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False Rumor (Fake) and Truth News Spread During a Social Crisis

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Abstract

During a social crisis, the truthfulness of information becomes very important, particularly in determining if the information will spark extreme social engagement. We test a research model to examine major determinants of message spread during the 2016 Charlotte, North Carolina protests which occurred after false online rumors spread related to the shooting of Keith Lamont Scott. We hypothesize relationships between message spread (retweets) and extremity, negative emotions (sadness and fear), and social ties (reciprocal reply and location proximity), and Twitter experience. Using Poisson regression, we evaluate and compare two separate models (rumor and truth). Results of the analysis indicate that rumors and truths spread differently. More extreme messages spread less if they are truths, and fear does not relate to the spread of rumors. The results of the study provide theoretical and practical insights into the current research in the areas of information diffusion and social engagement.

1. Introduction

With more than one billion users, Social Network Sites (SNSs) such as Twitter are an essential part of many peoples' lives and are an important source of real-time information during emergencies [75]. Unfortunately, we are also experiencing an increase in the spread of false information through rumors. SNS providers are scrambling to find ways to allow freedom of speech but also limit harmful messages on their platforms.

SNS users are now news sources, sharers, and consumers of information [64]. Each users' multiple roles and the ease of re-sharing posts on SNSs, allows messages to spread quickly [35]. Sometimes, the impacts may go beyond the virtual world and cause extensive physical and lasting damage to society [70]. For example, SNSs have been used to organize social movements and spark social change, such as the Arab Spring [50], or Black Lives Matter [55]; however, rumor spread on SNSs have also incited recent incidents such as "Pizzagate," the Baltimore Protests, and the Charlotte Protests in the United States [1]. Arguably, more people are motivated by SNSs to participate in social movements than by their own friends and family [38].

Rumors are unverified suggestions of fact related to a topic of interest [5], and are the oldest form of mass media [30]. The term rumor does not require that the information is untrue, however, the connotation used colloquially implies falsehood, and that is how we will use it throughout. As a juxtaposition, truth is something that is factually correct. The notion truth requires materially adequate and formally correct information [62]. In the SNS context during uncertain crisis events, the availability of real facts becomes scarce. Separating false information such as rumors from trustworthy content is a big challenge. Recent research proposes different models to detect rumors [46], but still falls short of discerning rumors and truths, specifically during the social crisis spark on SNSs. A social crisis has five criteria: it is an uncertain condition, it is implausible to happen, it occurs over a short time, it is unexpected, and it requires a decision [51]. Because of these elements, social crises are a time of great uncertainty for many people, who are anxious to resolve the unknown.

Understanding rumor diffusion in online environments has been the focus of many studies in recent years [39]. However, isolating rumors and studying how they are distributed can be misleading without also considering the spread of truths [26]. In addition, research has recognized the importance of regional and locational attributes in analyzing sentiment during crisis [48, 57]. The way rumors spread is influenced by the absence of truths and truth presence may affect rumor diffusion [61]. In addition, emotions significantly impact the diffusion of messages on SNSs over time [77]. In the areas of

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rumor and truth diffusion on SNSs, this gap highlights the following research questions:

- What are the antecedents of truth and rumor diffusion during a social crisis on SNSs?
- How does message spread differ for rumors and truths during a social crisis?

This study addresses these research questions by achieving the following objectives. First, we propose a research model, grounded in Oh et al.'s (2013) rumormongering model, that explains rumor *and* truth diffusion on Twitter. Second, we test and verify the proposed model with a sentiment mining technique to analyze rumors and truths on Twitter data collected during the Charlotte protests in 2016.

2. Literature Review

2.1. SNSs and Message Spread

SNS functionalities are changing the historical methods people used to generate and distribute information [49]. As a result, motivations to use SNSs are broad, including communicating [19], information seeking [19], building identity [22], and information sharing [29]. On SNSs, certain patterns of communication about politics, brands, crises, and entertainment represent shared beliefs around topics [8]. The structure of SNSs allow for information to spread rapidly. Due to their nature, SNSs are threatened by misinformation (false information), and disinformation (information that is deliberately false) [31]. The virtual linked structure of SNSs does not necessarily reflect the actual relationships between users and when SNS users share content with their network, the recipient of the information may share it with others without knowing the originator of the content [29]. Further, sharing others content implies a form of validating the content and engaging with others in a conversation. By sharing, the user contributes to the conversation ecology and brings new people into a specific strand, indirectly motivating them to participate [7].

2.2. Rumors and Truths During a Social Crisis

The term "rumor" has different meanings in different contexts. Unverified propositions for beliefs related to a topic of interest and uncertain truths about an involved subject are both definitions of rumors [5]. Some researchers define rumors as claims of facts about people, groups, events, and institutions without any proof of being true [2]. Overall, every rumor is a distortion from reality [30]. Rumors can be classified into three basic types: (1) the pipe-dream or wish rumor, a circulated wishful thinking among a certain group of people; (2) the bogie rumor, a rumor that originates based on fear and anxiety; and (3) the wedge-driving or aggression rumor, based on hate and aggression [33]. Rumors transfer between people because people believe rumors are true information, [5].

To better understand how rumors are created, distributed, and controlled, the events that lead to a rumor should be emphasized as well as how the influence of the context on the rumor spread and control [46]. Rumors usually spread from users with low-influence and small networks to high-influence and large networks [37]. Therefore, even users with few connections are critical in the spread of rumors [17]. Further, individuals with a low critical thinking capacity may produce or spread more false rumors [9], indicating rumors can unintentionally spread through networks. Recent research reveals rumors travel faster and further than truths, indicating a great threat [68]. By and large, it takes over 12 hours for an online false claim to be exposed, as indicated by two recent undertakings that analyzed how misrepresentations and truths spread [79]. Once information begins to spread, it can have negative consequences. False rumors can be very problematic for a society and possibly lead to a social outburst. Halting rumors is difficult, but it is possible through improving identification of people and increasing trust in the source [76].

Rumors can spread in many contexts, but they are more prevalent in uncertain situations such as social crises [40]. Uncertain situations motivates individuals to fill in the blanks, improvise news, and spread rumors [40]. The uncertainty, accompanied by anxiety among the public also increases the seriousness of negative consequences of the spread of rumors [49]. People want to make sense of ambiguities, and thus it fosters a rumor generating environment in which different and opposing stories circulate in a short amount of time [50]. SNSs can be an important tool for emergency officials during social crises and disasters, but they also allow individuals to spread rumors more efficiently.

During social crises, SNSs are mainly used for information seeking and rapid information dissemination [45, 49]. To reduce uncertainties in crisis contexts, assembling evidence requires a wide range of resources, such as multiple SNSs [13]. For example, during the Paris Attacks in 2016, SNSs like Twitter, Facebook, and Instagram were overflowed with updates on the organized assault. Nonetheless, most of the information was inaccurate [71]. The distinction between misinformation and truth is not a trivial task due to a lack of a clear standard of judgment [2, 20]. During social crises, truths can be controlling mechanisms for the spread of rumors. Rooting from philosophy, truth is seen and debated from many angles including correspondence, coherence, consensual, and pragmatic [44]. Socrates, the Greek philosopher, explains that to identify information as truths, it must be believed to be true, there are justifiable facts and evidences, and it is in fact true [44]. The most obvious view of truth is described by correspondence theories. Satisfactory definition of truths is based on materially adequate and formally correct groundings [62]. This view is still ambiguous, as the extent of truths is not clear, which in turn must be determined by pre-defined conditions [62]. In this study, we apply the correspondence view of truths to identify truth messages during a social crisis.

2.3. Emotions and Message Spread

Rumors have been closely associated with emotions for a long time. In fact, "rumor satisfies. Mythology, folklore, and humor gather impetus from the emotional gratifications which they afford" [27]. Emotions historically considered in research are happiness, sadness, fear, anger, surprise, and disgust, also known today as primary emotions [18]. Primary emotions cause a reactive behavior mechanism in response to immediate needs such as danger [4, 14]. Primary emotions contain positivity and negativity [3]. Sadness and fear are salient in negativity [3]. Secondary emotions originate from developed cognitive processes [4]. Secondary emotions need evaluations of preferred outcomes, for example hope or relief [4]. A recent study simplified human emotions by grouping them into four main types: happy, sad, fear, and disgust [28].

Little research has considered the effect of emotions on rumor and truth spread. In one study, emotions were shown to positively influence trustworthiness of the messages [24]. During a social crisis, messages contain fear emotions are more likely to be trustworthy than neutral messages [24]. Emotions factor into rumors during a social crisis because of uncertainties. Rumor messages with emotional content are perceived differently by users [68] and emotionally charged information on SNSs tend to get retweeted faster than neutral ones [60].

3. Theoretical Background

Following [25] rumormongering model and correspondence theories of truth, we propose the following research model to explain rumor and truth spread during a social crisis (Figure 1). Content generation is a common practice on SNSs and users on Twitter freely express their opinions with negative, positive, or neutral sentiment. Extremity of a message can be defined as its deviance from the overall sentiment scores of the other messages and in general, extremity of a message increases engagement of other users with it [34]. During a social crisis, anxiety increases rumor transmission [49]. Assuming rumors contain more extreme information, logic suggests extreme messages will spread more rumors. Contrastingly, credible sources tend to send neutral messages and their message is known to be more trustworthy [40]. The neutral, and truthful, message, as a result, will be less extreme.

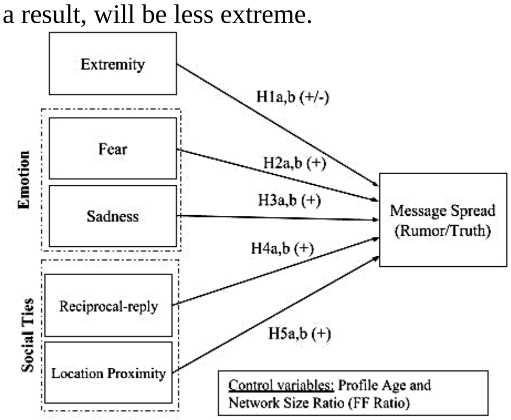

Figure 1. Proposed Rumor/Truth Diffusion Model

The influence of more extreme information is greater than neutral and moderate information [56]. Therefore, it can be deduced that extremity is negatively related with truth spread. We suggest:

H1a: Extremity is positively related with rumor spread.

H1b: Extremity is negatively related with truth spread.

Research shows different reasons for diffusion of information on SNSs including perceived information quality [35], user and network characteristics [53], and sentiment and emotions [60]. From the four primary emotions (happy, sad, fear, and disgust), we focus on sadness and fear because they are negative and more prevalent during disasters and catastrophes [78]. In addition, negative sentiments are useful for analyzing abnormal events [77]. Stress, such as a social crisis, affects individuals with better perceptions of fear and sadness more than other emotions [74]. When social control is high, fear is low, however during ambiguous times fear of future events and effects carries greater weight on rumor mongering [63]. Research shows negative thoughts such as sadness during crises are deemed more persuasive which could bread the misinformation [72].

Emotional framing of the messages may have a huge impact on reader's attention, resulting in more attention and engagement [60]. Considering both truths and rumors can be emotional, we hypothesize (H2a, H3a, H4a, and H5a represent rumor spread and H2b, H3b, H4b, and H5b represent truth spread):

H2a, b: Fear is positively related with rumor/truth spread.

H3a, b: Sadness is positively related with rumor/truth spread.

Previous research shows a relationship between social ties and message spread [49]. Social ties are traditionally thought of as a relationship between two people in the physical world; however, on SNSs social ties can be a combination of virtual and actual relationships.

On SNSs, replying to a message suggests a strong social tie, because there is direct communication between two users. Reciprocal-reply or directed reply confirm a directional interaction between users [6]. Retweets and directed replies on Twitter engage users in conversations [7]. On Twitter, if the directed message is replied, favorited, or retweeted by the second user it shows a strong tie between them [58]. On SNSs, if a message is received from a peer user with a social tie, there is a greater chance of the message spreading [49]. Social ties depend on trust and users are less likely to verify information if they have trust in their SNS network [64]. As a result, messages that show indications of social ties will spread regardless of the content of the message. Considering these social ties, and consistent with the extant literature of rumor spread, we hypothesize:

H4a, b: Reciprocal-reply is positively related with rumor/truth spread.

Similarly, social ties can be location proximity that unites users under one experience, or the direct communication between two users, who may or may not know each other. Prior research indicates location is an indicator of social ties, especially on SNSs [54]. During social crisis events, local residents would show different involvement and behavior compared to other more distant individuals [57]. Users that are concentrated in a location might perceive a specific issue to be more important due to proximity, and the perceived importance of a social crisis plays an important role in the spread of content [40]. Co-occurrence in space and time is an indicator of a strong social tie [11]. Research shows there is a relationship between social interactions and geographic distance [69] and the degree of diffusion of a message is significantly explained by reaction time and number of followers [39]. We hypothesize:

H5a, b: Location proximity is positively related with rumor/truth spread.

4. Research Methodology

Twitter is now one of the most important sources of news dissemination on the Internet [49]. Many people adopt Twitter as a primary source of information and news, as its reachability shows it has more than 326 million active users and 500 million daily tweets [59]. As a result, Twitter is a common place for sharing rumors and truths during a social crisis. A large-scale crisis situation provides an appropriate context for studying the spread of rumors [49]. To test our hypotheses, we downloaded tweets posted during the Charlotte protests from September 20 to September 23, 2016. The social crisis happened after the police involved shooting of Keith Lamont Scott around 4 pm on September 20 near University of North Carolina at Charlotte. The demonstration quickly erupted and became violent in the following hours. There are different versions of the shooting and the aftermath described by the Police and protesters. Police indicate there a gun recovered from the scene while the officer who was involved was not wearing a bodycam. Scott’s daughter mentioned his father did not have a gun and was reading a book while seating in the car to pick his son off the school bus. She went live on Facebook describing her story and protests began after it around 10 pm [23].

4.1. Data collection

Twitter provides programmers with a search API in which they are able to collect and download real time and archival tweets with certain constraints including the amount of collected tweets per time period, number of tweets per client request, and precluding downloading tweets older than two weeks [65]. During the period of the crisis, we collected more than 11,872 tweets related to the Charlotte protests event using the #CharlotteRiots hashtag and keyword. The API automatically removes non-English tweets. After removing duplicate and irrelevant tweets, 3,333 tweets remained. The chosen dataset represents a social crisis in which people actively used SNSs, specifically Twitter, to organize others [43, 67].

We removed non-informative tweets and focused only on informative and mixture information about known rumor and truth messages during a specific social crisis. Considering well-known false rumors went viral on SNSs following the police involved shooting in Charlotte and during the Charlotte protests, two researchers coded tweets as a rumor, a truth, or neither. Even though the office who shot did not wear a bodycam, but other officer’s bodycam and dashcam videos recorded some of the events. The known false rumors were: the officer who shot fire was white, the victim was unarmed, the victim was reading a book, and the victim had his hands in the air while shot [10]. Tweets containing any of these messages were identified as a rumor, while tweets containing the opposite of these were coded as truths. A total of 476 rumor or truth Tweets were extracted as the final dataset for analysis. The sample size is acceptable considering the specific focus on non-duplicate well-known rumor and truth messages for a specific period during the crisis. More specifically, several tweets were eliminated because they did not focus on the specific rumors and truths identified, even if they were appropriately related to the crisis. Using this coded dataset, we calculated sentiment scores, extremity values, fear and sadness emotions, and social ties.

4.2. Measures

SNS messages convey the emotional state and evaluation of the generator of messages on certain topics [60]. Sentiment analysis methods are developed to summarize user generated contents [60]. Sentiment analysis tools usually assign polarity to the words based on a lexical resource [66]. We used Python programming to calculate the sentiment score of each tweet based on lexical dictionary. For each message, the results include one value for a positive score and one value for a negative score. Sentiment extremity of each tweet is calculated using the difference between the message's total sentiment score and average of all sentiment scores.

Emotions are different from sentiments, as emotions are experienced in shorter duration and are less stable than sentiments [66]. Emotion types are usually not determined in traditional sentiment mining tools. The primary emotion indices were calculated using the Qemotion API. Qemotion uses an artificial intelligence (AI) algorithm to calculate emotion indices expressed in natural languages. Qemotion is based on a corpus of several million tests and has been used in practice [52]. The Qemotion algorithm is based on a word-mapping method and lemmatization to create emotion indices, as explained in previous research [32, 66]. Emotional results calculated by Qemotion have high accuracy. Research shows emotions could promote believability of fake news or misinformation, but not real news [42]. Higher level of emotional content in false stories than true stories is demonstrated in recent studies[36]. Qemotion calculates primary emotion indices ranging from 0 to 100. Location proximity is defined as the social involvement of the user sending the message with the location of the event. For this study, all tweets that has a location and are within the North Carolina and immediate proximal states (South Carolina, Kentucky, Georgia, Tennessee, Virginia) received a 1, otherwise a 0 was assigned for the location proximity variable. Finally, the dependent variable in this study is rumor/truth diffusion and hence the number of retweets is an appropriate measure.

5. Analysis and Results

To test the research model, a multi-step analysis is conducted. First, we calculated the descriptive statistics of the rumor and truth datasets (Table 1).

Table 1. Descriptive Statistics

Variable	Range	Median	Mean (SD)
Rumor Messages (n=266)			
Rumor Spread (Retweets)	0 – 66	1	4.64 (12.77)
Extremity	0.43 – 2.57	0.57	0.76 (0.51)
Fear	0 – 56	9.00	12.52 (13.13)
Sadness	0 – 36	7.00	8.61 (9.42)
FF Ratio	0.06 – 289	0.82	4.40 (27.68)
Profile Age (month)	0.07 – 102.3	43.36	46.51(30.65)
Truth Messages (n=210)			
Truth Spread (Retweets)	0 – 400	1	8.911 (49.59)
Extremity	0.37 – 1.63	0.63	0.81 (0.59)
Fear	0 – 54	18.50	23.05 (17.00)
Sadness	0 – 37	9.00	9.52 (10.18)
FF Ratio	0.00 – 59.27	0.89	2.49 (7.85)
Profile Age (month)	0.18 – 100.68	40.11	40.54 (33.75)

The dependent variable is message spread which is measured by number of retweets. Retweets are integers and cannot be less than zero. Poisson regression is an appropriate method for analyzing non-negative count data [15]. We tested our posited model using the following regression models:

$$\text{Rumor Spread} = \beta_0 + \beta_1 Extremity + \beta_2 Fear + \beta_3 Sadness + \beta_4 Reciprocal\ Reply + \beta_5 LocationProximity \qquad (\textbf{Model 1})$$

$$\text{Truth Spread} = \beta_0 + \beta_1 Extremity + \beta_2 Fear + \beta_3 Sadness + \beta_4 Reciprocal\ Reply + \beta_5 LocationProximity \qquad (\textbf{Model 2})$$

Time series investigation of emotion levels over time, shows fear levels are consistently lower than sadness levels for rumor tweets; on the other hand, fear levels are consistently greater for truth tweets. At the beginning of the formation of a social crisis, the fear level is the highest for truthful tweets (fear is 54) and the sadness level is medium for rumor tweets (sadness is 33, compared to its maximum of 56). Next, we analyzed correlations and results indicate low correlations, except between fear and sadness. The high correlation between fear and sadness is expected as they are the main negative emotions during disasters [78].

Finally, we performed Poisson regression for model 1 and model 2. To run the Poisson regression and test model fit of models 1 and 2, STATA 14.0 was used. Results of the analysis are summarized in Figure 2. Results confirm significance of H1a, H3a, H4a, and H5a for model 1 (rumor). Furthermore, H1b, H3b, and H4b were significant for model 2 (truth). H2a was not significant for model 1 (rumor). For model 1 (rumor), both H2b and H5b relationships were significant but opposite to the hypothesized direction. Of the two control variables, profile age was significant in model 2 (truth) and FF ratio was significant in model 1 (rumor).

We examined the goodness of the fit of the two models using an Omnibus test that compares each model with the null model [47]. The likelihood ratio Chi-square indicating a significant model fit for model 1 (likelihood ratio=97.96, df=5, p<0.000) and for model 2 (likelihood ratio=1261.82, df=5, p<0.000). To evaluate the goodness of fit and explanatory power of models, McFadden pseudo R-square was used [41]. Pseudo R-square (McFadden) for Model 1 was 0.18 and for Model 2 was 0.39, indicating significant prediction of the rumor and truth spread. Summary of results are provided in Table 2.

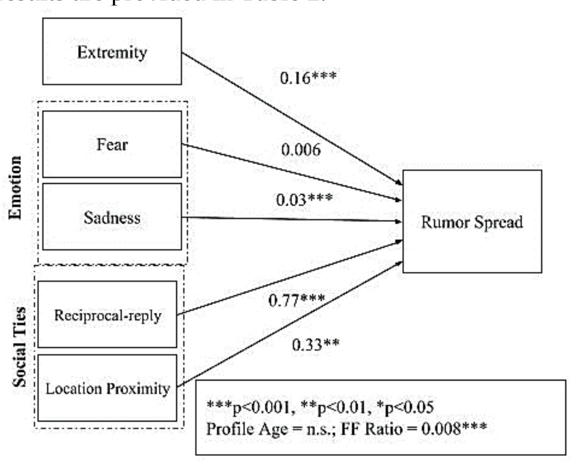

Figure 2. Results of the Rumor Model Analysis

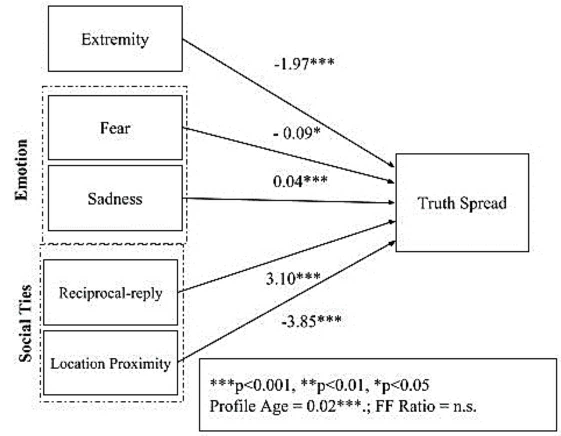

Figure 3. Results of the Truth Model Analysis

Table 2. Hypothesis Testing	
Rumor Model	
Hypothesis	Supported/Not Supported
H1a	Supported
H2a	Not Supported
H3a	Supported
H4a	Supported
H5a	Supported
Truth Model	
H1b	Supported
H2b	Not Supported
H3b	Supported
H4b	Supported
H5b	Not Supported

6. Discussion

6.1. Findings

The results of this study highlight differences between the spread of rumors and truths on SNSs during a social crisis. Our model hypothesized extremity would be different in the spread of rumor and truth; however, several other factors are also drawn out that indicate differences between the spread of rumors and truths. The extremity of a message is reflective of how the message stands out amongst other messages in terms of the sentiment. People espousing the truth send more neutral messages [40]. A person armed with the truth is usually confident in their knowledge and calm in their delivery. Contrastingly, those trying to spread rumors get noticed by being the loudest voice in the conversation. As a result, our hypothesis (H1) holds that extreme messages are related to rumor spread, but not truth spread. Practically, this indicates that extreme messages during a social crisis should be viewed with some skepticism. They could be an attempt to gain credibility simply by being extreme, and therefore can add even more confusion.

Secondly, the emotion of fear in a message relates differently to rumor and truth spread. We hypothesized (H2) that fear would encourage both rumors and truths. Our analysis indicates rumors are not related to fear, and there is a negative relationship with the spread of truths. Upon further consideration, a social crisis is a special time. Normally, emotional messages spread more [33]; however, a social crisis is a period of uncertainty [51]. During this uncertainty, fear could be embedded in the crisis, suggesting that fear itself would not help spread rumors. Instead, people might be reaching to SNSs for comfort and calmness, suggesting that rumors do not spread due to a fear component. On the other hand, fear is part of the backbone of a crisis. Therefore, messages that spread with fear are truthful. As hypothesized (H3), sadness is negatively related with both rumor and truth spread. Sadness is an emotion that encourages message spread because people feel empathy in a sad situation. Sharing sadness is a human experience and therefore is something that people relate to.

Also, as hypothesized (H4), message reply is positively related with both rumor and truth spread. For anything to spread it must have a mechanism for that spread; historically, this has been through multiple interactions across a network [9]. In other words, people telling each other information and then those people telling more people. On SNSs, that spread occurs by replying and reposting messages. Much like the physical world, on SNSs this creates a web of multiple interactions for both rumors and truths to spread.

The final difference between the rumor and truth spread models tested is related to location proximity. Our model hypothesized (H5) that both rumor and truth spread would increase near the crisis; however, this was not the case for the spread of truths. SNSs allow a more rapid spread of information [16], suggesting people do not need to be near an event to be involved. On the surface this is counterintuitive, but considering the nature of a social crisis, this is reasonable. Physical proximity is usually associated with more hostile feelings [12]. Our findings suggest that people near the crisis encourage rumor spread, likely because they are under the most uncertainty and might be reacting without thoroughly vetting information. People directly involved with a crisis may be looking for calming rumors to reduce their stress and affect appraisal of the situation [21]. In short, they are so close to the crisis it is hard to make sense of what is a rumor or truth, causing rumors to spread. Contrastingly, those that are more removed will not have the first reactionary experiences and must rely on the dissemination of information. The time that it takes to become involved is enough time to reduce rumors and encourage truths. There is less of a sense of urgency to create information and more care can be put into the quality of the information. Practically, emergency professionals should be weary of information from people in the epicenter of the social crisis, as they might be reactionary more than truthful.

Some of the control variables also demonstrate significance. The significance of FF ratio for rumor spread (model 1) indicates some users might share rumors to get attention and increase their audience size, regardless of the consequences. On the other hand, the positive relationship between profile age and truth spread (model 2) indicates the higher consideration of more experienced users in sharing truthful content on SNSs during crises.

6.2. Implications

This research has interdisciplinary theoretical implications in its scope and reach, including communication, marketing, media, e-commerce, and information systems. Theoretically, this research provides several new insights. First, this research focuses on the spread of both rumors and truths in one context, specifically a social crisis. Through the lens of the rumor mongering model, we provide further insights about the use of SNSs during a social crisis. On SNSs, the debates taking place during a social crisis could quickly escalate and extremify. During a social crisis replied messages between SNS users with similar perspectives on the topic can intensify the individuals' opinions [73]. The psychological and emotional impact of false rumors on the external environment and people living in it could be severe. This research suggests the need to theoretically differentiate between rumor and truth diffusion.

Second, we include emotional factors and emphasize the sentiment extremity of information on SNSs during a social crisis and how it can influence the rumor and truth spread. Most sentiment analysis research only considers sentiment scores and polarity. In this research, we have added two emotion types (fear and sadness) to better explain message spread during a social crisis.

Third, we offer location proximity as a factor in the spread of SNS messages. This provides new theoretical grounding for future research with SNSs. Finally, we expand research in this area by evaluating a unique data set during a social crisis. We unite text mined variables with features of a system to better understand the spread of content on SNSs. By developing this model, we create a foundation for future comparisons.

Practically, this research is useful for identifying how rumors and truths spread differently during a social crisis. Considering several emergency personnel use SNSs during social crises, it is important to evaluate how SNSs are used both positively and negatively. Our findings indicate that emergency professionals should be skeptical of extreme posts as they are likely related to rumor spread. Contrastingly, posts of fear and from a distance are more likely to be related to truths. It is certainly not our suggestion that these findings are a firm rule, but instead a heuristic to help guide some decision making when there is limited time to react.

Our findings are also helpful to SNS developers who are struggling to decide how to regulate content. SNSs such as Facebook are trying to reduce the use of their platform to spread "fake news" and the impact it has on societies [1]. SNS users increasingly rely on SNSs for news [64], and therefore it is important to understand how (in)accurate information spreads through SNSs.

Sensibly, practitioners should battle the spread of misinformation by identifying the location of the sender of the message. Due to the higher psychological and emotional involvement of people close to incidents, they might have a higher tendency for generating false information leading to unintended consequences. Location proximity does not always convey access to completely accurate and truthful information because many incidents happen over short time periods and not everyone who is nearby has actually seen the full event. Bystanders should provide evidence of such sensitive incidents as soon as possible to try to halt the spread of uncertain speculations.

6.3. Limitations and future research

Our research is subject to several limitations. First, generalizability to all social crises is questionable. A social crisis that relates to a social movement could have different actors and emotions than a social crisis surrounding something like a terrorist attack. It is important to understand all social crises and understand that different motivations could greatly impact the way SNSs are used to spread rumors and truths. Future research should investigate other social crises to increase generalizability.

Secondly, our research is limited by the data that is publicly available. SNSs allow users to change privacy settings that prohibit others from seeing messages. As a result, we are only able to use publicly viewable data for our analysis. Overall, this is acceptable because our context is the spread of messages, and private messages are only able to spread within a known network.

Finally, the inclusion of only two emotion types in the research model limits the interpretations of the results. While this is an important focus for social crisis events, in other contexts it could be beneficial to include other primary emotions. Similarly, future research could investigate emotion changes over time and study the longitudinal emotional models of message spread.

7. Conclusions

This study serves as an initial investigation of the differences between truth and rumor spreads on SNSs during a social crisis. We provided a research model to investigate the differences between rumor and truth spread. Our findings show there are different features of rumors and truths that encourage spread. As a result, there are implications for law enforcement and SNS developers who try to reduce misinforming the public. This research also contributes to research by providing a framework for investigating the spread of content on SNSs during a social crisis, as well as differences between the spread of different types of content.

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