2014 Australian bush fire. *Information Systems Frontiers, 20*, 729–740. https://doi.org/10.1007/s10796-017-9789-4
2. Alam, F., Ofli, F., & Imran, M. (2018). CrisisMMD: Multimodal Twitter datasets from natural disasters. *Proceedings of the International AAAI Conference on Web and Social Media, 12*(1), 465–473. https://doi.org/10.1609/icwsm.v12i1.14983
3. Al-Zaabi, S., & Al-Zadjali, S. (2022). Qualitative analysis of early warning: A case study from Oman. *International Journal of Disaster Risk Reduction, 68*, Article 102731. https://doi.org/10.1016/j.ijdrr.2021.102731
4. Atwell Seate, A. A., Liu, B. F., Kim, J. Y., Lee, S., & Hawblitzel, D. (2024). The what and how of warning messages: An experimental examination of instructing information and linguistic features use. *Journal of Contingencies and Crisis Management, 32*(4), Article e12630. https://doi.org/10.1111/1468-5973.12630
5. Avvenuti, M., Cresci, S., Del Vigna, F., & Tesconi, M. (2018). On the need of opening up crowdsourced emergency management systems. *AI & Society, 33*, 55–60. https://doi.org/10.1007/s00146-017-0709-4
6. Bruns, A., & Stieglitz, S. (2012). Quantitative approaches to comparing communication patterns on Twitter. *Journal of Technology in Human Services, 30*(3–4), 160–185. https://doi.org/10.1080/15228835.2012.744249
7. George, D., & Mallery, P. (2019). *IBM SPSS Statistics 26 step by step: A simple guide and reference* (16th ed.). Routledge.

8. Jin, X., & Spence, P. R. (2021). Understanding crisis communication on social media with CERC: Topic model analysis of tweets about Hurricane Maria. *Journal of Risk Research, 24*(10), 1266–1287. https://doi.org/10.1080/13669877.2020.1848901
9. Kim, H., Jang, S. M., Kim, S.-H., & Wan, A. (2018). Evaluating sampling methods for content analysis of Twitter data. *Social Media + Society, 4*(2), 1–10. https://doi.org/10.1177/2056305118772836
10. Kim, J., & Hastak, M. (2018). Social network analysis: Characteristics of online social networks after a disaster. *International Journal of Information Management, 38*(1), 86–96. https://doi.org/10.1016/j.ijinfomgt.2017.08.003
11. Kinsky, E. S., Chen, L., & Drumheller, K. (2021). Crisis and emergency risk communication: FEMA's Twitter use during the 2017 hurricane season. *Public Relations Review, 47*(4), Article 102094. https://doi.org/10.1016/j.pubrev.2021.102094
12. Liu, W., & Xu, W. (2019). Tweeting to (selectively) engage: How government agencies target stakeholders on Twitter during Hurricane Harvey. *International Journal of Communication, 13*, 4917–4939.
13. Lombard, M., Snyder-Duch, J., & Bracken, C. C. (2002). Content analysis in mass communication: Assessment and reporting of intercoder reliability. *Human Communication Research, 28*(4), 587–604. https://doi.org/10.1111/j.1468-2958.2002.tb00826.x
14. Mehta, A. M., Murray, S., McAndrew, R., Jackson, M., & Tippett, V. (2022). Encouraging evacuation: The role of behavioural message inputs in bushfire warnings. *International Journal of Disaster Risk Reduction, 67*, Article 102673. https://doi.org/10.1016/j.ijdrr.2021.102673
15. Mojtahedi, M., & Oo, B. L. (2017). Critical attributes for proactive engagement of stakeholders in disaster risk management. *International Journal of Disaster Risk Reduction, 21*, 35–43. https://doi.org/10.1016/j.ijdrr.2016.10.017
16. Neuendorf, K. A. (2002). *The content analysis guidebook*. SAGE Publications.
17. Panagiotopoulos, P., Barnett, J., Bigdeli, A. Z., & Sams, S. (2016). Social media in emergency management: Twitter as a tool for communicating risks to the public. *Technological Forecasting and Social Change, 111*, 86–96. https://doi.org/10.1016/j.techfore.2016.06.010
18. Pourebrahim, N., Sultana, S., Edwards, J., Gochanour, A., & Mohanty, S. (2019). Understanding communication dynamics on Twitter during natural disasters: A case study of Hurricane Sandy. *International Journal of Disaster Risk Reduction, 37*, Article 101176. https://doi.org/10.1016/j.ijdrr.2019.101176
19. Reynolds, B., & Seeger, M. W. (2005). Crisis and emergency risk communication as an integrative model. *Journal of Health Communication, 10*(1), 43–55. https://doi.org/10.1080/10810730590904571
20. Seneviratne, K., Nadeeshani, M., Senaratne, S., & Perera, S. (2024). Use of social media in disaster management: Challenges and strategies. *Sustainability, 16*(11), Article 4824. https://doi.org/10.3390/su16114824
21. Spence, P. R., Lachlan, K. A., Lin, X., & Del Greco, M. (2015). Variability in Twitter content across the stages of a natural disaster: Implications for crisis communication. *Communication Quarterly, 63*(2), 171–186. https://doi.org/10.1080/01463373.2015.1012219
22. Splendiani, S., & Capriello, A. (2022). Crisis communication, social media and natural disasters: The use of Twitter by local governments during the 2016 Italian earthquake. *Corporate Communications: An International Journal, 27*(3), 509–526. https://doi.org/10.1108/CCIJ-03-2021-0036
23. Terry, J. P., Al Ruheili, A., Boldi, R., Gienko, G., & Stahl, H. (2022). Cyclone Shaheen: The exceptional tropical cyclone of October 2021 in the Gulf of Oman. *Weather, 77*(10), 364–370. https://doi.org/10.1002/wea.4193
24. Veil, S. R., Reynolds, B., Sellnow, T. L., & Seeger, M. W. (2008). CERC as a theoretical framework for research and practice. *Health Promotion Practice, 9*(4 Suppl.), 26S–34S. https://doi.org/10.1177/1524839908322113
25. Vos, S. C., & Buckner, M. M. (2016). Social media messages in an emerging health crisis: Tweeting bird flu. *Journal of Health Communication, 21*(3), 301–308. https://doi.org/10.1080/10810730.2015.1064495
26. Wukich, C. (2016). Government social media messages across disaster phases. *Journal of Contingencies and Crisis Management, 24*(4), 230–243. https://doi.org/10.1111/1468-5973.12119