Doing Big Things in a Small Way: A Social Media Analytics Approach to Information Diffusion During Crisis Events in Digital Influencer Networks

Shohil Kishore
The University of Auckland, Auckland, New Zealand
s.kishore@auckland.ac.nz

Amy Errmann
Auckland University of Technology, Auckland, New Zealand

Abstract

Digital influencers play an essential role in determining information diffusion during crisis events. This paper demonstrates that information diffusion (retweets) on the social media platform Twitter (now X) highly depends on digital influencers' number of followers and influencers' location within communication networks. We show (study 1) that there is significantly more information diffusion in regional (vs. national or international) crisis events when tweeted by micro-influencers (vs. meso- and macro-influencers). Further, study 2 demonstrates that this pattern holds when micro-influencers operate in a local location (are located local to the crisis). However, effects become attenuated when micro-influencers are situated in a global location (outside of the locality of the event). We term this effect 'influencer network compression' – the smaller in scope a crisis event geography (regional, national, or international) and influencer location (local or global) becomes, the more effective micro-influencers are at diffusing information. This shows that those who possess the most followers (meso- and macro-influencers) are less effective at attracting retweets than micro-influencers situated local to a crisis. As online information diffusion plays a critical role during public crisis events, this paper contributes to both practice and theory by exploring the role of digital influencers and their network geographies in different types of crisis events.

Keywords: information diffusion, public crisis events, digital influencers, influencer network compression, computationally intensive methods.

1 Introduction

Throughout the last decade, public crisis events, defined as events that interrupt the typical dynamics of economic, cultural, social, or political life (Martínez-Rojas et al., 2018) of regional, national, or international significance (Hagar, 2011), have been exposed to the effectiveness of social media platforms to disseminate information (Mirbabaie, Bunker, Stieglitz, Marx, & Ehnis, 2020; Roy et al., 2020). Since the Arab Spring event in 2010, information diffusion of crisis events now rely on platforms such as Twitter (now known as X) to share and spread information (Jones, 2013) rather than relying on traditional one-way television, newspapers, and radio (Bang et al., 2021; Schneider & Check, 2010). The connectedness of the 'everyday person' on social media to key information, experts, and influential opinion leaders (Aleti et al., 2016) makes it a convenient and rapid way for users with access to a smart device to diffuse information online. Twitter has emerged as one of the key social media platforms during such crisis events (J. Kim et al., 2018; Oh et al., 2013), driven by features such as brief narrative text, simple retweeting, and #hashtag topic handles that allow for the diffusion of information (Rao et al., 2020). Crises rapidly increase information communication (Laylavi et al., 2017) and initial

impressions of crisis news are now more regularly shared on social media rather than traditional news sources (J. Kim & Hastak, 2018).

Important actors in public crisis events on Twitter are influential opinion leaders who play a role in how information is shared amongst networks (Aleti et al., 2016). One important actor group with an increasingly significant impact on crisis events are digital influencers (Bonnevie et al., 2020; Singh et al., 2020), becoming an important topic in Information Systems (IS) research (Harrigan et al., 2021; Robinson, 2020). Prior research has shown that only a few social media users with a high number of followers become highly effective at diffusing information (Roy et al., 2020). In contrast, alternative research has argued that active peer-to-peer sharing of influencer content plays a more crucial role than a large followership (Zhang et al., 2019). To understand the effectiveness of digital influencers in the diffusion of information during crisis events, it is important to explore which influencer types (Mirbabaie, Bunker, Stieglitz, Marx, & Ehnis, 2020) are the most effective at diffusing information (Boerman, 2020; Kay et al., 2020). Therefore, this study concentrates on comparing the information diffusion potential of different influencer types (micro-, meso- and macro-influencers) in a variety of settings. Existing research assumes that meso- or macro-influencers, who possess the most followers, are more effective at spreading information during a crisis (Roy et al., 2020), whereas we explore how smaller-sized networks possess greater magnitude in information diffusion in micro-influencers.

We query whether there is more information diffusion in regional (vs. national or international) crisis events when tweeted by micro-influencers (vs. meso- or macro-influencers). In doing so, we aim to identify if information diffusion potential is heightened when micro-influencers operate in locations that are local (i.e., located local to the crisis) rather than situated in locations that are global (i.e., outside of the locality of the event). We explore this theoretically through what we term as 'influencer network compression' which encapsulates that the smaller the geography of the crisis event (regional vs. national vs. international) and the closer the proximity of the influencer (local vs. global) to the crisis event, the greater the potential information diffusion amongst micro-influencers might be. Such knowledge is important as understanding how social media users share peer-to-peer information (Rathore et al., 2021) and how influencers lead the dissemination of information (Aleti et al., 2016) is crucial. This knowledge offers valuable insights for researchers and policymakers as it provides guidance on the regulation and design of information communication technologies to appropriately channel the diffusion of crisis-related information.

The remainder of the paper has been divided into five main sections. Section 2 includes a theoretical underpinning for our hypotheses on how information is defused via retweets during regional, national, and international crisis events and how this interacts with digital influencers and their local or global location in proximity to crisis events. Section 3 introduces three case backgrounds for regional, national, and international crisis events used in the research. In Section 4, we then introduce our methodology and data collection process within the context of our crisis event cases. Subsequently, Section 5 explores the results of the analysis and our research findings in relation to our hypotheses. The last of the main sections, Section 6, discusses the implications of our research including limitations and future research. Lastly, we conclude the paper with our final remarks in Section 7.

2   Theoretical underpinning

2.1   Information diffusion during crisis events

Dissemination of pertinent information to relevant stakeholders during crisis situations presents a challenging problem as insufficient access to information reduces decision-making capabilities of both individual actors and collective entities (Y. Wang et al., 2021; Xu et al., 2020). The scarcity of on-the-ground information sources accessible through conventional media channels further delays information consumption (Mirbabaie, Bunker, Stieglitz, & Deubel, 2020). In this regard, social media platforms such as Twitter emerge as a viable real-time source of information that can supplement existing sources (Oh et al., 2013; Reuter et al., 2019). In fact, Twitter is widely known as the preeminent social media platform in the context of news consumption (Walker & Matsa, 2021). Rapid diffusion of information through platforms such as Twitter is attributed to the inherent design of social networks. Social networks can be conceptualised as graphs, "where nodes are users and edges are relationships" between users and the content that they generate (Guille et al., 2013, p. 18). Retweets serve as directed relationships within social networks, as numerous users have the ability to retweet a singular tweet. This action exposes the tweet to one's network of followers, who in turn may further retweet the tweet, thereby expanding its reach (Stieglitz & Dang-Xuan, 2013).

Observing retweets during crisis events is considered as a valid mechanism to understand how information is diffused within online social networks (Firdaus et al., 2018). In this research, information diffusion is operationalized as average retweets per day per 10,000 followers. This approach is particularly useful as the majority of tweets typically do not receive retweets (Boyd et al., 2010). Thus, adopting this operationalization of information diffusion not only facilitates quantitative data analysis but also enhances interpretability by offering clear effect sizes and p-values. Important to this definition of information diffusion on Twitter, self-managed functions such as retweets improves both the agility of rapid communication as well as funnels information hierarchies based on the volume of peer-to-peer sharing (Rao et al., 2020). In this way, retweets become a tool to self-manage information to make sense of the events (Stieglitz et al., 2018), as well as navigate users to central networks (Martínez-Rojas et al., 2018).

One theory helpful in guiding how users may funnel information during times of crisis is homophily. This theory posits that individuals in a social system have an inclination to bond more intensely with those who share similarities with them (De Choudhury et al., 2010; McPherson et al., 2001). Although research on homophily has historically been oriented towards similarities in characteristics such as ethnicity, age, religion, or gender (McPherson et al., 2001), we extend the conceptualization to refer to geographic location (Bastos et al., 2018). Research indicates that spatial proximity, as a component of homophily, influences the formation of online relationships. Huang et al. (2013) demonstrated that proximity between individuals impacts interactions in digital environments. Following the reasoning that spatial proximity between individuals influences online relationships, this may extend to geographical proximity and networks. Homophily may disrupt how information spreads within networks. Information that flows through networks tends to be localized (Wang et al., 2019), whilst overall, information diffusion is more viral when the source of information is closer to the crisis event (King & Wang, 2021). In times of crisis, the geographic location of a crisis may have a significant impact on how users share information.

Homophily may play a role in shedding light on the dynamics of information diffusion during regional crisis events, as compared to national or international events. In such circumstances, the process of information dissemination tends to concentrate around a central network of influential opinion leaders. The significance of opinion leaders, as highlighted by the two-step flow theory (Katz, 1957; Lazarsfeld et al., 1968), becomes particularly evident in understanding the media's impact on the public, especially within the context of social media platforms such as Twitter (Choi, 2015). During crises, opinion leaders situated in close proximity to events play an especially critical role in distributing emergency information.

While the two-step flow theory does not specifically address the geographic proximity of opinion leaders to crisis events, it emphasizes the role of opinion leaders in mediating the flow of information (Katz & Lazarsfeld, 1964). Geographic proximity to a crisis event may lead opinion leaders to have firsthand experiences and perspectives that align more closely with the realities of the event itself. This firsthand knowledge might make their information more credible to users in any location seeking updates about the crisis. Audiences instinctively seek out trusted sources on social media, perceiving them as pivotal nodes connected to crisis events (Zhang et al., 2019). This behavior highlights the value of verified sources, known individuals or reputable organizations that have established interpersonal trust with their followers (Mehta et al., 2017; Zhang et al., 2019). Individuals that perceive communicators to be close in proximity to a crisis event may deem them to be more credible (Thomson et al., 2012). Additionally, civilians value local sources and local information more than sources distant from the crisis event (Starbird & Palen, 2011).

Second, theory on network patterns helps shed light on why social media users may navigate to smaller and more central networks in times of crisis; specifically, between regional, national, and international crisis events. Regional events, such as Tropical Storm Cindy which occurred in the U.S., rely on news sources close to the event, as they are both agile in their information timing and have 'on-the-ground' knowledge (J. Kim et al., 2018). Important to our research is the understanding of how such patterns are disseminated. During regional crisis events it has been found that the 'betweenness' of centrality in networks has different roles (J. Kim & Hastak, 2018). In one aspect, homophily helps explain why regional crisis events may be more conducive to central opinion leaders who can be perceived as proximal to the event, while on the other hand 'on-the-ground' knowledge of proximal sources may be viewed as more agile and timely.

2.2 The role of influencers in information diffusion during crisis events

We define micro-influencers as users possessing between 1,000 and 10,000 followers, meso-influencers as users possessing between 10,001 and 100,000 followers, and macro-influencers as users possessing over 100,001 followers, based on a combination of current research categorizing influencers (Boerman, 2020; Kay et al., 2020). Categorizing influencers into different types allows us to explore the different roles influencers may play in different types of crisis events (Mirbabaie, Bunker, Stieglitz, Marx, & Ehnis, 2020) and the diffusion of information in such events.

Micro-influencers have been shown to elicit greater trust among their followers than meso- or macro-influencers (Kay et al., 2020). Such trust has been attributed to an increased feeling of social closeness towards micro-influencers in comparison to meso- or macro-influencers

(Campbell & Farrell, 2020) who may appear further away from 'peer-to-peer' relationships due to their celebrity-like status (Martínez-López et al., 2020). Further, micro-influencers may appear to be more similar to the general citizen than meso- or macro-influencers who hold a perceived celebrity-like status, making them more psychologically distant to followers (Park et al., 2021). From this perspective, micro-influencers have been shown to attain high levels of credibility (Park et al., 2021) and trust (Kay et al., 2020), as they appear 'just like friends' to followers online (Alampi, 2019). This intimacy may enhance micro-influencers' 'stickiness' (Farivar et al., 2021; Hu et al., 2020) in crisis contexts where opinion leaders may be viewed as 'peer-to-peer' (King & Wang, 2021) and as connected to grassroots knowledge in the locations in which they operate (Bonnevie et al., 2020).

Such connectedness micro-influencers have with their audiences may be a pull factor that motivates peer-to-peer sharing (Hodis et al., 2015). Rather than using tweet activity as a predictor of information diffusion, an impacting factor is the dynamic 'pull' strategy of how users engage with social media influencers. The interactive nature of social media allows for users to engage in conversations and diffuse influencer messages through retweeting, which pulls audiences towards digital influencers, rather than by information being pushed out by traditional channels with limited capacity for interaction (Hodis et al., 2015). Essentially, as crisis event communication may be motivated by peer-to-peer sharing and depends on the pull factor of influential opinion leaders and their content, digital influencers play a significant role. Because micro-influencers may appear closer to sources of news and more trustworthy, they may have more effective pull strategies that motivates followers to retweet their tweets.

In contrast, national and international events, such as the COVID-19 outbreak, rely on broad tools of governance, regulation, and system-level push controls to diffuse information (Janssen & van der Voort, 2020). Such tools differ from regional events in that they do not naturally encapsulate agility and adaptive governance. Pressure to create consistency of information as crisis events expand in their reach creates a dichotomy between sources viewed as 'official' (e.g., government, reporters, NGOs) and sources viewed as 'unofficial' (e.g., civilian users) (Rao et al., 2020). Meso- and macro-influencers may be viewed as unofficial information sources during national or international crisis events, as they oscillate between a celebrity-like status and being an individual source of information unrelated to the official crisis context. Unofficial information may result in an insignificant push to diffuse information about disaster control, alarm, or reassurance (Rao et al., 2020). Further, there is a loss in the ability to be agile, broadly connect with audiences, and the opportunity to seize time. For instance, micro-influencers may have an advantage in seizing trends or zeitgeists with more agility in what they say and when they say it in comparison to meso- and macro-influencers (Hu et al., 2020).

Overall, the intersection of homophily, network patterns during crisis, and influencer theory suggests that if users find that micro-influencers appear similar to themselves (De Choudhury et al., 2010), are more credible the closer they are in proximity to a crisis event (Thomson et al., 2012), and more agile in their timing and 'on-the-ground' knowledge, they may have more effective pull strategies that motivate followers to retweet their tweets. Therefore, we argue that micro-influencers are critical to understanding information diffusion during crisis events, as the trust they hold in networks may influence how the public may disseminate important information (Singh et al., 2020). We predict that the information diffusion associated with each crisis event type will depend on the type of influencer generating the content:

H1. *Average retweets during regional (vs. national or international) crisis events will be significantly higher for micro-influencers (vs. meso- or macro-influencers).*

2.3 Information diffusion in local and global influencer locations

Research recognizes that information diffusion may diverge based on an influencer's location during public crisis events (Kotlarsky et al., 2022). Whether an influencer is situated local to the event (i.e., inside local proximity of the event) or in a global location (i.e., outside local proximity of the event) (Hogan, 2008) may impact diffusion. For instance, it has been shown that localized networks tend to be favored (X. W. Wang et al., 2019). This is due to the perception of the public having a belief that more accurate information is found in locality of crisis events. As an outcome, diffusion may be more viral and diffused at a greater rate when the source of information is closer to the crisis event (King & Wang, 2021).

We can look to prior explanations that information diffusion may follow through proximity of key communicators. Huang et al. (2013) argues that offline proximity, where a communicator is physically located, plays an important role in digital environments. As discussed previously, in times of crisis, citizens look to opinion leaders with 'on-the-ground' knowledge (J. Kim et al., 2018) and may be more likely to retweet information when it is perceived to come from close to the crisis event (X. W. Wang et al., 2019). Further, physical proximity plays a role in how audiences find information to be credible, and therefore worthy of sharing. Individuals that perceive communicators to be close in proximity to a crisis event may deem them to be more credible (Thomson et al., 2012) and value local sources and local information more than sources distant from the crisis event (Starbird & Palen, 2010).

Thus, influencers who are local in proximity to the crisis event may be seen to have more accurate and credible information. We argue that micro-influencers possess greater potential for information dissemination in comparison to meso- and macro-influencers when participating in a local location (inside local proximity of the event). However, when influencers participate in a crisis from a global location (outside local proximity of the event), they may not appear as informed to the crisis, therefore there will be no difference amongst any influencer types:

H2. *Average retweets during regional (vs. national or international) crisis events will be significantly higher for micro-influencers (vs. meso or macro-influencers) in local networks, however, will attenuate in global networks.*

3 Regional, national, and international crisis events: Case backgrounds

Major crisis events rapidly garner international attention and support. We differentiate three cases based on the locality of the effected population. This is an important distinction to make as observers often rely on those directly impacted for accurate updates (Kotlarsky et al., 2022; Liu & Xu, 2018). The regional case, which focuses on the murder of George Floyd, saw Minneapolis as the center of discourse and single source of truth which motivated international protests (AP News, 2022). The national case centers on the Russo-Ukrainian war which severely affected the population of Ukraine (United Nations Office for the Coordination of Humanitarian Affairs, 2022). Thus, those outside of Ukraine relied on Ukrainian sources to create and disseminate content. Conversely, our international case concentrates on the COVID-19 pandemic which severely impacted numerous populations simultaneously across

the globe (Cucinotta & Vanelli, 2020). While London and the United Kingdom (UK) was significantly impacted in the early stages of the pandemic, there are multiple sources of truth rather than a singular reliable source which demonstrates the unique characteristics of each event. Each of these cases are discussed in detail in the following sections.

3.1 Regional event: George Floyd

On the 25th of May 2020, George Floyd was murdered by Derek Chauvin, a police officer in the Minneapolis Police Department. This murder, closely following the controversial deaths of Breonna Taylor and Ahmaud Arbery, sparked widespread protests fuelled by longstanding racial injustice in the U.S., mainly portrayed in the context of the Black Lives Matter movement. Violent protests erupted in Minneapolis on the 26th and 27th of May, rapidly spreading to cities across the U.S. including Memphis, Los Angeles, Atlanta, and New York (Taylor, 2020). Between 15 and 26 million people in the U.S. alone participated in Black Lives Matter protests in 2020 (Buchanan et al., 2020).
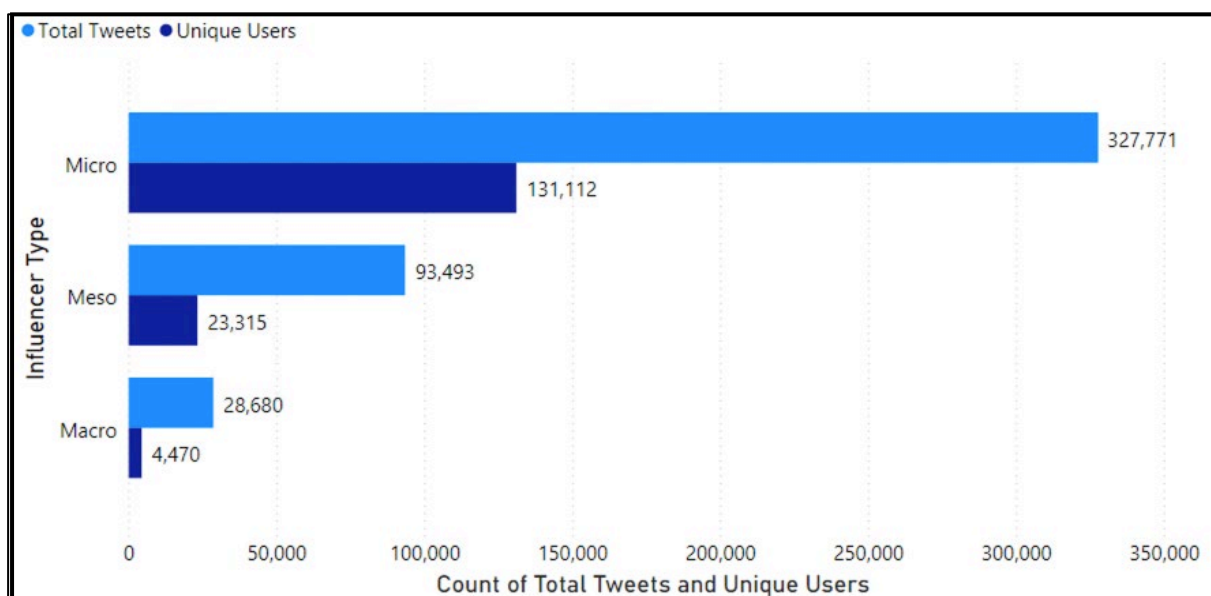

Figure 1. Total tweets and unique users by influencer type in the George Floyd case

As shown in Figure 1, the scale of these protests received widespread media attention and were driven by an exponential increase in online activism related to George Floyd and Black Lives Matter (Nguyen et al., 2021). As events continued to unfold in Minneapolis, the city was continually the focal point of discussion and progress (AP News, 2022). Thus, we focus on the murder of George Floyd in the city of Minneapolis as our regional case study.

3.2 National event: Russo-Ukrainian war

Russia invaded Ukraine on the 24th of February 2022, causing widespread civil unrest and the swift condemnation of Russia's actions. Within less than a month, 6.48 million Ukrainians were displaced, creating a humanitarian emergency for the country (United Nations Office for the Coordination of Humanitarian Affairs, 2022). Combined with widespread televised media coverage, this crisis took place in a world where access to social media platforms is ubiquitous as evident in Figure 2.
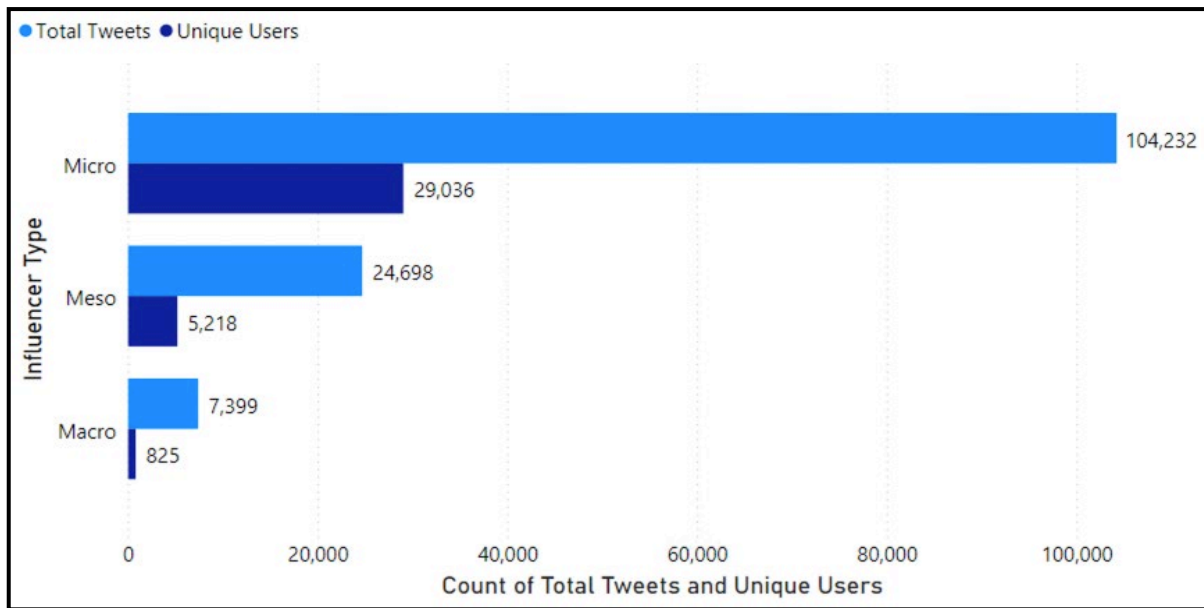
Figure 2. Total tweets and unique users by influencer type in the Russo-Ukrainian war case

Russia has been known to spread misinformation online through the Internet Research Agency (IRA), a Russian organization specializing in spreading online propaganda (Bastos & Farkas, 2019). This organization has spread misinformation related to Ukraine since 2014, when Russia annexed Crimea (Brown, 2022). Recent reports show that Russia has conducted similar misinformation campaigns targeted at Ukraine during the recent invasion (Scott, 2022). However, in this occurrence, both sides are using social media to support the spread of both information and disinformation (Chen & Ferrara, 2022). For example, Ukraine has used social media to crowdsource a virtual army to support humanitarian causes (Brown, 2022; Cohen, 2022; Garner, 2022). As multiple cities were targeted within Ukraine, the country as a whole was severely affected by the invasion, and therefore, we utilize the Russo-Ukrainian war for our national case study.

3.3 International event: COVID-19 pandemic

On the 11th of March 2020, the World Health Organization (WHO) characterized COVID-19 as a pandemic, an outbreak affecting the entire world (Cucinotta & Vanelli, 2020). This announcement produced an enormous amount of public engagement as depicted in Figure 3. Two weeks later, on the 23rd of March, the UK entered its first national lockdown (Sample, 2021). Deaths in the UK reached a five-year high in 2020, even when excluding deaths explicitly related to COVID-19 (Office for National Statistics, 2020). While COVID-19 was an international event, in the initial stages, the UK and the pressures on the National Health Service (NHS) were regularly reported in the international media (NHS England, 2021; Roxby et al., 2020). In combination with the fact that the UK contains a substantial proportion of Twitter users (Statista, 2022a), we focus on the UK as our point of reference for local networks. Specifically, we use the COVID-19 pandemic as our international case study and focus on the capital of the UK, London, to identify local micro-, meso-, and macro-influencers.
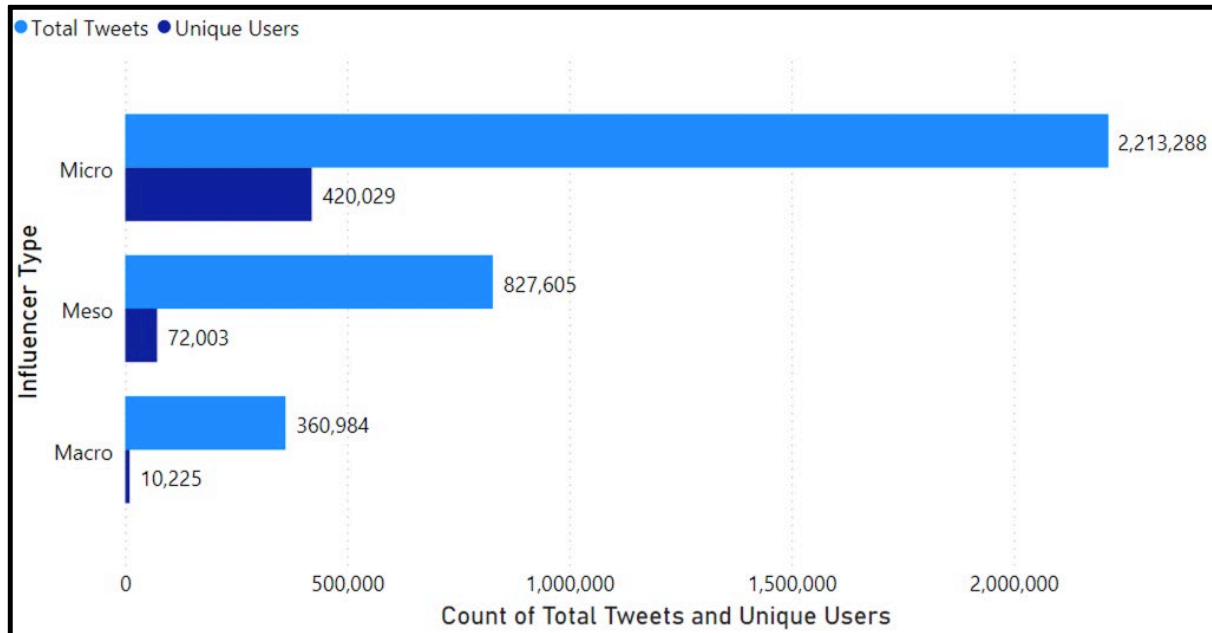
Figure 3. Total tweets and unique users by influencer type in the COVID-19 pandemic case

4 Method

The exponential increase in the availability of time-stamped digital trace data, such as social media trace data, creates new opportunities for researchers to envision, reformulate, replace and extend both theory and practice (Berente et al., 2019; Grisold et al., 2023; Miranda et al., 2022; Pentland et al., 2021). It allows researchers to develop theoretical implications through an iterative process of data exploration, analysis, and theorization using data-driven and computationally intensive techniques (Bachura et al., 2022; Berente et al., 2019; Miranda et al., 2022). In particular, this type of data extends our capacity to develop theory pertaining extreme events (Kishore et al., 2022; Kotlarsky et al., 2022; Oh et al., 2013). This paper takes advantage of this opportunity by collecting and intensively analyzing data from Twitter.
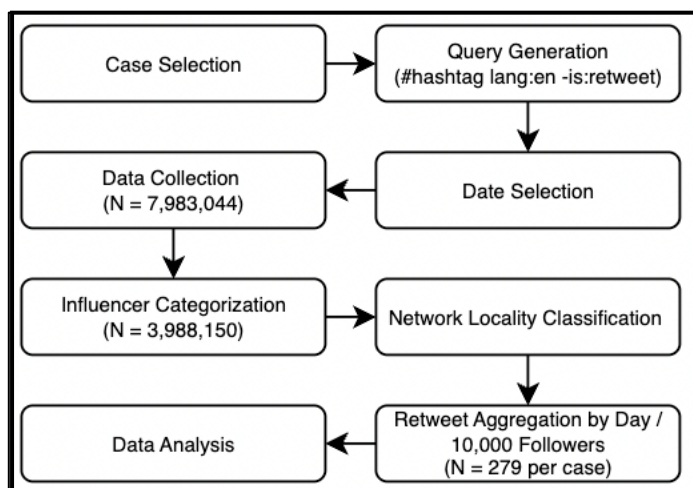

Figure 4. Data collection and pre-processing stages

Twitter was selected as the primary source of empirical data as it represents the most popular social media platform in terms of news consumption, with 59% of its users regularly using the platform to seek information on current events (Walker & Matsa, 2021). With over 211 million

active daily users (Statista, 2022b), Twitter allows users to create and maintain a public profile, follow others, post short pieces of text containing up to 280 characters (known as tweets) and repost other's messages (known as retweets). A summary of the data collection and pre-processing stages are presented in Figure 4 above. Each stage is discussed in detail in the following sections.

Each case was selected due to the varying scales of each event as it occurred. While it could be argued that all crises portrayed on social media rapidly become international events with global reach and reaction, the crux of each event is primarily discussed by those directly impacted by the crisis. On-the-ground information provided by first-hand observers possesses the highest potential for information diffusion (Kotlarsky et al., 2022; Tim et al., 2017). For instance, those experiencing or participating in the initial protests related to George Floyd in Minneapolis were seen as the primary sources of information whereas other online and offline actors were primarily redistributing and discussing content generated at the source. These initial protests sparked other protests outside of Minneapolis, but Minneapolis remained as the focal point of news coverage and social media discourse for an extended period (AP News, 2022). In comparison to the initial announcement of the COVID-19 pandemic, the outbreak affected different regions simultaneously. Thus, the region in focus was rapidly changing over time, making it difficult to focus on one region as the central point of discourse. This, in turn, made this crisis an international event from the onset.

Data collection and analysis centers on three influencer types (micro-, meso-, and macro-influencers), three event types (regional, national, and international), and two influencer locations in relation to the crisis (local or global). We categorize events into different types as each crisis possesses a locality where individuals within the locality are impacted by the crisis more so than those outside of the locality. Thus, we classified the protests related to George Floyd as regional in nature as the crisis locality was Minneapolis, whereas the Russo-Ukrainian war impacted an entire country (i.e., national), and the COVID-19 pandemic impacted multiple localities simultaneously (i.e., international).

Query generation represents the first step towards collecting data from Twitter. The authors identified the most popular unique hashtag for each case through multiple iterations. Specifically, #GeorgeFloyd, #UkraineWar and #COVID19. Hashtags play a critical role in information dissemination as they allow tweets to be contextualized and grouped as a crisis rapidly unfolds (Oh et al., 2013). Hashtags emerge naturally over time and allow users to take note of important information quickly as well as participate in relevant dialogue in real-time as information is created and disseminated (Palen et al., 2009; Rao et al., 2020). By selecting one hashtag for each case study, we focus on the dominant discourse related to each event.

To collect data, the authors utilized the full-archive search endpoint available via Twitter API V2 (Twitter, 2022). Upon approval, this API provides academic researchers with free access to the entire archive of tweets which enables replicability and reproducibility. The authors used a custom toolkit for query generation, query testing, and data collection (Kishore et al., 2019). To focus each of the cases on the initial occurrence of the event, all English tweets (excluding retweets) were collected one month following the beginning of each crisis (N = 7,983,044). While Ukrainian is the dominant language in Ukraine (Translators without Borders, 2022), we chose to focus on English tweets to maintain comparability. Retweets were excluded as the focus of this study is to understand how the locality of different types of influencers effect

information dissemination. Original tweets include the total number of retweets which is sufficient in the context of this study.

Upon completion, each influencer was categorized as either a micro- (1,000 to 10,000 followers), meso- (10,001 to 100,000 followers) or macro-influencer (> 100,001 followers) based on a combination of current research categorizing influencers (Boerman, 2020; Kay et al., 2020). For the purpose of this paper, those with less than 1,000 followers were excluded to focus on the core categories of influencers (Boerman, 2020; Kay et al., 2020) which decreased the total number of tweets (N = 3,988,150) and primarily consisted of micro-influencers from the COVID-19 case (Table 1).

	Total Micro-Influencer Tweets	Total Meso-Influencer Tweets	Total Macro-Influencer Tweets	Total
George Floyd	327,771	93,493	28,680	**449,944**
Russo-Ukrainian War	104,232	24,698	7,399	**136,329**
COVID-19 Pandemic	2,213,288	827,605	360,984	**3,401,877**
Total	**2,645,291**	**945,796**	**397,063**	**3,988,150**

Table 1. Tweet distribution across cases and influencer types

In addition, each influencer was categorized as local if their location information included Minneapolis (for the George Floyd case), Ukraine (for the Russo-Ukrainian case), or London (for the COVID-19 pandemic case). If the influencer's location did not match any of these locations, they were labelled as global in terms of their proximity to the crisis. As discussed, Ukraine was selected for the Russo-Ukrainian case study as it swiftly impacted the entire country, whereas Minneapolis was a clear starting point of the protests related to the murder of George Floyd. This also strengthens the results as it includes local influencers at different regionalities. Overall, coding this data enabled the investigation of different types of influencers and their impact on information dissemination in local and global networks.

Constructs	Data	Description	Variables
Network	Total number of followers per user account	Each account was categorized as either a micro- (1,000 to 10,000 followers), meso- (10,001 to 100,000 followers) or macro-influencer (> 100,001 followers) to identify the different types of influencers participating in the various crisis events.	Influencer type (micro, meso, macro)
Information diffusion	Total number of retweets received per user account	For each influencer type, average retweets per day per 10,000 followers was calculated to enable statistical analysis.	Average retweets
Crisis event geography	N/A	Each case was selected to represent different crisis scales. Regional (George Floyd), national (Russo-Ukrainian war) and international (COVID-19 pandemic).	Event type (regional, national, international)
Influencer location	User account location	Each account was categorized as either local (if their account location was local to the specific crisis event) or global.	Influencer location (local, global)

Table 2. Summary of constructs and operationalized variables

Lastly, to facilitate quantitative data analysis, data was aggregated by day. Specifically, average retweets per day per 10,000 followers was calculated and utilized for data analysis across the different influencer categories and networks. As the majority of tweets do not get retweeted (Boyd et al., 2010), evaluating the average number of retweets per day per 10,000 followers enables both interpretability and analysis. Aggregation makes the patterns that exist clearer to analyze and separate (Kar & Dwivedi, 2020). This also reduced the sample size which allowed for the application of standard statistical methods which produces more interpretable and realistic p-values and effect sizes (N = 279 per case). A summary of the constructs and operationalized variables are presented in Table 2 above.

5 Results

5.1 Study 1

Hypothesis 1 was tested using a two-way ANOVA model, exploring the interaction of crisis event type as an independent variable (event type: regional (code = 1), national (code = 2), and international (code = 3) and influencer type as the second independent variable (influencer type: micro (code = 1), meso (code = 2), and macro (code = 3)). The dependent variable was average retweets.
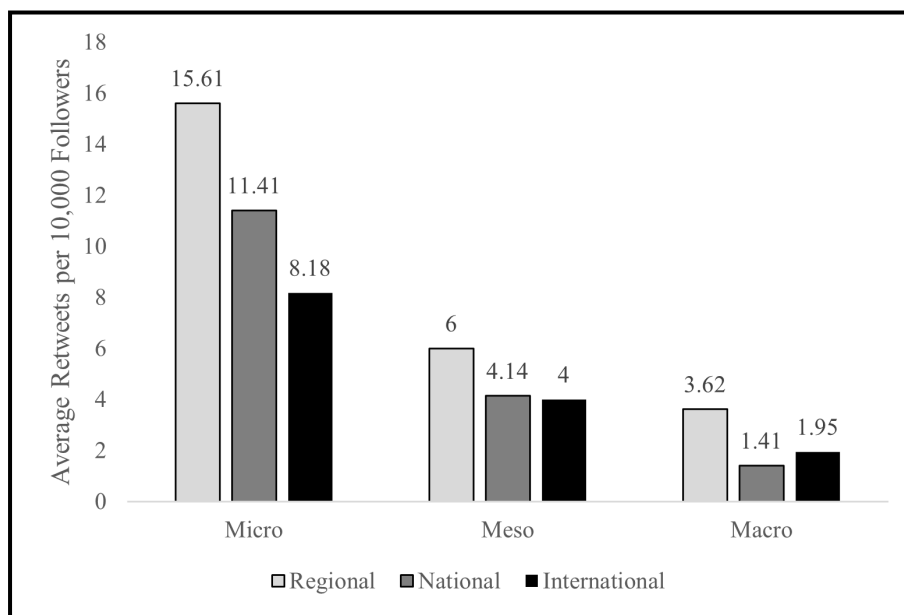

Figure 5. Average Retweets for Crisis Events by Influencer Type

The two-way ANOVA revealed a significant main effect for event type, $F_{(2, 266)} = 6.99$, $p = .001$. There was a main effect of influencer type, $F_{(2, 266)} = 44.35$, $p < .001$. There was no significant interaction effect between event type and influencer type on average retweets, $F_{(2, 266)} = 1.70$, $p = .149$. However, more importantly, pairwise comparisons revealed that retweets in regional event types (M = 15.61, SD = 1.26) had significantly more information diffusion than national (M = 11.41, SD = 1.30) or international (M = 8.18, SD = 1.24) events when the influencer type was micro, $F_{(2, 258)} = 8.80$, $p < .001$. There was no significant effect on retweets in regional event types (M = 6.00, SD = 1.26) when compared to national (M = 4.14, SD = 1.30) or internanational (M = 4.00, SD = 1.24) events when the influencer type was meso, $F_{(2, 258)} = .78$, $p = .459$. Further, there was no significant effect on retweets in regional event types (M = 3.62, SD = 1.26) when compared to national (M = 1.41, SD = 1.30) or international (M = 1.95, SD =

1.24) events when the influencer type was macro, $F(2, 258) = .81$, $p = .443$ (see Figure 5; Table 3).

Analysis of Variance (ANOVA) Results		
	DV: Average Retweets	
Source of Variation	***F* Statistic**	***p* Value**
Event Type X Influencer Type	1.70	.149
Event Type X Influencer Type: Micro	**8.80**	**.000**
Event Type X Influencer Type: Meso	.78	.459
Event Type X Influencer Type: Macro	.81	.443
Event Type (1 = Regional, 2 = National, 3 = International)	**6.99**	**.001**
Influencer Type (1 = Micro, 2 = Meso, 3 = Macro)	**44.35**	**.000**

Table 3. Analysis of Variance (ANOVA) Results for Study 1

5.2 Study 2

Hypothesis 2 was tested using a three-way ANOVA model, exploring the interaction of crisis event type as an independent variable (event type: regional (code = 1), national (code = 2), and international (code = 3), influencer type as the second independent variable (influencer type: micro (code = 1), meso (code = 2), and macro (code = 3)), and influencer location (influencer location: local (code = 1) and global (code = 2)) . The dependent variable was average retweets.
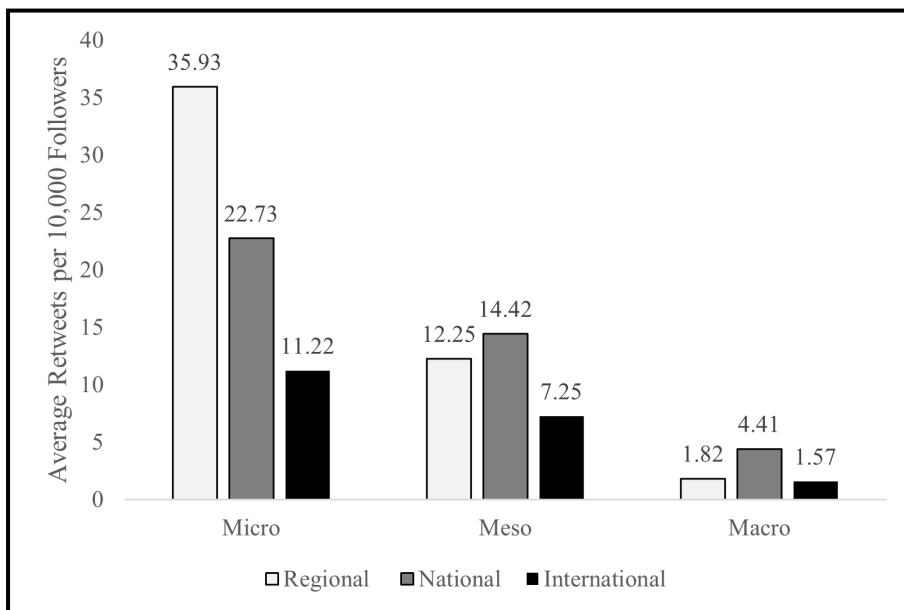

Figure 6. Average Retweets for Crisis Events by Influencer Type in Local Locations

The three-way ANOVA revealed a significant main effect for event type, $F(2, 533) = 3.43$, $p = .033$. There was a main effect of influencer type, $F(2, 533) = 16.33$, $p < .001$. Finally, there was a main effect of influencer location, $F(1, 534) = 8.24$, $p = .004$. There was no significant interaction effect between event type X influencer type X influencer location on average retweets, $F(4, 533) = .662$, $p = .619$. However, more importantly, pairwise comparisons revealed that local influencer locations follow the same pattern as the prior study. In local networks, retweets in regional event types (M = 35.92, SD = 93.52) had significantly more information diffusion than national (M = 22.73, SD = 23.21) or international (M = 11.22, SD = 11.65) events when the

influencer type was micro, $F(2, 516) = 7.46$, $p < .001$. There was no significant effect on retweets in regional event types (M = 12.25, SD = 21.00) when compared to national (M = 14.42, SD = 27.79) or international (M = 7.25, SD = 6.44) events when the influencer type was meso, $F(2, 516) = .64$, $p = .524$. Further, there was no significant effect on retweets in regional event types (M = 1.82, SD = 1.56) when compared to national (M = 4.41, SD = 9.06) or international (M = 1.57, SD = 2.21) events when the influencer type was macro, $F(2, 516) = .11$, $p = .892$ (see Figure 6; Table 3).
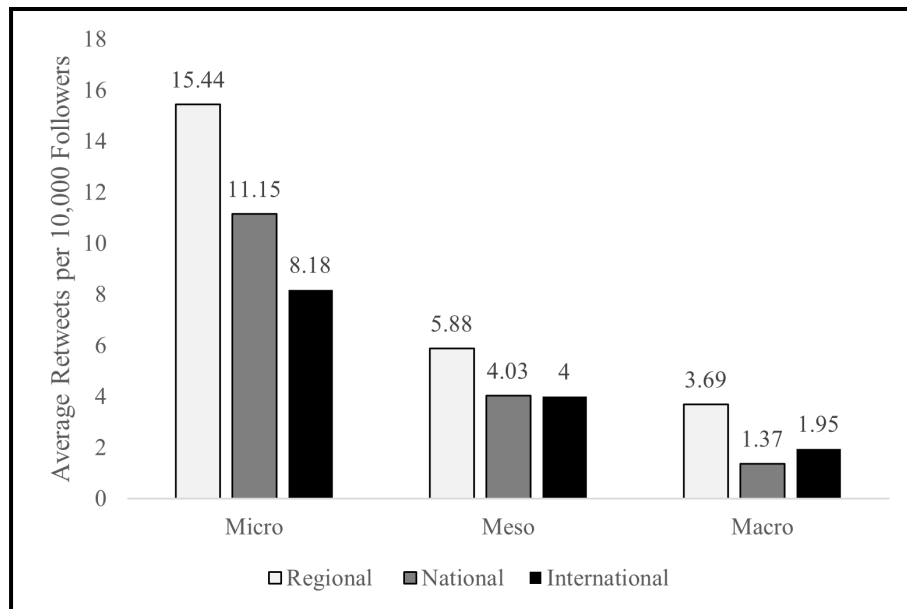

Figure 7. Average Retweets for Crisis Events by Influencer Type in Global Locations

Analysis of Variance (ANOVA) Results		
	DV: Average Retweets	
Source of Variation	***F* Statistic**	***p* Value**
Event Type X Influencer Type X Influencer Location	.662	.619
Event Type X Influencer Type: **Micro** X Influencer Location: **Local**	**7.46**	**.000**
Event Type X Influencer Type: **Meso** X Influencer Location: **Local**	.64	.524
Event Type X Influencer Type: **Macro** X Influencer Location: **Local**	.11	.892
Event Type X Influencer Type: **Micro** X Influencer Location: **Global**	.65	.523
Event Type X Influencer Type: **Meso** X Influencer Location: **Global**	.05	.946
Event Type X Influencer Type: **Macro** X Influencer Location: **Global**	.06	.934
Event Type (1 = Regional, 2 = National, 3 = International)	**3.43**	**.033**
Influencer Type (1 = Micro, 2 = Meso, 3 = Macro)	**16.33**	**.000**
Influencer Location (1 = Local, 2 = Global)	**8.24**	**.004**

Table 4. Analysis of Variance (ANOVA) Results for Study 2

In global locations, retweets in regional event types (M = 15.44, SD = 18.96) was not significantly different in information diffusion than national (M = 11.15, SD = 4.84) or international (M = 8.18, SD = 2.32) events when the influencer type was micro, $F(2, 516) = .65$, $p = .523$. Aligned with this pattern, there was no significant effect on retweets in regional event types (M = 5.88, SD = 3.86) when compared to national (M = 4.03, SD = 1.98) or international

(M = 4.00, SD = 1.21) events when the influencer type was meso, $F(2, 516) = .05$, $p = .946$. Further, there was no significant effect on retweets in regional event types (M = 3.69, SD = 3.76) when compared to national (M = 1.37, SD = .86) or international (M = 1.95, SD = .60) events when the influencer type was macro, $F(2, 516) = .06$, $p = .934$ (see Figure 7; Table 4).

6   Discussion

6.1   General discussion

This paper demonstrates that influencers, specifically micro-influencers, are critical to understanding information diffusion on Twitter during crisis events. We show that information diffusion during regional, national, or international public crisis events depends on the type of influencer (e.g., micro, meso, or macro) disseminating the information, as well as the location of the influencer (e.g., local, or global) in proximity to the crisis event. By applying a social media analytics approach to a large set of tweets, we analyzed three different crisis events (regional, national, and international) one month following the beginning of each crisis (N = 7,983,044).
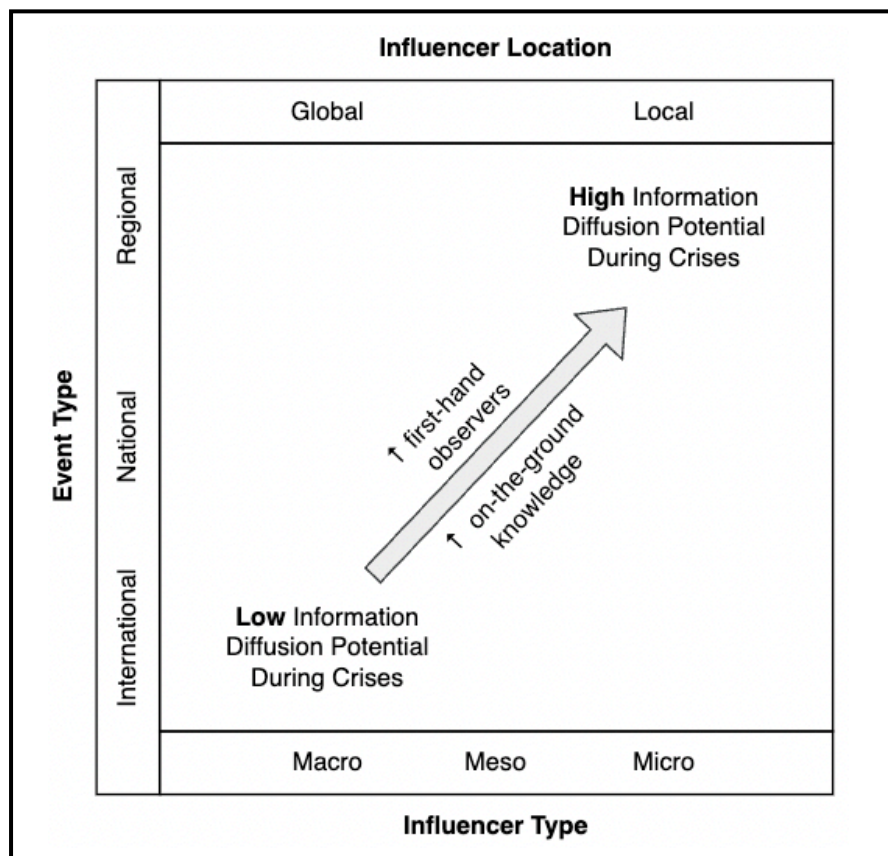

Figure 8. Influencer network compression

In study 1, we show that there is significantly more information diffusion in regional (vs. national or international) crisis events when tweeted by micro-influencers (vs. meso- or macro-influencers). Further, study 2 demonstrates that this pattern holds when micro-influencers operate in locations that are local (i.e., are located local to the crisis), however, effects become

attenuated when micro-influencers are situated in locations that are global (i.e., outside of the locality of the event). We term this effect 'influencer network compression' – the smaller in scope a crisis event geography (regional, national, or international) and network locality (local or global) becomes, the more effective micro-influencers are at diffusing information. Further, micro-influencers that participate in regional crisis events have the highest potential for information diffusion – and those with local proximity in networks, rather than global proximity, have the most potent effect on information diffusion (Figure 8 above).

The observed effects can be attributed to the active involvement of locally situated micro-influencers in generating and disseminating up-to-date information relevant to crises. This phenomenon can be explained by their possession of unique on-the-ground knowledge and potential first-hand observation of the crisis, which becomes more attainable in regional crisis scenarios. Hence, the distinct role played by locally situated micro-influencers emerges as a critical element in crisis information dissemination, response, and management, primarily due to their ability to contribute tangible and contextually rich insights.

6.2 Theoretical contributions

This work demonstrates that there is significantly more information diffusion in regional (vs. national or international) crisis events when tweeted by micro-influencers (vs. meso- or macro-influencers) and that this pattern is consistent when micro-influencers operate in local networks, whilst effects become attenuated when micro-influencers are situated in global networks. We contribute this effect to 'influencer network compression,' which proposes that the smaller in scope a crisis event location (regional, national, or international) and network (local or global) becomes, the more effective micro-influencers are at diffusing information online. Influencer network compression contributes to a greater understanding of scholars' theoretical knowledge of influencers and their diffusion of information when it comes to crisis events. Micro-influencers that participate in regional crisis events have the most significant potential for information diffusion – and those with local proximity in networks, rather than global proximity, have the most potent effect on information diffusion.

We theorize that micro-influencers situated locally (vs. globally) to regional (vs. national or international) crises are more likely to possess on-the-ground knowledge and may be first-hand observers of the crisis as it unfolds. We build upon the theoretical frameworks of homophily (De Choudhury et al., 2010) and network patterns (J. Kim & Hastak, 2018) to explore how opinion leaders with varying geographic proximities to a crisis event, might possess firsthand information. Such proximity may lead to experiences that align closely with the event's realities, thereby enhancing their credibility. During crises, on-the-ground knowledge is highly valuable as different types of online influencers, such as individual citizens and journalists, can broadcast breaking news to their networks before traditional media outlets (Fichet et al., 2016). Those situated local to the crisis have the added advantage of utilizing their local knowledge, typically unavailable to collective entities, to provide localized situational information to affected local communities (Li & Rao, 2010; Oh et al., 2013). As real-time information can significantly enhance the decision-making process of a disaster-affected-community, the inherent value of this type of information is heightened, thereby increasing its widespread propagation throughout a network (Abedin & Babar, 2018). Consequently, the dissemination of real-time, locally informed information through the networks of micro-influencers become critical components in crisis communication and response efforts.

Further, understanding information diffusion in crisis events is still in the early stages (Kotlarsky et al., 2022; Mirbabaie, Bunker, Stieglitz, Marx, & Ehnis, 2020; Zhang et al., 2019). Our findings help shed light on characteristics of social media, specifically Twitter, in disasters. For example, we find granularity and nuance of information diffusion in regional, national, and international events, and how these may be amplified through different types of influencers. Our research finds both commonalities and differences with existing research. For instance, our findings are in contrast to the 'power law', which implies that centralized users with a large number of followers and trending posts dominate information diffusion (Zhang et al., 2019). However, in our case we isolate information diffusion to crisis events to help highlight how they are different in dissemination than typical social network sharing. As such, crisis events may heighten the 'power law' to be isolated to influencers or users closer in proximity to the event. By examining these unique dynamics, we contribute to a deeper understanding of how information flows and propagates during crisis events, thereby expanding our knowledge of the role played by various types of influencers and users in crisis communication on social media platforms.

6.3   Practical contributions

From a practical perspective, this research demonstrates micro-influencers' significant influence in local networks and settings during crises. Micro-influencers local to Minneapolis during protests related to the murder of George Floyd were, on average, more likely to be retweeted than local meso- and macro-influencers with significantly larger networks. This goes against the expectation that a more extensive network size corresponds to an increase in information dissemination during crises. However, the prominence of micro-influencers in information dissemination pertaining to local crises carries significant implications. On one hand, their role is crucial in disseminating timely and relevant information to affected communities. However, on the other hand, it is important to recognize that micro-influencers also possess the potential to propagate misinformation and disinformation during crises.

Misinformation, which refers to the unintentional dissemination of false information, and disinformation, which involves the deliberate spread of false information, both contribute to problematic dynamics during crises, primarily due to their impact on public opinion (Tran et al., 2021). An example can be seen in the case of George Floyd, where discussions surrounding social injustice frequently cited the Black Lives Matter movement. However, intense online discourse also gave rise to the oppositional movement, All Lives Matter, leading to polarization and further division within public sentiment (Carney, 2016).

Given the influential role of micro-influencers in shaping public opinion during crises, it becomes imperative for government agencies, policymakers, and social media platforms to acknowledge their significance and take appropriate measures. In particular, these stakeholders should ensure that micro-influencers, who possess heightened information dissemination potential, are encouraged to cite factual sources when creating and disseminating content online during an unfolding crisis. To increase accurate information dissemination social media platforms should also consider incorporating behavioral nudges and source ratings (A. Kim et al., 2019) primarily targeted at this group. This is especially crucial when micro-influencers engage with emergent crisis-related hashtags that rapidly spread to a large population in a short timeframe. Strategies aimed at promoting information accuracy, fact-checking, and promoting critical thinking skills among both micro-influencers

and their audiences can be instrumental in mitigating the adverse effects of false or misleading information during crises.

6.4   Limitations and future research

This research should be viewed considering its intrinsic limitations. While the dataset is complete and replicable as all data was collected from the Twitter API, the API only provides access to public tweets. Therefore, the tweets of users with private accounts were not available for data collection and analysis. In addition, this study focuses on average retweets per day per 10,000 followers to reveal interpretable results. While statistical results were consistent when data was aggregated at different levels, meso- and macro-influencers may possess hundreds of thousands, if not millions, of followers. By using an aggregate approach, their relative influence was potentially diluted. Nevertheless, this research shows that possessing a large online following does not ensure that followers will reshare content at the same rate as micro-influencers, which may possess a smaller, yet more engaged, followership (Kwak et al., 2010). Furthermore, as only original tweets were collected, we are unable to analyze the network dynamics at play. Future research should consider collecting retweets in a similar context to analyze the different types of networks influencers engage with.

The authors consciously decided to exclude a control group. This would usually make the results difficult to justify, however, this has been accommodated for by evaluating multiple case studies. In addition, location information on Twitter is often limited to a small percentage of public user accounts. Furthermore, as location information can be manually edited, some users may list incorrect location information on their profiles (Burns & Eltham, 2009). However, this is unlikely to occur on a large scale.

As each case utilized a single hashtag during data collection, it is likely that a proportion of relevant tweets were excluded. Furthermore, while Ukrainian is the dominant language in Ukraine (Translators without Borders, 2022), we chose to focus on English tweets only. As this study's aim is to compare trends in influencer types rather than identify influential individuals, we narrowed our data collection scope to maintain comparability and consistency. Future studies focusing on networks or individuals should consider an iterative approach to identify all relevant parameters (Kishore et al., 2022).

Future research should also consider the relationship between temporality and distinct categories of influencers. Temporality, or time, is an important, yet understudied, construct in IS (Venkatesh et al., 2021). Micro-influencers locally situated to an unfolding crisis may be quicker to post content on social media as they are experiencing the crisis first-hand. In some contexts, they may be reporting breaking news and news updates before traditional media agencies and news reporters which may partially explain why their content is being retweeted significantly more often in local networks. This finding is in line with current developing research (Kotlarsky et al., 2022), however, this relationship requires further examination. In addition, delving into multi-step dissemination offers an additional avenue for future research examining the temporal dynamics of networks. Given the potential for tweets to be retweeted by various types of influencers and users, the original tweet may reach a considerably larger network of followers over time, leading to subsequent retweets. Consequently, investigating the roles of influencers, both situated locally and globally, within the context of multi-step dissemination may yield promising insights on the dynamics at play within networks.

Interestingly, alternative research also shows that virality is higher for misinformation, novel tweets, and tweets with negative sentiment (King & Wang, 2021). Specific to the cases we explored, misinformation during crisis events is a risk due to complexity of the information, and further, polarization among networks may occur when there are large networks with multiple actor motivations (Törnberg, 2018). Although our research focused specifically on how information diffuses amongst networks, it is of great interest to explore risks of misinformation within information diffusion, as well as the centrality of key actors and what role they play in this situation.

Future research may also explore the content of influencer tweets, rather than the effectiveness of information diffusion, to understand if different types of influencers are more adept at spreading misinformation or negative sentiment. It would be revelatory to apply Natural Language Processing (NLP) methods to understand how discourse is evolving over time during crisis events, and how this discourse varies between regionalities and influencer types.

7   Conclusion

This paper investigates how different types of influencers (micro, meso, and macro) participating in different public crisis event geographies (regional, national, and international) and different network localities (local and global) effects information diffusion on the social media platform, Twitter. Online information diffusion plays a critical role during public crisis events. We show (study 1) that there is significantly more information diffusion in regional (vs. national or international) crisis events when tweeted by a micro-influencer (vs. meso-influencers or macro-influencers). Further, study 2 demonstrates this pattern holds when micro-influencers operate in local networks (are located local to the crisis), however, effects become attenuated when the micro-influencer is situated in a global network (outside of the locality of the event). We term this effect 'influencer network compression' – the smaller in scope a crisis event geography and the network becomes, the more effective micro-influencers are at diffusing information. In summary, this research sheds light on how micro-influencers have the power to do big things in a small way.

References

Abedin, B., & Babar, A. (2018). Institutional vs. non-institutional use of social media during emergency response: A case of twitter in 2014 Australian bush fire. *Information Systems Frontiers*, *20*(4), 729–740. https://doi.org/10.1007/s10796-017-9789-4

Alampi, A. (2019). The future is micro: How to build an effective micro-influencer programme. *Journal of Digital & Social Media Marketing*, *7*(3), 203–208.

Aleti, T., Harrigan, P., Cheong, M., & Turner, W. (2016). An investigation of how the Australian brewing industry influence consumers on Twitter. *Australasian Journal of Information Systems*, *20*. https://doi.org/10.3127/ajis.v20i0.1350

AP News. (2022, October 23). *Timeline of events since George Floyd's arrest and murder*. AP News. https://apnews.com/article/death-of-george-floyd-minneapolis-police-reform-d109eb0d3094119ddbcb560676467f19

Bachura, E., Valecha, R., Chen, R., & Rao, H. R. (2022). The OPM Data Breach: An Investigation of Shared Emotional Reactions on Twitter. *MIS Quarterly*, *46*(2), 881–910. https://doi.org/10.25300/MISQ/2022/15596

Bang, C. C., Lee, J., & Rao, H. R. (2021). The Egyptian protest movement in the twittersphere: An investigation of dual sentiment pathways of communication. *International Journal of Information Management*, *58*. https://doi.org/10.1016/j.ijinfomgt.2021.102328

Bastos, M., & Farkas, J. (2019). "Donald Trump is my President!": The internet research agency propaganda machine. *Social Media+ Society*, *5*(3). https://doi.org/10.1177/2056305119865466

Bastos, M., Mercea, D., & Baronchelli, A. (2018). The geographic embedding of online echo chambers: Evidence from the Brexit campaign. *PloS One*, *13*(11), e0206841. https://doi.org/10.1371/journal.pone.0206841

Berente, N., Seidel, S., & Safadi, H. (2019). Research commentary—Data-driven computationally intensive theory development. *Information Systems Research*, *30*(1), 50–64. https://doi.org/10.1287/isre.2018.0774

Boerman, S. C. (2020). The effects of the standardized Instagram disclosure for micro-and meso-influencers. *Computers in Human Behavior*, *103*, 199–207. https://doi.org/10.1016/j.chb.2019.09.015

Bonnevie, E., Rosenberg, S. D., Kummeth, C., Goldbarg, J., Wartella, E., & Smyser, J. (2020). Using social media influencers to increase knowledge and positive attitudes toward the flu vaccine. *PLoS One*, *15*(10). https://doi.org/10.1371/journal.pone.0240828

Boyd, D., Golder, S., & Lotan, G. (2010). Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. *43rd Hawaii International Conference on System Sciences*, 1–10. https://doi.org/10.1109/HICSS.2010.412

Brown, S. (2022). *In Russia–Ukraine War, Social Media Stokes Ingenuity, Disinformation*. MIT Sloan School of Management. https://mitsloan.mit.edu/ideas-made-to-matter/russia-ukraine-war-social-media-stokes-ingenuity-disinformation

Buchanan, L., Bui, Q., & Patel, J. K. (2020). Black Lives Matter may be the largest movement in US history. *The New York Times*, *3*. https://www.nytimes.com/interactive/2020/07/03/us/george-floyd-protests-crowd-size.html

Burns, A., & Eltham, B. (2009). *Twitter free Iran: An evaluation of Twitter's role in public diplomacy and information operations in Iran's 2009 election crisis*. Communications Policy and Research Forum, Sydney, Australia. https://vuir.vu.edu.au/15230/1/CPRF09BurnsEltham.pdf

Campbell, C., & Farrell, J. R. (2020). More than meets the eye: The functional components underlying influencer marketing. *Business Horizons*, *63*(4), 469–479. https://doi.org/10.1016/j.bushor.2020.03.003

Carney, N. (2016). All lives matter, but so does race: Black lives matter and the evolving role of social media. *Humanity & Society*, *40*(2), 180–199. https://doi.org/10.1177/0160597616643868

Chen, E., & Ferrara, E. (2022). Tweets in time of conflict: A public dataset tracking the twitter discourse on the war between Ukraine and Russia. *arXiv Preprint arXiv:2203.07488*. https://doi.org/10.48550/arXiv.2203.07488

Choi, S. (2015). The two-step flow of communication in Twitter-based public forums. *Social Science Computer Review*, *33*(6), 696–711. https://doi.org/10.1177/0894439314556599

Cohen, R. (2022). *A surge of unifying moral outrage over Russia's war*. The New York Times. https://www.nytimes.com/2022/03/01/world/europe/zelensky-ukraine-war-outrage.html

Cucinotta, D., & Vanelli, M. (2020). WHO declares COVID-19 a pandemic. *Acta Bio Medica: Atenei Parmensis*, *91*(1), 157. https://doi.org/10.23750/abm.v91i1.9397

De Choudhury, M., Sundaram, H., John, A., Seligmann, D. D., & Kelliher, A. (2010). "Birds of a Feather": Does User Homophily Impact Information Diffusion in Social Media? *arXiv Preprint arXiv:1006.1702.*, 1–31. https://doi.org/10.48550/arXiv.1006.1702

Farivar, S., Wang, F., & Yuan, Y. (2021). Opinion leadership vs. Para-social relationship: Key factors in influencer marketing. *Journal of Retailing and Consumer Services*, *59*. https://doi.org/10.1016/j.jretconser.2020.102371

Fichet, E. S., Robinson, J. J., Dailey, D., & Starbird, K. (2016). Eyes on the Ground: Emerging Practices in Periscope Use during Crisis Events. *Thirteen's International Conference on Information Systems for Crisis Response and Management (ISCRAM 2016)*, 1–10.

Firdaus, S. N., Ding, C., & Sadeghian, A. (2018). Retweet: A popular information diffusion mechanism–A survey paper. *Online Social Networks and Media*, *6*, 26–40. https://doi.org/10.1016/j.osnem.2018.04.001

Garner, I. (2022). *How is the war going for Putin on social media? Not great.* Washington Post. https://www.washingtonpost.com/outlook/2022/03/04/russian-social-media-ukraine-vk-propaganda/

Grisold, T., Kremser, W., Mendling, J., Recker, J., vom Brocke, J., & Wurm, B. (2023). Generating Impactful Situated Explanations through Digital Trace Data. *Journal of Information Technology*. https://doi.org/10.1177/02683962231208724

Guille, A., Hacid, H., Favre, C., & Zighed, D. A. (2013). Information diffusion in online social networks: A survey. *ACM SIGMOD Record*, *42*(2), 17–28. https://doi.org/10.1145/2503792.2503797

Hagar, C. (2011). *Crisis Information Management: Communication and technologies*. Amsterdam, The Netherlands: Elsevier.

Harrigan, P., Daly, T. M., Coussement, K., Lee, J. A., Soutar, G. N., & Evers, U. (2021). Identifying influencers on social media. *International Journal of Information Management*, *56*, 102246. https://doi.org/10.1016/j.ijinfomgt.2020.102246

Hodis, M. A., Sriramachandramurthy, R., & Sashittal, H. C. (2015). Interact with me on my terms: A four segment Facebook engagement framework for marketers. *Journal of Marketing Management*, *31*(11–12), 1255–1284. https://doi.org/10.1080/0267257X.2015.1012535

Hogan, B. (2008). Analyzing social networks via the internet. In *The SAGE Handbook of Online Research Methods* (pp. 141–160). New York, NY, USA: Sage Publications. https://doi.org/10.4135/9780857020055

Hu, L., Min, Q., Han, S., & Liu, Z. (2020). Understanding followers' stickiness to digital influencers: The effect of psychological responses. *International Journal of Information Management*, *54*, 102169. https://doi.org/10.1016/j.ijinfomgt.2020.102169

Huang, Y., Shen, C., & Contractor, N. S. (2013). Distance matters: Exploring proximity and homophily in virtual world networks. *Decision Support Systems*, *55*(4), 969–977. https://doi.org/10.1016/j.dss.2013.01.006

Janssen, M., & van der Voort, H. (2020). Agile and adaptive governance in crisis response: Lessons from the COVID-19 pandemic. *International Journal of Information Management*, *55*(June), 102180. https://doi.org/10.1016/j.ijinfomgt.2020.102180

Jones, S. G. (2013). *The mirage of the Arab Spring: Deal with the region you have, not the region you want*. Foreign Affairs; HeinOnline. https://www.foreignaffairs.com/articles/syria/2012-12-03/mirage-arab-spring

Kar, A. K., & Dwivedi, Y. K. (2020). Theory building with big data-driven research–Moving away from the "What" towards the "Why." *International Journal of Information Management*, *54*, 102205. https://doi.org/10.1016/j.ijinfomgt.2020.102205

Katz, E. (1957). The two-step flow of communication: An up-to-date report on an hypothesis. *Public Opinion Quarterly*, *21*(1), 61–78. https://doi.org/10.1086/266687

Katz, E., & Lazarsfeld, P. F. (1964). *Personal Influence*. Piscataway, NJ, USA: Transaction Publishers.

Kay, S., Mulcahy, R., & Parkinson, J. (2020). When less is more: The impact of macro and micro social media influencers' disclosure. *Journal of Marketing Management*, *36*(3–4), 248–278. https://doi.org/10.1080/0267257X.2020.1718740

Kim, A., Moravec, P. L., & Dennis, A. R. (2019). Combating fake news on social media with source ratings: The effects of user and expert reputation ratings. *Journal of Management Information Systems*, *36*(3), 931–968. https://doi.org/10.1080/07421222.2019.1628921

Kim, J., Bae, J., & Hastak, M. (2018). Emergency information diffusion on online social media during storm Cindy in U.S. *International Journal of Information Management*, *40*(January), 153–165. https://doi.org/10.1016/j.ijinfomgt.2018.02.003

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

King, K. K., & Wang, B. (2021). Diffusion of real versus misinformation during a crisis event: A big data-driven approach. *International Journal of Information Management*, 102390. https://doi.org/10.1016/j.ijinfomgt.2021.102390

Kishore, S., Peko, G., & Sundaram, D. (2019). Looking Through the Twitter Glass: Bridging the Data– Researcher Gap. *Proceedings of the Americas Conference on Information Systems*, 8–16. https://aisel.aisnet.org/amcis2019/social_computing/social_computing/4

Kishore, S., Sundaram, D., & Myers, M. (2022). Retweeting my feelings? Exploring the temporal effects of the COVID-19 pandemic on social media use. *Proceedings of the Australasian Conference on Information Systems*. Australasian Conference on Information Systems, Melbourne, Australia. https://aisel.aisnet.org/acis2022/56/

Kotlarsky, J., Kishore, S., Branicki, L., & Sullivan-Taylor, B. (2022). How the World Understood the White Island Eruption: The Tales that Different Social Media Actors Tell Us. *Proceedings of the European Conference on Information Systems*. European Conference on Information Systems, Timişoara, Romania. https://aisel.aisnet.org/ecis2022_rip/17/

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media? *Proceedings of the 19th International Conference on World Wide Web*, 591–600. https://doi.org/10.1145/1772690.1772751

Laylavi, F., Rajabifard, A., & Kalantari, M. (2017). Event relatedness assessment of Twitter messages for emergency response. *Information Processing & Management*, *53*(1), 266–280. https://doi.org/10.1016/j.ipm.2016.09.002

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1968). *The people's choice: How the voter makes up his mind in a presidential campaign*. New York, NY, USA: Columbia University Press.

Li, J., & Rao, H. R. (2010). Twitter as a rapid response news service: An exploration in the context of the 2008 China earthquake. *The Electronic Journal of Information Systems in Developing Countries*, *42*(1), 1–22. https://doi.org/10.1002/j.1681-4835.2010.tb00300.x

Liu, F., & Xu, D. (2018). Social roles and consequences in using social media in disasters: A structurational perspective. *Information Systems Frontiers*, *20*, 693–711. https://doi.org/10.1007/s10796-017-9787-6

Martínez-López, F. J., Anaya-Sánchez, R., Fernández Giordano, M., & Lopez-Lopez, D. (2020). Behind influencer marketing: Key marketing decisions and their effects on followers' responses. *Journal of Marketing Management*, *36*(7–8), 579–607. https://doi.org/10.1080/0267257X.2020.1738525

Martínez-Rojas, M., Pardo-Ferreira, M. del C., & Rubio-Romero, J. C. (2018). Twitter as a tool for the management and analysis of emergency situations: A systematic literature review. *International Journal of Information Management*, *43*(April), 196–208. https://doi.org/10.1016/j.ijinfomgt.2018.07.008

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, *27*(1), 415–444. https://doi.org/10.1146/annurev.soc.27.1.415

Mehta, A. M., Bruns, A., & Newton, J. (2017). Trust, but verify: Social media models for disaster management. *Disasters*, *41*(3), 549–565. https://doi.org/10.1111/disa.12218

Miranda, S., Berente, N., Seidel, S., Safadi, H., & Burton-Jones, A. (2022). Computationally Intensive Theory Construction: A Primer for Authors and Reviewers. *MIS Quarterly*, *46*(2). https://misq.umn.edu/misq/downloads/download/editorial/756/

Mirbabaie, M., Bunker, D., Stieglitz, S., & Deubel, A. (2020). Who Sets the Tone? Determining the Impact of Convergence Behaviour Archetypes in Social Media Crisis Communication. *Information Systems Frontiers*, *22*(2), 339–351. https://doi.org/10.1007/s10796-019-09917-x

Mirbabaie, M., Bunker, D., Stieglitz, S., Marx, J., & Ehnis, C. (2020). Social media in times of crisis: Learning from Hurricane Harvey for the coronavirus disease 2019 pandemic response. *Journal of Information Technology*, *35*(3), 195–213. https://doi.org/10.1177/0268396220929258

Nguyen, T. T., Criss, S., Michaels, E. K., Cross, R. I., Michaels, J. S., Dwivedi, P., Huang, D., Hsu, E., Mukhija, K., & Nguyen, L. H. (2021). Progress and push-back: How the killings of Ahmaud Arbery, Breonna Taylor, and George Floyd impacted public discourse on race and racism on Twitter. *SSM-Population Health*, *15*, 100922. https://doi.org/10.1016%2Fj.ssmph.2021.100922

NHS England. (2021). *Reducing burden and releasing capacity to manage the COVID-19 pandemic*. https://www.england.nhs.uk/coronavirus/documents/reducing-burden-and-releasing-capacity-to-manage-the-c-19-pandemic/

Office for National Statistics. (2020). *Coronavirus (COVID-19): 2020 in charts*. https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/articles/coronaviruscovid192020incharts/2020-12-18

Oh, O., Agrawal, M., & Rao, H. R. (2013). Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises. *MIS Quarterly*, *37*(2), 407–426. https://www.jstor.org/stable/43825916

Palen, L., Vieweg, S., Liu, S. B., & Hughes, A. L. (2009). Crisis in a networked world: Features of computer-mediated communication in the April 16, 2007, Virginia Tech event. *Social Science Computer Review*, *27*(4), 467–480. https://doi.org/10.1177/0894439309332302

Park, J., Lee, J. M., Xiong, V. Y., Septianto, F., & Seo, Y. (2021). David and Goliath: When and Why Micro-Influencers Are More Persuasive Than Mega-Influencers. *Journal of Advertising*, *50*(5), 584–602. https://doi.org/10.1080/00913367.2021.1980470

Pentland, B., Vaast, E., & Wolf, J. R. (2021). Theorizing Process Dynamics with Directed Graphs: A Diachronic Analysis of Digital Trace Data. *MIS Quarterly*, *45*(2), 967–984. https://doi.org/10.25300/MISQ/2021/15360

Rao, H. R., Vemprala, N., Akello, P., & Valecha, R. (2020). Retweets of officials' alarming vs reassuring messages during the COVID-19 pandemic: Implications for crisis management. *International Journal of Information Management*, *55*, 102187. https://doi.org/10.1016/j.ijinfomgt.2020.102187

Rathore, A. K., Maurya, D., & Srivastava, A. K. (2021). Do policymakers use social media for policy design? A Twitter analytics approach. *Australasian Journal of Information Systems*, *25*. https://doi.org/10.3127/ajis.v25i0.2965

Reuter, C., Kaufhold, M.-A., Schmid, S., Spielhofer, T., & Hahne, A. S. (2019). The impact of risk cultures: Citizens' perception of social media use in emergencies across Europe. *Technological Forecasting and Social Change*, *148*(1), 1–17. https://doi.org/10.1016/j.techfore.2019.119724

Robinson, B. (2020). Towards an ontology and ethics of virtual influencers. *Australasian Journal of Information Systems*, *24*. https://doi.org/10.3127/ajis.v24i0.2807

Roxby, P., Butcher, B., & England, R. (2020). *Pressure on hospitals "at a really dangerous point."* BBC. https://www.bbc.com/news/health-55362681

Roy, K. C., Hasan, S., Sadri, A. M., & Cebrian, M. (2020). Understanding the efficiency of social media based crisis communication during hurricane Sandy. *International Journal of Information Management*, *52*(December 2019), 102060. https://doi.org/10.1016/j.ijinfomgt.2019.102060

Sample, I. (2021). *Covid timeline: The weeks leading up to first UK lockdown*. The Guardian. https://www.theguardian.com/world/2021/oct/12/covid-timeline-the-weeks-leading-up-to-first-uk-lockdown

Schneider, S., & Check, P. (2010). Read all about it: The role of the media in improving construction safety and health. *Journal of Safety Research*, *41*(3), 283–287. https://doi.org/10.1016/j.jsr.2010.05.001

Scott, M. (2022). *As war in Ukraine evolves, so do disinformation tactics*. POLITICO. https://www.politico.eu/article/ukraine-russia-disinformation-propaganda/

Singh, J., Crisafulli, B., Quamina, L. T., & Xue, M. T. (2020). 'To trust or not to trust': The impact of social media influencers on the reputation of corporate brands in crisis. *Journal of Business Research*, *119*(January 2019), 464–480. https://doi.org/10.1016/j.jbusres.2020.03.039

Starbird, K., & Palen, L. (2011). "Voluntweeters" self-organizing by digital volunteers in times of crisis. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1071–1080. https://doi.org/10.1145/1978942.1979102

Starbird, K., & Palen, L. (2010). *Pass it on?: Retweeting in mass emergency*. Proceedings of the 7th International Information Systems for Crisis Response and Management (ISCRAM 2010). https://idl.iscram.org/files/starbird/2010/970_Starbird+Palen2010.pdf

Statista. (2022a). *Leading countries based on number of Twitter users as of January 2022*. https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries/

Statista. (2022b). *Number of monetizable daily active Twitter users (mDAU) worldwide from 1st quarter 2017 to 1st quarter 2022*. https://www.statista.com/statistics/970920/monetizable-daily-active-twitter-users-worldwide/

Stieglitz, S., Bunker, D., Mirbabaie, M., & Ehnis, C. (2018). Sense-making in social media during extreme events. *Journal of Contingencies and Crisis Management*, *26*(1), 4–15. https://doi.org/10.1111/1468-5973.12193

Stieglitz, S., & Dang-Xuan, L. (2012). Social media and political communication: A social media analytics framework. *Social Network Analysis and Mining*, *3*(4), 1277–1291. https://doi.org/10.1007/s13278-012-0079-3

Taylor, D. B. (2020). George Floyd protests: A timeline. *The New York Times*, *10*. https://www.nytimes.com/article/george-floyd-protests-timeline.html

Thomson, R., Ito, N., Suda, H., Lin, F., Liu, Y., Hayasaka, R., Isochi, R., & Wang, Z. (2012). *Trusting tweets: The Fukushima disaster and information source credibility on Twitter*. Proceedings of the 9th Information Systems for Crisis Response and Management (ISCRAM 2012). https://idl.iscram.org/files/thomson/2012/216_Thomson_etal2012.pdf

Tim, Y., Pan, S. L., Ractham, P., & Kaewkitipong, L. (2017). Digitally enabled disaster response: The emergence of social media as boundary objects in a flooding disaster. *Information Systems Journal*, *27*(2), 197–232. https://doi.org/10.1111/isj.12114

Törnberg, P. (2018). Echo chambers and viral misinformation: Modeling fake news as complex contagion. *PLoS One*, *13*(9), e0203958. https://doi.org/10.1371/journal.pone.0203958

Tran, T., Valecha, R., Rad, P., & Rao, H. R. (2021). An Investigation of Misinformation Harms Related to Social Media during Two Humanitarian Crises. *Information Systems Frontiers*, *23*(4), 931–939. https://doi.org/10.1007/s10796-020-10088-3

Translators without Borders. (2022). *Language data for Ukraine*. https://translatorswithoutborders.org/language-data-for-ukraine/

Twitter. (2022). *Academic Research access*. https://developer.twitter.com/en/products/twitter-api/academic-research

United Nations Office for the Coordination of Humanitarian Affairs. (2022). *Update on IDP Figures in Ukraine*. https://www.unocha.org/publications/report/ukraine/update-idp-figures-ukraine-18-march-2022-enuk

Venkatesh, V., Sykes, T. A., Aljafari, R., & Poole, M. S. (2021). The future is now: Calling for a focus on temporal issues in information system research. *Industrial Management & Data Systems, 121*(1). https://doi.org/10.1108/IMDS-08-2020-0506

Walker, M., & Matsa, K. E. (2021). *News Consumption Across Social Media in 2021*. Pew Research Center. https://www.pewresearch.org/journalism/2021/09/20/news-consumption-across-social-media-in-2021/

Wang, X. W., Cao, Y. M., & Park, C. (2019). The relationships among community experience, community commitment, brand attitude, and purchase intention in social media. *International Journal of Information Management*, *49*(July), 475–488. https://doi.org/10.1016/j.ijinfomgt.2019.07.018

Wang, Y., Hao, H., & Platt, L. S. (2021). Examining risk and crisis communications of government agencies and stakeholders during early-stages of COVID-19 on Twitter. *Computers in Human Behavior*, *114*, 106568. https://doi.org/10.1016/j.chb.2020.106568

Xu, L., Qiu, J., Gu, W., & Ge, Y. (2020). The dynamic effects of perceptions of dread risk and unknown risk on SNS sharing behavior during EID events: Do crisis stages matter. *Journal of the Association for Information Systems*, *21*(3), 545–573. http://dx.doi.org/10.17705/1jais.00612

Zhang, C., Fan, C., Yao, W., Hu, X., & Mostafavi, A. (2019). Social media for intelligent public information and warning in disasters: An interdisciplinary review. *International Journal of Information Management*, *49*(March), 190–207. https://doi.org/10.1016/j.ijinfomgt.2019.04.004