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Emotions as Causes and Effects of Online Information Sharing: Multi-Method Causal Analyses Using Computational and Experimental Techniques

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Emotions as Causes and Effects of Online Information Sharing:
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Dissertation Abstract

Social media platforms' ubiquity has fundamentally reshaped how individuals communicate, share information, and engage with one another in the digital age. This dissertation investigates the complex dynamics of online information sharing, focusing on the role of emotions in these processes. Through three interconnected studies, this work contributes to understanding how emotions shape online interactions and influence the spread of information.

The first study extends Pennebaker's (1993) offline stage model in the aftermath of large-scale upheavals to the online environment, exploring the temporal dynamics of emotional expressions on social media in the aftermath of earthquakes. By analyzing Twitter data from three events and using methods such as change point analysis, analysis of variance, time series clustering, and Granger-causality tests, the study identifies different stages of online communication that align with Pennebaker's model. The findings highlight the importance of considering the temporal dimension in understanding online emotional dynamics and provide insights into the role of low arousal emotions as drivers of information sharing in crisis communication.

The second study investigates the role of emotions in the information diffusion of social media content, focusing on the differences between lean-back (passive) and lean-forward (proactive) sharing behaviors. Through the analysis of six case studies across political affairs, natural disasters, and sporting events on Twitter, the study combines Natural Language Processing techniques and Structural Causal Modeling to understand the differences between lean behaviors. The findings reveal that the arousal dimension of emotions is more relevant than

valence in distinguishing between lean behaviors and emphasize the influence of the topics on the emotional differences between these behaviors. Moreover, the study detects the emergence of emotional synchronization within information cascades, highlighting the importance of considering lean behaviors simultaneously when studying online information sharing.

The third study examines the relationship between context (mood), content (credibility), and individuals' emotions to understand the online misinformation sharing of short videos. Utilizing a preregistered survey experiment with a single-factor design, the study demonstrates that mood and emotions play a joint role in the sharing process, with positive mood having both direct and indirect effects on sharing behavior, while negative mood influences sharing behavior mediated by negative emotions. The findings also suggest that more credible misinformation has a stronger impact on the relationship between negative emotions, moods, and content sharing than less credible information.

While existing literature has established a relationship between emotions and information sharing, particularly in describing the types of emotions that make content viral (typically high-arousal negative emotions), there is a gap in understanding the complementary role of emotions as both causes and effects of information sharing. This dissertation contributes to filling this gap by conceptualizing the information sharing behavior as a flow generated by emotions, which also produces content that evokes emotions. The results of this research uncover the significant role of low arousal emotions, such as sadness, interest, and disgust, as drivers in information sharing. These findings show that these emotions can trigger the expression of higher-arousal emotions like anger, revealing a nuanced mechanism in which low arousal emotions play a latent role, motivating content sharing actions that complement the effects of high arousal emotions. Understanding these emotional interactions is crucial for explaining the complex pathways through which different emotional states contribute to spreading information within the digital ecosystem.

This dissertation uses a comprehensive methodological approach, combining computational methods, observational data, and experimental design with causal inference analyses to provide a thorough understanding of the role of emotions in online communication and information diffusion.

Chapter 1: The Role of Emotions in Online Information Sharing

The creation and exponential growth of social media in the last 15 years have changed how people communicate and share information, creating new opportunities for social interactions and emotional expressions. This phenomenon has attracted significant attention from researchers seeking to understand the factors influencing information sharing behaviors on social media (Bazarova & Choi, 2014; H. Lin et al., 2014). One factor of this behavior that has appeared as key is the role of emotions in information sharing (Stieglitz & Dang-Xuan, 2013).

Emotions are fundamental to human communication and social interaction (Scherer, 2005). In the context of social media, the expression of emotions, initially done via text, can now be expressed through various formats, such as emojis, emoticons, images, or videos. Studies have shown that emotional content tends to be shared more frequently and rapidly on social media compared to neutral content (Berger & Milkman, 2012; W. J. Brady et al., 2017). This evidence suggests that emotions may serve as a critical driver of information diffusion on social media platforms.

In the context of this dissertation, information sharing refers to the act of exchanging, distributing, or providing access to information to others (Savolainen, 2017) which in online environments is made through digital platforms, such as social media, websites, or messaging apps. It is a specific aspect of communication that focuses on the dissemination of information from one party to another or to a larger audience. Information sharing differs from the broader concept of communication, which encompasses various forms of exchanging ideas, thoughts, feelings, and experiences (Littlejohn & Foss, 2010). Moreover, information sharing is distinct from concepts such as information creation or dissemination. Information creation refers to the generation of new information or knowledge through research, analysis, or creative processes

(Case & Given, 2016). Information creation precedes information sharing. Dissemination, on the other hand, is a term that describes planned efforts to persuade groups to adopt ideas or innovations (Greenhalgh et al., 2004). Online information sharing is a specific form of dissemination that occurs through online platforms, enabling individuals to actively participate in the spread of information.

This chapter aims to provide an overview of the theoretical definitions and empirical research that have examined the relationship between emotions and information sharing, which serves as the overarching framework for this dissertation. It also introduces the three studies that comprise this work. Two of these studies have been published in peer-reviewed journals (Flores & Hilbert, 2023b, 2023a), while the third one is currently in preparation for submission to an academic journal. They have been edited to fit the overall narrative of this dissertation, showing the cohesion of my research project in a streamlined and non-redundant manner. The studies highlight the role of emotion in information sharing in crisis communication, emotional contagion, and misinformation. They all use different types of causal analysis, which is the main methodological backbone used throughout this dissertation.

1.1 Emotion Definition

Defining emotion has been a long-standing challenge for the scientific community, as researchers from various disciplines have struggled to reach a consensus on a comprehensive definition. This dissertation, however, does not aim to engage in the theoretical debate on the nature of emotion. Instead, it focuses on examining how emotion influences communication processes in online environments. For the purpose of this work, emotion is conceptualized as personal experiences directed toward specific objects, evoking strong feelings that encompass both physiological responses and instrumental behaviors (Fischer et al., 1990). While the theoretical debate about emotions continues, scholars agree that emotions generally consist of various components working together (Izard, 2010). There are five components that usually emerge in emotion research (Nabi, 2002): a cognitive component (appraisal), a phenomenological component (subjective feeling), a motivational component (emotion predisposes people to act), a somatic component (neurophysiological responses), and a motor-expressive component (facial, bodily activity). It is important to note that although emotion and mood can be defined as affect, they differ. In contrast to moods, emotions tend to be short-lived, intensely felt, and triggered by a specific cause (Beedie et al., 2005).

1.2 Basic and Dimensional Approaches to Emotion

In examining how studies on emotions in social media have operationalized the concept, two main approaches for their classification are applied: the use of discrete emotions and a the dimensional approach. The discrete approach suggests that emotions are distinct from one another, characterized by specific attributes that allow for categorization into different groups. In contrast, the dimensional approach views emotions as affective states that vary along two main dimensions: valence (the positivity or negativity of the emotion) and arousal (the intensity of the emotion). For defining categories within the discrete approach, the theory of basic emotions (Ekman, 1992) is commonly used, whereas the concept of core affect (Russell & Barrett, 1999) is utilized in the dimensional approach. The following paragraphs provide an overview of these approaches to understand their differences better.

The concept of basic emotions, proposed by Paul Ekman (1992), suggests that a set of universal, innate emotions that are biologically rooted exist across all cultures. This theory of basic emotions was highly influenced by the work of Charles Darwin and his observations of emotional expressions in animals and humans (Ekman, 1999). Through his studies on facial expressions, Ekman initially identified six core emotions: happiness, sadness, anger, fear, surprise, and disgust (Ekman & Friesen, 1971), but the list was expanded later, adding contempt (Ekman & Friesen, 1986). Ekman argues that these basic emotions are distinguishable by unique facial expressions, physiological responses, and triggering events, playing a crucial role in helping individuals adapt to their social and physical surroundings (Ekman, 1992, 1999). Although Ekman's theory has been very influential in emotion research, it has also encountered critiques, particularly regarding its claims on the universality of these basic emotions (Barrett, 2006; Russell, 1994).

The dimensional approach to emotions suggests that emotions can be conceptualized as elements with coordinates in a two-dimensional space, defined by valence and arousal (Russell, 1980). Valence refers to the positivity or negativity of an emotion, while arousal measures the level of physiological activation or intensity associated with it. According to this approach, any emotion can be described by combining these two independent dimensions. Emotions with similar characteristics are positioned closer together in this two-dimensional space, whereas those more dissimilar should be located farther apart (Russell & Barrett, 1999). This approach provides a simplified method for understanding the similarities and differences between emotions and has significantly influenced emotion research (Remington et al., 2000). Despite its influence, the dimensional approach has been subject to critics and proposed modifications, with some scholars advocating for the inclusion of additional dimensions beyond valence and arousal to capture the complexity of emotional experiences more accurately (Fontaine et al., 2007)

1.3 Emotions and Social Information Sharing

One of the most significant transformations introduced by social media is the unprecedented ease with which individuals can now access and share a vast amount of information with others. In communication, the idea of sharing mediated information is part of one of the first models for studying media effects, the two-step flow model of communication (Katz & Lazarsfeld, 1955). Although the two-step flow model originally referred to how information from media was passed to opinion leaders who then disseminated the information to a broader audience in a pre-internet offline setting, Hilbert et al. (2017) have shown that the underlying principles of this sharing process can be extended and validated in social media. Furthermore, given the potential for any social media user to reach and influence an extensive network of connections, the traditional distinction between opinion leaders and the general audience has become increasingly blurry.

In the sharing process previously described, information refers to the general concept of a message or set of messages transmitted from a sender to a receiver through a specific channel. This dissertation focuses on a particular aspect of shared information: the affective dimension associated with the content and the experiences of individuals involved in the sharing process. This focus is grounded in the understanding that emotions embedded in messages significantly influence the dissemination of ideas. They do so by mediating personal cognitive information understanding and interactive social behaviors of individuals (Forgas, 1990). Research in emotions and social information sharing has shown that when a story evokes emotion in the listener, it can be expected that the listener will share the story with others in what is known as secondary sharing (Christophe & Rimé, 1997). According to a study by Curci and Belleli (2004), in which participants needed to recall a daily episode shared with them for 15 days. 75% of the time, participants reported producing secondary social information sharing, with no difference based on the emotional valence of the episode (negative or positive). These results are similar to the findings obtained by Christophe and Rimé (1997), where the rate of secondary sharing ranged from 66% to 86%. On many occasions, it is possible to observe that an episode is shared with more than one individual in different conversational situations (Rimé, 2009; Rimé et al., 1998). The more intense the emotion a person experiences, the more likely they are to speak about it (Rimé, 2017).

The social information sharing of emotions is a phenomenon that is particularly evident in collective events, such as team sports finals, political elections, or natural disasters. These events create a shared experience among a group of people, generating conversations and emotional exchanges (Rimé, 2017). According to Rimé (2009), the process of highly emotional information sharing can be defined as a "process that takes place in the minutes, hours, days, even weeks and months—and sometimes years, or even an entire life—following an emotional episode. The process entails a description of the emotional event in a socially shared language by the person who experienced it to another" (p. 65). The impact of these collective events can be further amplified by the involvement of mass and social media, which facilitate the dissemination of information with emotional content on a larger scale. This widespread information sharing process resembles a chain reaction with emotional content shared in every direction (Rimé, 2017). Empirically, the analysis of this phenomenon has observed social sharing of emotionally charged episodes at the secondary and tertiary levels (Curci & Bellelli, 2004; Harber & Cohen, 2005). These findings suggest that people have a natural inclination to share emotionally charged stories and that the propagation of these stories within social networks is driven more by emotional selection than informational selection (Rimé, 2017). This preference for emotionally engaging content highlights emotions' significant role in shaping social interactions and spreading information within communities.

1.4 Emotions and Information Sharing in Social Media

In the field of communication, it has long been recognized that emotions play a substantial role in shaping human interaction and message effectiveness (Dillard & Nabi, 2006). The emergence of social media has amplified the role of emotions in communication, as users are exposed to a constant stream of emotionally charged content that can be easily accessed from the cellphones in their pockets. Within this context, the study of how emotions influence information sharing on social media can be broadly categorized into two distinct areas of analysis: the emotionality of the content itself and the emotional state experienced by the individual sharing it.

The research focused on the emotionality of the content examines how emotions in messages, measured using either a categorical or dimensional approach, affect the virality and reach on social media platforms. In one of the first studies in the area, Berger and Milkman (2012) analyzed around 7,000 articles from the New York Times, discovering that content with positive emotions tends to be more viral. However, the relationship between emotions and virality is more nuanced, as content eliciting strong arousal—whether positive (such as awe) or negative (such as anger or anxiety)—tends to be more widely shared. Similar results were observed by Trilling et al. (2017), who analyzed the shareability of news articles on social media, finding that articles evoking high-arousal emotions and a positive emotional tone are more likely to be shared. Brown et al. (2020) explored the news coverage related to the Ice Bucket Challenge. They found that content with a high prevalence of positive emotional appeals, such as happiness, inspiration, and community, contributed to the shareworthiness of the news pieces. In examining emotional valence, Stieglitz and Dang-Xuan (2013) explored the relationship between sentiment and sharing behavior on Twitter concerning political content. Their results showed that emotionally charged, positive, and negative tweets are more likely to be retweeted than neutral ones, with negative tweets having a stronger influence on sharing behavior. Additionally, in political communication, it has been noted that influential users often express more negative sentiments, significantly affecting political discourse. Furthermore, messages with negative sentiments are more likely to be reshared, underscoring the influence of negativity bias on disseminating political information (Dang-Xuan et al., 2013).

Concerning the emotions experienced by individuals when sharing content, Myrick (2017) studied the categorical emotions that prompt people to share information following the death of a celebrity from cancer. This study found that feelings of surprise or anger linked to the event were associated with a higher likelihood of information sharing, whereas emotions such as sadness, anxiety, and hope did not significantly influence this behavior. In a related study, Myrick and Willoughby (2019) examined how media-induced nostalgia following a celebrity's death influences individuals' social sharing behavior. Their results indicated that nostalgia triggered by media coverage was positively correlated with intentions to share content related to the celebrity's death on social media. Furthermore, Hasell and Weeks (2016) investigated how partisan news influences political news sharing. They observed that anger, incited by partisan news, significantly promotes information sharing on social media, suggesting that partisan media outlets may increase information sharing by producing anger in their audience.

The digital landscape of social media networks incorporates a complex social dynamic between users, extended beyond emotional release for information sharing. Additional motivations for engaging in these platforms include the desire for social support, persuasion, and retribution (Hasell & Nabi, 2023). Related to social support, individuals who experience emotional responses to events may turn to social media platforms to seek support, validation, and connection with others who share similar feelings (Bazarova et al., 2015; Rimé, 2009). By sharing emotional content and personal experiences online, individuals can receive comfort and build social bonds with their network (Ellison et al., 2011; R. Lin & Utz, 2015). This process of social sharing of emotions has been found to help individuals cope with negative experiences and regulate their emotions (Nilsen et al., 2018; Tandoc & Takahashi, 2017). Furthermore, a meta-analysis observed a positive relationship between social media use and perceived emotional support (D. Liu et al., 2018).

Regarding persuasion, users share emotional content with the motivation to persuade others to adopt their viewpoints, change attitudes or behaviors, or take action on a particular issue. For example, in recent years, social media fake news and political campaigns have been designed to exploit citizen's emotional responses to politics, intending to influence their voting decisions (Bennett & Livingston, 2018). Moreover, studies have shown that sharing emotional political information is frequently motivated by the desire to persuade others (Ardèvol-Abreu et al., 2017; Weeks et al., 2017). By using the influence of emotions, individuals can capture attention, increase message salience, and motivate others to engage with the shared content (Dillard & Nabi, 2006).

Retribution is another motivation for sharing emotional content on social media. Individuals can use emotional content to seek revenge, punish, or publicly shame those who have engaged in unacceptable behavior (Crockett, 2017). By sharing emotionally charged content, such as stories or videos generating moral outrage (W. J. Brady et al., 2017), individuals can mobilize others to condemn the targets of their retribution (Obeidat et al., 2018). Moreover, public shaming through emotion-driven information sharing can serve as a form of social control, enforcing norms and deterring future transgressions (Jacquet, 2016).

1.5 Dissertation Overview

In the following chapters, this dissertation develops studies in the area of online information sharing, addressing questions on the subjects of collective emotions in crises, emotions in online information cascades, and how emotions affect misinformation sharing. Figure 1.1 represents the conceptual framework of the role of emotions as causes and effects in the information sharing process, it depicts how triggering information about different events can affect individuals who decide to engage or not in the information sharing process that can be cyclical, sequential or a combination of both.

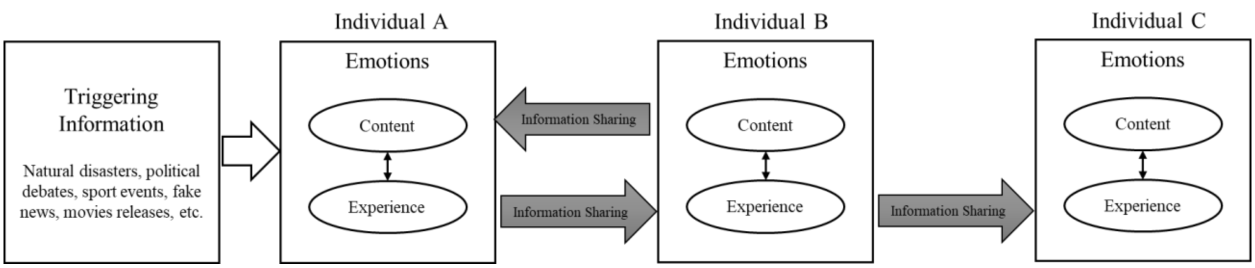

Figure 1.1 Conceptual framework of the role of emotions in information sharing

Chapter 2 provides a review of the causal analysis utilized in the empirical studies of Chapters 3, 4, and 5. It highlights the variety and incremental use of causal logic in the different dissertation studies, beginning with the concept of causation inferred from associations with time variables, progressing to causation with observed variables, and finishing with causation through experimentation.

Chapter 3 focuses on collective emotions following earthquakes, employing a model proposed by Pennebaker (1993). This chapter examines whether structural changes in the number of messages shared on social media align with Pennebaker's theoretical model and, from the extraction of emotions in the content, whether a cycle of collective emotions can be derived from the information shared in different stages of the model. The results suggest that structural changes in the shared information follow the proposed model. Although it is impossible to extract a stage model of emotions, emotions characterized by low arousal levels, such as interest and sadness, are expressed in higher proportions and are the most useful for predicting the expression of emotions with higher arousal.

Chapter 4 examines two basic modes of information sharing on social media within information cascades: sharing information without changes (lean-back) and adding or modifying the content in the original message (lean-forward). Using data from six Twitter cases, this study contrasts emotions in passive versus proactive information diffusion. The analysis indicates no significant differences in emotional valence between the two dissemination behaviors but does find differences in the arousal level of emotions. Furthermore, in proactive lean-forward communication, disgust, and joy synchronize with the emotions of lean-back messages. A structural causal model of lean-forward information sharing reveals that disgust provokes a consistent increment of itself while it also decreases the appearance of anger in political topics.

Chapter 5 explores the impact of video in spreading information on social media, particularly focusing on sharing misinformation through short-form video content, like TikToks, reels, and shorts. Through an online experiment with a representative sample from the U.S., this study seeks to understand how the context (mood), content credibility, and emotions experienced while watching short videos influence the propensity to share misinformation. The results suggest that mood and emotions play a joint role in the sharing process, with positive mood having both direct and indirect effects on sharing behavior, while negative mood influences sharing behavior mediated by negative emotions. Furthermore, the level of visibility (affordance) chosen for sharing misinformation is predominantly influenced by positive mood and happiness.

Finally, Chapter 6 summarizes the principal conclusions, methodological contributions, and suggests future directions for research.

Chapter 2: Causal Methodological Approach

An important objective of this dissertation is to review and employ methods that open new opportunities for addressing research questions within the field of communication. Specifically, the empirical studies presented in the subsequent chapters of this dissertation use various forms of causal analysis. This chapter introduces the set of techniques utilized in this dissertation positioning them within the broader spectrum of causal analysis. It also explains the statistical properties of the analyses that will be applied in Chapters 3, 4, and 5.

2.1 Causation Theories

Since Aristotle classified causation into four distinct types—formal causes, material causes, efficient causes, and final causes—scholars have analyzed the concept by dividing it into different categories. Over the last 40 years, the literature has introduced classifications such as probabilistic causal arguments (Goertz & Starr, 2003; Spohn, 1983; Waldner, 2002); correlational causal analysis, and the analysis of causal mechanisms (Dessler, 1991; Elster, 1989; George & Bennett, 2005; Hedström & Swedberg, 1998; Mahoney, 2001); top-down and bottom-up explanations (S. Glennan, 2002; Kitcher, 1989; Salmon, 1989); and the dependence and production causes (Hall, 2004).

More recently, Pearl and Mackenzie (2018) categorize causation into three distinct levels. The first level, association, enables researchers to identify regularities through observation, facilitating predictions based on passive observations. Statistical methods such as correlation or regression are typically used to reduce a large body of data into associations. The second level, called intervention, involves not just seeing but also altering the variables of the mechanism under study. Experiments are the gold standard method in academia to answer questions of "How?" or "What will happen if?" but the authors make the case that it is possible to answer causal queries with observational data as long as the researchers can produce a sufficiently strong and accurate causal model. The third level, known as counterfactuals, which is intuitive for our mind, presents challenges for experiments and data because they cannot tell us what could have happened in an imaginary world where the observed variables are negated. Here, the causal models are key to performing the analysis.

In the social sciences, Brady (2011) identifies four approaches to causation: the neo-Humean regularity theory (Beauchamp & Rosenberg, 1981; Hempel, 1965), which focuses on temporal precedence and the consistent observation of conjunction and correlation between cause and effect; the counterfactual theory (Lewis, 1973, 1974), which examines the possible outcome if the cause were absent; the manipulation theory (Gasking, 1955; Menzies & Price, 1993; Wright, 2004), related to the experimental tradition and the directionality of cause and effect; and the theory of mechanisms and capacities (Cartwright, 1994; S. S. Glennan, 1996; Harré, 1975), which appeals to the operation of a mechanism behind causal processes. Acknowledging the differences among these approaches, Brady (2011) argues that robust causal inference should meet the criteria of all four perspectives. This means that causation should (1) demonstrate a consistent conjunction of causes and effects, (2) show an absence of the effect when the cause is absent, (3) reveal the effect following the manipulation of the cause, and (4) explain the activities and processes that link causes and effects through an identifiable mechanism.

The previous definitions of causality reveal that there are different theoretical constraints depending on the type of causation required from a process. These varying degrees of causation have also been translated into specific methodologies. For instance, correlation techniques and linear regressions are employed to analyze associations (Pearl & Mackenzie, 2018) or to apply the neo-Humean regularity approach (H. E. Brady, 2011). Conversely, experiments are better suited for studying interventions (Pearl & Mackenzie, 2018) or manipulation-based causation (H. E. Brady, 2011). To establish a coherent methodological progression in exploring causation, this dissertation employs various methodologies: association with time variables (Granger causality in Chapter 3), causation with observed variables (Front criterion for Structural Causal Model in Chapter 4), and causation through experimentation (Chapter 5).

2.2 Association with Time Variables

One of the first phrases we hear at the beginning of our statistical learning is that "correlation is not causation." The mathematical construction of the Pearson correlation coefficient makes it impossible to discern the order of influence between the variables under comparison. However, causation can be considered a specific case of correlation in which the direction of the influence is unequivocally established (Pearl, 2009). Thus, correlations thoughtfully analyzed may shed light on causal processes.

Time series, by their very nature, possess a specific temporal order in which the past precedes the present, and the present precedes the future. While temporal structure is a necessary condition for causation, it is not sufficient on its own (Granger, 1980). Nevertheless, examining associations over time can be a valuable tool in uncovering causal mechanisms.

In their examination of the “temporal turn” in communication research, Wells et al. (2019) argue that integrating computational methods with time series analysis can significantly enhance the study of various phenomena. These include issue attention cycles, physiological responses to communication exposure, observing changes in mass opinion, and analyzing dynamics within social media. Lukito (2020) exemplifies this approach by investigating the disinformation campaign conducted by the Russian Internet Research Agency across Facebook, Twitter, and Reddit. The aim was to identify patterns of temporal coordination across these platforms. Through Granger-causality analysis, Lukito discovered that activity on Reddit could predict subsequent activity on Twitter, demonstrating a temporal influence.

Freelon et al. (2018), employed Granger-causality to establish a predictive relationship in their paper on social media power and elites. The study presented three theoretical metrics of social power: unity, numbers, and commitment. These metrics were applied to the tweets of the Black Lives Matter movement, the Political Conservatives (a counter-movement), and mainstream media outlets. Additionally, the activity of the political elite was measured on the platform. After completing all possible pairwise Granger-causality analyses, the results revealed that the information posted about the Black Lives Matter movement predicts mainstream news coverage of police brutality and that the metric of commitment best predicts elite responses. Similarly, Bastos et al. (2015), investigated the relationship between online social movements and onsite protests. They discovered that contentious communication on Twitter and Facebook and onsite protests during the Indignados and Occupy movements were part of a bidirectional Granger-causal process. In contrast, during the Brazilian Vinegar demonstrations, there was a Granger-causal relationship between communication on Facebook and Twitter and, separately, between protestors' actions and onsite injuries/arrests.

In addition to the new theoretical questions that researchers can answer using time series analysis, it is also possible to review applications of established theories that did not previously use this tool. The case of agenda-setting theory (McCombs & Shaw, 1972) is a good example. Although the majority of studies on agenda-setting have been conducted using Pearson correlations (Wanta & Ghanem, 2007), there have been attempts to use time series analysis to examine the theory. Russell Neuman et al. (2014) employed Granger causality to compare the agendas of traditional and social media. Their results indicated that the issues on the agendas do not follow a one-way pattern from traditional media to social media, but rather involve a dynamic interaction between the two. Similarly, Meraz (2011) used traditional media and online news blogs, along with Granger causality analysis, and found a comparable dilution of traditional media's role as a singular agenda-setting influencer.

These studies demonstrate the potential for time series analysis to provide new insights into well-established theories, such as agenda-setting, by examining the temporal dynamics and causal relationships between different media platforms and their respective agendas.

2.2.1 Granger Causality

In an attempt to determine if the relationship between pairs of inter-related stochastic processes could be broken down into a pair of one-way relationships, and using the idea proposed by Wiener (1956) that prediction theory could be used to define causality between time series, Clive Granger created a practical adaptation of Wiener's concept known as Granger causality. The term is a misnomer, as "Granger predictability" might be a more accurate description. However, due to his pragmatic definition, Granger's work has been widely cited.

Figure 2.1 illustrates that Granger causality is essentially a form of prediction, where the information contained in one time series allows the observer to predict, with a time lag, the behavior of another time series of interest. The time lag provides the theoretical justification for directionality in the correlation between the two variables. However, it is important to note that this does not guarantee that some other (unobserved) variable might have been the true "cause" of what is observed, and the observed variable is simply a confounder. The founding axioms of Granger causality are: the cause happens before the effect, and the cause has unique information about the future values of its effects (Granger, 1969).

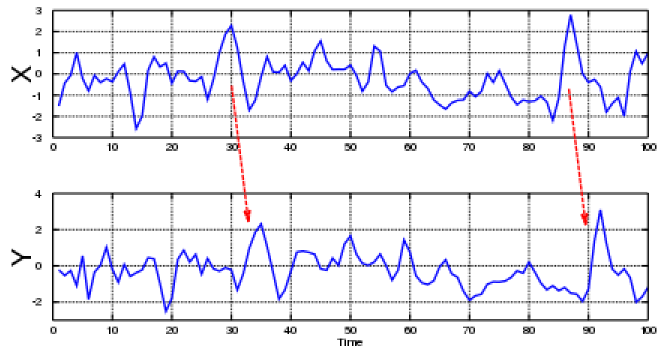

Figure 2.1 Granger-causality
Note. *Visualization of Granger Causality*. From Wikipedia.
(https://en.wikipedia.org/wiki/Granger_causality).

2.2.2 Analysis

Granger analysis uses linear autoregressive models, and its mathematical formulation is represented by:

$$X(t) = \sum_{j=1}^{p} \alpha_j X(t-j) + \varepsilon_1(t) \tag{2}$$

$$X(t) = \sum_{j=1}^{p} \alpha_j X(t-j) + \sum_{j=1}^{p} \beta_j Y(t-j) + \varepsilon_2(t) \tag{3}$$

Where p represents the maximum number of lagged observations included in the model. The selection of an appropriate number of lags p is an important decision to make before performing the analysis, this choice can be based on statistical criteria for information such as FPE, AIC, HQIC, and BIC. These are measures that compare the inherent trade-off between model complexity and the model's predictive power, following Occam's insight that models should only be as complex as necessary. However, theoretical considerations are also important to select the final number of lags to be included in the model.

Finally, using the models (2) and (3) an F-test is performed with the null hypothesis of $X(t)$ equals to model (1) against the alternative hypothesis of $X(t)$ equals to model (2). The result allows us to evaluate if Y Granger causes X or not. The conclusion is that Y Granger causes X if the null hypothesis is rejected.

2.2.3 Limitations

The study of Granger causality was initially designed for linear equations. Nowadays, there are extensions to nonlinear cases, but those extensions can be more difficult to understand and use, moreover, their statistical meaning is less comprehensive. Among the extensions, some approaches divide the global nonlinear data into smaller locally linear neighborhoods (Freiwald et al., 1999) or the use of a radial basis function method to perform global nonlinear regression (Ancona et al., 2004). Another limitation is that Granger causality requires stationary which means (in a weak sense) that the mean and variance should maintain constant over time. Non-stationary time series can be transformed into stationary using the method of differentiation. Additionally, assuming that short windows of non-stationary data produce locally stationary signals it is possible to perform the analysis in such windows (Hesse et al., 2003).

2.3 Causation with Observed Variables

There are situations in which researchers cannot intervene in processes using experiments due to various reasons, such as ethical concerns or budgetary constraints. In these cases, the ability to use observational data to study causal questions without the need for intervention deserves important attention (Rubin, 2005). Observational studies, when carefully designed and analyzed, can provide valuable insights into causal relationships, even in the absence of experimental manipulation (Pearl, 2009).

The use of experiments in studies of online information sharing may face limitations in terms of scale and external validity. Additionally, conducting such studies often requires collaboration with private companies. In these cases, it is crucial to acknowledge that the main goal of private organizations is profit, which can result in experiments being carried out under suboptimal (R. M. Bond et al., 2012) or ethically questionable conditions (Kramer et al., 2014). Given these challenges, research into online communication has found an alternative in the use of instrumental variables, a technique originated in economics (Angrist et al., 1996), as an alternative approach to investigating causality.

Coviello et al. (2014) studied the process of emotional contagion in a massive social network using instrumental variables. In their work, the authors utilized rainfall as an instrument because it directly influences the emotional content on Facebook messages of users in the affected area, while it should not influence the emotional content of users outside this area. Thus, this instrument can inform about the emotional contagion produced purely through interactions in the social platform. The results showed that within Facebook that for every person affected directly, rainfall alters the emotional expression of about one to two other people through Facebook, therefore, it is possible to indicate that there is a causal mechanism within the platform that magnifies the emotional synchrony.

In another study Aral and Nicolaides (2017) developed a comprehensive analysis to explore social influence on exercise behavior, progressing from correlations to using an instrumental variable. They analyzed data from 1.1 million individuals within an online network of runners who share their running achievements with friends, complemented with daily exercise data captured through electronic devices. The researchers discovered that exercise behavior exhibits social contagion, which varies depending on the relative activity levels and gender relationships among friends. Similar to the study by Coviello et al. (2014), the instrumental variable employed in this research was weather-related.

These studies highlight the value of observational studies in making causal inferences when experiments are not feasible. Using statistical methods such as instrumental variables, researchers can isolate the causal effects of social influence on behaviors and outcomes. The insights gained from these observational studies can inform the design of interventions and policies that use the power of social networks to promote positive behaviors and emotional well-being.

2.3.1 Structural Causal Modeling (SCM)

The Structural Causal Model framework developed by Judea Pearl combines elements of the structural equation models, the potential outcome framework, graphical models developed for probabilistic reasoning (Bayesian networks), and causal analysis (Pearl, 2009). The framework addresses fundamental challenges in causal inference due to the following list of features (Kline, 2015) :

1. Causal hypotheses are represented both graphically and in expressions that are a kind of mathematical language subject to theorems, lemmas, and proofs.
2. The SCM provides a precise language for communicating the assumptions behind causal questions to be answered.
3. The SCM explicitly distinguishes between questions that can be empirically tested versus those that are unanswerable, given the model. It also provides ways to determine what new measurements would be needed to address an “unanswerable” question.
4. Finally, the SCM subsumes other useful theories or methods for causal inference, including the potential outcomes model and SEM.

As SCM is represented using causal network graphs, three basic building blocks characterize all possible patterns of arrows in the network:

1. Chain: ($X \rightarrow W \rightarrow Y$) where W represents a mediator.
2. Fork: ($X \leftarrow W \rightarrow Y$) where W represents a common cause or confounder.
3. Collider ($X \rightarrow W \leftarrow Y$)

These building blocks have implications for the covariate selection in regression analysis. Given a causal model, it is appropriate to control for the confounders to avoid confounder bias; inadvertently controlling for a mediator might eliminate some or all the causal effects in the chain, and controlling for a collider can lead to collider bias, which induces spurious correlation.

2.3.2 Analysis.

Causal diagrams present the problem that noncausal paths can generate confounding, potentially leading to wrong causal claims. To address this issue and correctly de-confound two given variables of interest, such as X and Y, it is necessary to block all noncausal paths between them without interfering with any causal paths. Given the complexity of this task, researchers can use three primary techniques to identify the appropriate set of controls for making accurate adjustments and estimating causal effects: back-door criterion, front-door criterion, and instrumental variables (Shalizi, 2013). The following description will focus exclusively on the front-door criterion, as it is the method employed in the analysis presented in Chapter 4.

2.3.3 Front-door Criterion.

For this criterion, it is necessary to find a set of variables M which mediate all causal influence of X on Y, Identifying the effect of M on Y, and X on M, then it is possible to combine both to get the effect of X on Y. This test is called the front-door criterion. A set of variables M satisfies the front-door criterion if (1) M blocks all the direct paths from X to Y, (2) there are no unblocked back-door paths from X to Y, and (3) X blocks all back-door paths from M to Y. Figure 2.2 presents an SCM where all the effect of X on Y is mediated by the effect of X on M. With this configuration, it is possible to obtain the effect of X on M because the back-door is blocked by the collider Y, and the effect of M on Y is isolated controlling by X. With these results, the effect of X on Y can be calculated**.**

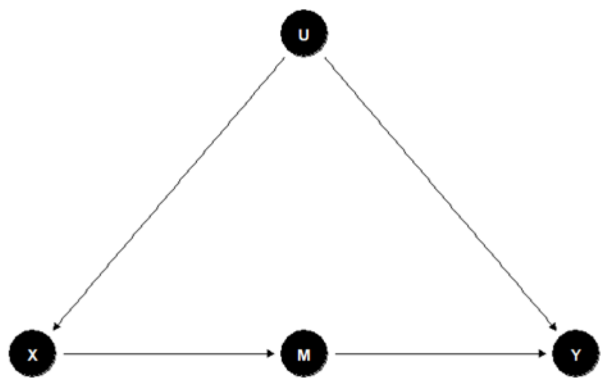

Figure 2.2 Diagram of Front-door criterion

2.3.4 Limitations

The main assumption of an SCM is that models must be created based on theoretical grounds. By combining models, structural equations, and observational data, researchers should be able to draw causal conclusions as long as they justify the logic behind their assumptions. However, researchers often avoid making causal claims, as the focus in Structural Equation Modeling (SEM) seems to have shifted toward model fit issues rather than the theoretical implications underlying it.

2.4 Causation through Experiments

Conducting interventions that involve manipulating certain variables to measure their impact on a specific outcome is recognized as the gold standard in science for answering cause-effect questions. Randomized controlled experiments, or simply experiments, are a powerful methodological tool for comparing groups that receive interventions against a control group. One of the main advantages of using experiments is that they address the problem of confounding variables, which can be complex when the analysis is done with observational data. Another aspect to consider is that the increasing data and connectivity available in online environments have made digital experiments cheaper and easier to implement using communication technologies. As a result, the literature on experiments in online social systems has been growing steadily.

In the case of information diffusion, important experimental studies in major social media platforms have been conducted. Through intervention in Facebook's News Feed, Bakshy et al. (2012) created a large-scale field experiment that randomized the exposure to signals about friends' information sharing behaviors. The results indicated that those exposed to the signals are significantly more likely to spread information sooner than those not exposed. By comparing strong and weak ties, it was possible to notice that even though the former is more influential, the latter is responsible for the propagation of novel information, as suggested for the rationale of the strength of weak ties (Granovetter, 1973). Twitter also has been the subject of this type of research. In an experiment using bots (Mønsted et al., 2017), researchers compared whether information spread according to simple or complex dynamics in the network. Using Bayesian statistical models to compare the competing hypotheses, the authors provided evidence that the complex contagion model describes the diffusion dynamic better than simple contagion.

Experimental research on emotions and information has shown that individuals who rely more on emotion when making judgments are more likely to believe fake news headlines (Martel et al., 2020). This finding suggests that emotionally appealing content can override the rational evaluation of the information. Similarly, Greenstein & Franklin (2020) found that anger may increase susceptibility to misinformation by impairing cognitive processes involved in evaluating information accuracy. Furthermore, Weeks (2015) used a survey experiment to assess how anger and anxiety moderate the relationship between partisan bias and misinformation. The results indicated that anger strengthens the effect of partisan bias, while anxiety weakens it.

The last study included in this section is the work conducted by Kramer et al. (2014) on emotional contagion. In their experiment, conducted through manipulation of Facebook's News Feed, the authors established four conditions: a negative-reduced group, where posts containing negative words were randomly blocked; a positive-reduced group, where posts with positive words were similarly blocked; and two control groups, where posts were blocked at the same rate as the reduced groups but without considering the emotional content of the posts. The findings showed that participants in the negative-reduced condition used more positive and fewer negative words, while the opposite trend was observed in the positive-reduced condition. However, the observed effects were minor, and the large volume of data might have influenced the statistical significance. This study faced significant ethical criticisms from both the academic community and the press, primarily because the Facebook scientists experimented without obtaining consent from the users and without subjecting the experimental design to any substantial third-party ethical review. The ethical concerns raised were so significant that the journal published an editorial expression of concern (Verma, 2014).

A common critique of experimental studies is that, while experiments are effective in estimating causal effects, they are typically not designed to uncover the mechanisms underlying causal processes. A promising approach to addressing this gap is through digital experiments, which offer the opportunity to collect extensive data throughout the process, employ comprehensive factorial designs, and evaluate multiple related treatments (Salganik, 2019). The mechanisms identified through these methods can then be directly tested in experiments specifically designed for this purpose (Imai, Tingley, & Yamamoto, 2013; Pirlott & MacKinnon, 2016). By leveraging the advantages of digital experiments and designing studies focused on uncovering mechanisms, researchers can better understand the causal processes underlying the observed effects.

Chapter 3: Temporal Communication Dynamics in the Aftermath of Large-scale Upheavals: Do Digital Footprints Reveal an Emotional Stage Model? [1]

3.1 Introduction

Social media has emerged as a rich source for social science research, reflecting the complex interactions of an increasingly connected world. The growing number of users across various platforms, such as Facebook and Twitter, continuously establishes new communication networks. It is, therefore, no surprise that significant societal phenomena such as protests, elections, and polarization are subject to analysis within these online environments. This chapter focuses on utilizing Twitter's digital footprint to trace the evolution of information sharing following a natural disaster.

Specifically, this work explores communication dynamics to understand the evolution of information sharing in the aftermath of a large-scale upheaval, extending to social media the offline framework of social stages defined by Pennebaker (1993). Pennebaker is a leading pioneer in linguistic inquiry, with a strong emphasis on using word count and dictionaries (i.e., LIWC). His social stage model (1993) presents a theoretical framework based on the rate (count) of talking people maintain in the aftermath of large-scale upheavals. Being a pioneer in automated sentiment analysis, Pennebaker also speculated about the role of emotions in such situations, which leads to questions about their transmission and how this process evolves, considering the dependencies between emotions over time.

[1] This chapter is an adaptation of the article Flores, P. M., & Hilbert, M. (2023). Temporal communication dynamics in the aftermath of large-scale upheavals: Do digital footprints reveal a stage model? Journal of Computational Social Science, 6(2), 973–999. https://doi.org/10.1007/s42001-023-00218-7

Armed with much more data and new tools, this chapter revisits Pennebaker's research agenda to investigate how contemporary computational methods can enhance our understanding of the phenomenon. Data was collected from social media for three distinct earthquakes: in Southern California, USA, on July 5, 2019; Oaxaca, Mexico, on June 23, 2020; and the Aegean Sea, Turkey, on October 30, 2020. Emotion analysis was conducted employing Natural Language Processing tools, complemented by a methodological approach that includes change point analysis, analysis of variance, time series clustering, and Granger-causality tests.

The aim of this work is to develop a more profound comprehension of the processes of social information sharing and the communication of emotions via social media. This understanding can offer invaluable insights for disaster management efforts and contribute to the broader knowledge of societal responses following large-scale upheavals.

3.2 Literature Review

3.2.1 Toward a Social Media Stage Model in the Aftermath of Large-scale Upheaval

To explain how individuals personally deal with the process of coping in the aftermath of traumatic events, different stage models have been proposed (Kübler-Ross, 1969; Rando, 1984; Worden, 1996). In essence, stage models establish that every person faces a progression of phases through time to handle the trauma. For example, Kübler-Ross (1969) argued that individuals evolve through five stages in the aftermath of experiencing the death of someone close: denial, anger, bargaining, depression, and acceptance. However, these psychological stage models for individuals do not consider that human beings also face responses to traumatic events in a social context. Undoubtedly, the emotional communication process after a traumatic event is shaped by people’s social world. This reasoning inspired Pennebaker (1993) to propose a model of social temporal stages to understand the communicational dynamics in the aftermath of large-scale upheavals.

To elaborate his model, Pennebaker surveyed people in the aftermath of two traumatic events, the earthquake of Loma Prieta in 1989 that struck the San Francisco Bay Area and the beginning of the Gulf War in 1991. He asked the participants about the number of conversations and thoughts related to the incidents. The resulting model comprised three social stages: emergency, inhibition, and adaptation (For details, see Figure 9.4 in Pennebaker (1993, p. 216)). The emergency phase is characterized by heightened anxiety and an elevated level of reported talks and thoughts about the event. The inhibition phase shows a drop in discussions about the issue and a more constant number of thoughts. Finally, the adaptation phase reveals a return to normalcy with a low activity level related to the incident, signaling that the event is psychologically over for most community members.

The crisis and risk communication field also has proposed models with different stages to describe communication processes (Coombs, 2021; Fink, 1986; Reynolds & Seeger, 2005). However, it is important to notice that the difference between both types of communication is that risk communication addresses events that can potentially become a crisis. Still, they are not at that point yet. According to the study of Spence et al. (2015), a stage model that can be relevant to the study of social media technology is the model proposed by Fink (1986). Fink’s model defined a “crisis life cycle” into four stages. First, the promodal stage comprises a period of buildup with hints and clues about an impending crisis that can occur. Second, an acute stage is produced by a trigger event. During this stage, damage can be caused to vulnerable publics or organizations. Third, the chronic stage, where the reputation of organizations or communities can suffer for a period in which they struggle to return to normalcy. Finally, the termination stage corresponds to when the crisis resolves and the original situation becomes irrelevant to the actors involved. Another model used in social media studies and crisis communication is the Crisis and Emergency Risk Communication model (CERC) (Jin & Spence, 2021; Meadows et al., 2019). The CERC model (Reynolds & Seeger, 2005) assumes that crises develop in predictable ways evolving from risk to crisis, recovery, and evaluation. It comprises five stages: pre-crisis, initial, maintenance, resolution, and evaluation. Compared with Fink's model, the CERC model seems more comprehensive because it considers the need to educate the public about the risks in the pre-crisis stage and adds an evaluation stage that allows for assessing responses, including communication effectiveness. In contrast with Pennebaker's model, crisis and risk communication approaches describe the lifecycle of a critical event until it is resolved, while Pennebaker studies the dynamics of conversations and thoughts right after the event, not focusing on the managerial aspect of disasters.

Building on Pennebaker's work, the first goal of this study is to analyze to what extent the model replicates in social media. Pennebaker (1993) suggests that "thinking and talking about a trauma tend to dissipate at different rates over time" (p. 215). As such, the sharing process is characterized by an emergency phase with a high number of conversations, followed by inhibition and adaptation phases in which the quantity of discussions drops. By using digital footprint data, this work focuses on the rate of talking of the model to answer the question:

RQ1: Is it possible to identify different stages of social information sharing on social media in the aftermath of a catastrophic event?

3.2.2 Emotions and Large-scale Upheavals in Social Media.

The quantitative formalization of Pennebaker (1993) focused first and foremost on different stages in terms of the "rate of thoughts and talking" (p. 216). It is possible to speculate that this reasoning might be linked to his methodological focus on the word count (i.e., LIWC). Yet, he also reflected on the role of feelings during "these emotion-laden interviews" (Pennebaker, 1993, p. 208). In a review of the psychological meaning of words, Tausczik and Pennebaker (2010) establish that "language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand." (p. 25). As such, emotions conveyed in messages play an essential role in transmitting ideas by mediating personal cognitive information understanding and interactive social behaviors of individuals (Forgas, 1990).

Studies analyzing social media during critical events have shown that individuals appear to use these platforms more for affective display than information seeking (David et al., 2016; Lachlan et al., 2014; Yi et al., 2022). Thanks to the availability of information on social media and the development of computational methods for text analysis many studies on the aftermath of natural disasters have been produced. These studies include but are not limited to, automatic processing and classification of sentiment after catastrophic events (Nagy & Stamberger, 2012; Ragini et al., 2018; Torkildson et al., 2014; Vo & Collier, 2013), identification of crisis-related information for disaster management (Buscaldi & Hernandez-Farias, 2015; Schulz et al., 2013), understanding the role of emergency responders and organizations (García et al., 2019; Simon et al., 2014; Xu, 2020), or determining the origin of events based on users posts and geolocated data (Kryvasheyeu et al., 2015; Lu et al., 2015).

In the area of the expression of emotions in the aftermath of large-scale upheavals, it has been shown that users exhibit sympathy for people affected by the event, share personal experiences (Takahashi et al., 2015), and praise people and organizations that provide support and help (Yi et al., 2022). Moreover, people use social media to cope with traumatic experiences.

For example, studying Facebook in the aftermath of typhoon Haiyan, Tandoc and Takahashi (2017) found collective coping strategies to help alert family and friends about survival, develop a social construction of the experience, and the management of feelings. Similarly, Nilsen et al. (2018) detected that survivors of terror attacks use online environments to mourn publicly and perform symbolic actions. Social media can be considered platforms where positive emotions contribute to emotional bonding, support-seeking, and therapeutic channels in the aftermath of critical events (Kušen & Strembeck, 2021b).

Considering the importance of emotions in the information sharing process in the aftermath of large-scale upheavals, this study seeks to broaden the understanding of Pennebaker’s model by examining the expressed emotions across the model stages. Therefore, a second research question is formulated:

RQ2: Is it possible to distinguish different stages of communicated emotions on social media in the aftermath of a catastrophic event?

RQ2 describes the communicated emotions using Pennebaker’s model, yet it is also of interest here to understand the dynamics of emotions in the process. Previous studies on how emotions evolve have shown mixed results. For example, Spence et al. (2015) found that relevant information becomes less prevalent during a crisis, and messages predominantly express negative emotions later. In comparison, Garcia and Rimé (2019) observed that individuals could change from negative to positive expressions of comfort and support in the aftermath of terrorist attacks. Considering these results, the goal to understand if an emotion X can influence a later surge of an emotion Y (X → Y). Moreover, if such influence happens in one stage of the model and a new Y → Z effect follows it in the next stage, it would be possible to establish the chain X

→ Y → Z to describe a stage model of emotions that presents emotional influence through time. This scenario is analyzed by exploring a third research question.

RQ3: Is it possible to identify the influence of emotions through stages in the aftermath of a large-scale upheaval? Does this influence generate chains of emotions?

3.3 Method

3.3.1 Data Collection

Three different datasets from Twitter following natural disaster events were collected, focusing on large earthquakes with a magnitude ≥ 7 Mw on the moment scale. The first dataset involves an earthquake in Southern California on July 5, 2019, with a magnitude of 7.1 Mw at 8:19 pm (UTC-7). The second dataset corresponds to an earthquake that struck Mexico on June 23 at 10:29 am (UTC-5) with a magnitude of 7.4 Mw. The third dataset is related to an earthquake in the Aegean Sea, Turkey, on October 30, 2020, with a magnitude of 7.0 Mw. For the first two cases, the collection of information was conducted using the Twitter API v1.1, while for the Aegean Sea case, Twitter API v2.0 was utilized. A triplicated analysis was ran to understand commonalities and differences between the same type of disasters and to try to avoid the omnipresent threat of the replication crisis (R. A. Klein et al., 2014; Open Science Collaboration, 2015)

Considering our interest in information shared on a social scale, historical archives of Twitter (*Export Public Twitter Data*, 2022; *Twitter Trending Archive*, 2022) were used to identify the most relevant trending topics related to the events in the country where the earthquakes struck. The first and second most relevant keywords were selected for the data collection from the trending topics identified for each event. As a result, the following keywords were gathered, for the LA case, #EarthquakeLA and #californiaearthquake; in the case of

Mexico, #Mexicoearthquake and #cdmsismo; and for the Turkey case, the keywords selected were #Izmir and #deprem. From this initial request using the Twitter APIs, all the tweets classified as undetermined language by the metadata provided by Twitter were filtered out. The analysis was constrained to 24 hours after the events. All the tweets resulting from this process were incorporated into the assessment of emotions in the following step.

3.3.2 Classification of Emotions

To measure the valence and emotions of the tweets, we used the IBM Watson Natural language understanding (NLU) tool (*NLU - IBM Cloud API Docs*, 2016). The NLU tool corresponds to out-of-the-box online services known as Machine Learning as a Service (MLaaS). NLU uses deep machine learning algorithms to extract metadata such as keywords, concepts, sentiment, emotions, or entities from text. For this study, the sentiment and emotion modules of NLU were used. The sentiment module evaluates the valence of tweets on a scale from -1 to 1, and the emotion module assigns values between 0 and 1 to the presence of fear, anger, disgust, sadness, and joy (Vergara et al., 2017). NLU is an effective text analysis tool used in different studies with Twitter data (Featherstone et al., 2020; Ruiz et al., 2021) and has shown that its results outperform other similar systems (Abdellatif et al., 2021; X. Liu et al., 2021). Following the validation process for automatic content analysis advised by Grimmer and Stewart (2013), Hilbert et al. (2018) validated the NLU emotions module against human coders.

The NLU emotions module only processes text in English; therefore, Google Translate translated all the non-English tweets in the datasets. Google Translate has been shown to be a viable and accurate tool for translating non-English language (Jackson et al., 2019; Vries et al., 2018), making this tool suitable for our study. Once the translation process was completed, all the tweets that Google could not translate were removed. The final step before assessing the emotions of the tweets in NLU was to remove the web links in the text. As NLU uses semantic analysis, eliminating words such as stop words from the tweets was unnecessary.

For the assessment of emotions, NLU assigns values between 0 and 1 to the presence of anger, disgust, fear, joy, and sadness. These five emotions are known as basic emotions in the literature on the categorical classification of emotions (Ekman, 1992). After processing the level of emotions for each case of study, the final numbers of tweets were N_{LA} = 144,095, N_{Mx} = 24,679, and N_{TR} = 286,115 for the LA, Mexico, and Turkey earthquakes, respectively.

Considering that joy is the only positive emotion identified by NLU and given the context of natural disasters, a detailed review of tweets expressing joy was conducted. Assuming that tweets exhibiting high levels of joy present a more accurate measurement of that emotion, a set of tweets with joy scores equal to or higher than 0.75 was extracted from each dataset. From these lists, a random sample of 100 tweets for each case was manually examined to understand the NLU assessment of joy and its relation to other positive emotions. This review was informed by the work of Hu et al. (2017), which demonstrated a significant correlation between joy and other positive emotions such as amusement, hope, inspiration, and interest. Employing the definitions of amusement, hope, inspiration, and interest as outlined by Fredrickson (2013), a manual re-coding of the sample of tweets was undertaken, following the methodology of Hu et al. (2017). The recodification process revealed that the NLU's assessment of joy could be reclassified as interest and hope 28% and 32% of the time, respectively. The amusement category is particularly noteworthy; in the case of the LA earthquake, it accounted for up to 42% of the recodification, while its presence was negligible for Turkey. Inspiration was found to not constitute significant percentages for any of the earthquakes (< 10%). Based on these findings, the term “joy” was redefined as “interest/hope” for the purposes of analyzing positive emotions related to earthquakes in this study (for simplicity, it is referred as interest in the text). This decision acknowledges the complexity of positive emotional dynamics but is also justified when classifying emotions in the bi-dimensional space of valence and arousal (Russell & Barrett, 1999), where joy, interest, and hope are characterized by positive valence with low arousal levels.

3.3.3 Time Series

Stage models explain how the variables of interest evolve in time, and time series analysis demands equidistant bins in time. Given the amount of data and its origin from social media posts, binning groups of tweets into one-minute timeframes were created to provide an adequate tradeoff between sample size and granularity. The decision regarding the timeframe was made because smaller timeframes (seconds) generated many data points with no information, and longer timeframes (> 1 minute) summarized a considerable amount of information at the initial stages of the process. Moreover, as time series analysis requires the use of lagged information in time, a timeframe of one minute seems adequate because it can be interpreted as a standard measure of time in social media consumption. The resulting time series had 1440 consecutive data points (24 hours x 60 minutes). When there was a whole minute without information retrieved, a data point with zero values was added to the database. No data points were added for the case of LA, 156 for Mexico, and 2 for Turkey. Seven time series for each case were created based on the one-minute binning. Five emotions (anger, disgust, fear, interest, and sadness) were assessed for each tweet, and all scores were summed within one minute. The resulting group of time series quantifies the total intensity of each emotion within the one-minute timeframe. Additionally, two more time series were calculated, one adding the number of tweets per minute, representing the total of messages shared about the event, and another with the sum of all five emotion scores, representing the total emotional intensity.

3.3.4 Analytical Procedure

Pennebaker's social sharing model refers to the number of times people talk and think about the preceding events. Using social media data, this analysis can only focus on the talking rate as people's thoughts are not accessible via social media.

To analyze RQ1, following Pennebaker's reasoning, the aggregated variable of the number of tweets collected for each point in the time series in our data represents how much people talk online about the event. Stage models are based on changes that happen over time. Still, because of the social nature of information sharing in the aftermath of large-scale upheavals, it seems unlikely that the extension of the stages is the same for all events. However, if an underlying process exists, its structure should change similarly. A changepoint analysis was performed in the time series to explore the existence of structural changes asked in RQ1. Changepoint analysis identifies points within the data where statistical properties change (Killick et al., 2012). Methodologically, it is linked to the logic of stationarity, common in econometrics (Wooldridge, 2015), which demands that general statistics do not change within the time series. In other words, the dynamic persists over time. Therefore, if the basic statistics change, there are identifiable different 'stages' within the data. The library changepoint in R was used to compute the changepoints based on a change in the variance for the time series.

After identifying stages based on the number of tweets, RQ2 was examined, which asks if it is possible to distinguish between different stages of communicated emotions. The analysis started with a descriptive approach to showcase the level of each emotion in different stages. The initial process allowed visualize the most prevalent emotions for the different stages and commonalities among cases. Then, two analytical methods to explore RQ2 we used in more detail: a differential and a relational analysis. First, I analyzed the differences of means using ANOVA with the post-hoc Tukey HSD test to determine if there are significant pairwise differences in the average emotional intensity within stages. Second, I looked at the relationship between emotions considering the time structure because even if the average intensity between emotions is not statistically different, it could be that those emotions do not group within stages. For grouping emotions, a hierarchical clustering for the time series was used. This model-free approach allows measure the proximity between time series considering the closeness of their values at specific points in time (Montero & Vilar, 2015). The following procedure was completed to identify the clusters within the stages found in RQ1. Initially, the time series for each emotion were normalized. Then, a metric of dissimilarity based on the autocorrelation function (ACF) was computed using the TSclust package in R. ACF was chosen because it represents the correlation between a time series and a lagged version of itself or other series; therefore, it accounts for the time structure of the data. Finally, the hierarchical clusters were computed using a complete agglomeration method implemented in R. The number of optimal clusters ($k = 2$) was determined using the silhouette coefficient.

To examine the influence between emotions through time and the existence of a chain of emotions for RQ3, it is necessary to determine the dependence between time series. The Granger causality test (Granger, 1969) was used to assess the predictive structure between emotions. The original formulation of Granger causality tests came with restrictive assumptions, one of which was the requirement for the time series to be stationary. A less restrictive extension for conducting Granger causality tests, proposed by Toda and Yamamoto (1995), allows for the inclusion of non-stationary and cointegrated time series in the analysis. The procedure for performing the causality test in this study includes several steps: testing the stationarity of time series using the Augmented Dickey-Fuller and KPSS tests; determining the maximum order of integration by adjusting an ARIMA model; defining the number of lags for each model by examining the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Hanna-Quinn information criterion (HQ); reviewing the stability and correlation of the residuals in the model; and, finally, conducting the test using the Toda-Yamamoto procedure. This study followed the implementation strategy of Lukito (2020) in R for testing Granger causality using the Toda-Yamamoto method.

3.4 Results

3.4.1 RQ1 Stage Model

RQ1 asks if it is possible to identify a stage model in the communication process on social media in the aftermath of a catastrophic event. In Pennebaker's model (1993), the variable used to describe the social process was the number of times people talked about the event. In this study, the variable representing how much people talked about the event corresponds to the number of tweets (count) posted online.

To find the structural changes in the social talking process on social media, the variance structure of tweets count was analyzed. Using changepoint analysis, it is possible to split the time series into chunks with time frames of stable variance. The structural changes found were also used to separate the time series of the different emotions for subsequent analysis. This decision was based on the fact that the time series of emotions were created as the sum of emotions in tweets for each minute; therefore, a high and positive correlation between the time series of tweets count, and emotions should be expected. As a reference, the smaller correlations for the LA and Mexico cases were between tweets count and anger with values of $r(1438) = .97$, $p <$

.001, and *r*(1438) = .94, $p < .001$, respectively. While for the Turkey earthquake, the smallest correlation occurred between tweets count and disgust, *r*(1438) = .95, $p < .001$. These results show the number of tweets as a good proxy to use its structural changes to divide emotions' time series.

Figure 3.1 shows the different timeframes defined by the changepoints and their intersection with Pennebaker's model. The LA case is divided into five timeframes, while the Mexico and Turkey cases are in six. The review of variance reveals that LA ($SD_{LA,1} = 260.44, SD_{LA,2} = 63.55, SD_{LA,3} = 28.29, SD_{LA,4} = 13.50, SD_{LA,5} = 13.89$) and Mexico ($SD_{ME,1} = 39.88, SD_{ME,2} = 6.81, SD_{ME,3} = 5.26, SD_{ME,4} = 4.41, SD_{ME,5} = 3.31, SD_{ME,6} = 1.28$) maintain a structure that decreases variability, whereas Turkey ($SD_{TK,1} = 68.55, SD_{TK,2} = 76.47, SD_{TK,3} = 41.25, SD_{TK,4} = 45.68, SD_{TK,5} = 27.86, SD_{TK,6} = 17.84$) is more variable. To map the results of the change point analysis onto Pennebaker's model, I rely on the characteristics of the stages proposed by the author. First, the emergency phase is characterized by a high number of reported talks about the event. In the analysis, it can be observed that after the peak in the number of tweets, a changepoint is detected when the quantity and variability of tweets decrease; therefore, by Pennebaker's model, this initial period is the emergency. Second, to differentiate between inhibition and adaptation phases, the original definition says that the former shows a drop in the level of discussions while the latter returns to normalcy with low activity levels. Based on the timeframes defined by the changepoints, a decline after the emergency phase is present and, at the end of the process, a constant activity follows it. To separate between the inhibition and adaptation phases, the data's linear trends were reviewed, noting that small slopes with low activity levels and variability respond to the definition of adaptation. Thus, I incorporate the adaptation phase timeframes with the slopes of linear trends close to 0. In the case of LA, timeframes four ($m_{LA,4} = -0.36$) and five ($m_{LA,5} = -0.03$), for Mexico timeframes four ($m_{MX,4} = 0.01$), five ($m_{MX,5} = -0.01$), and six ($m_{MX,6} = 0.00$), and for Turkey, timeframes five ($m_{TK,5} = 0.02$) and six ($m_{TK,6} = -0.06$) were part of the adaptation phase. The previous definition left two timeframes in the inhibition phase for each case. Considering that the earthquake in Turkey shows a different behavior in the first part of the inhibition phase, this phase was divided into two.

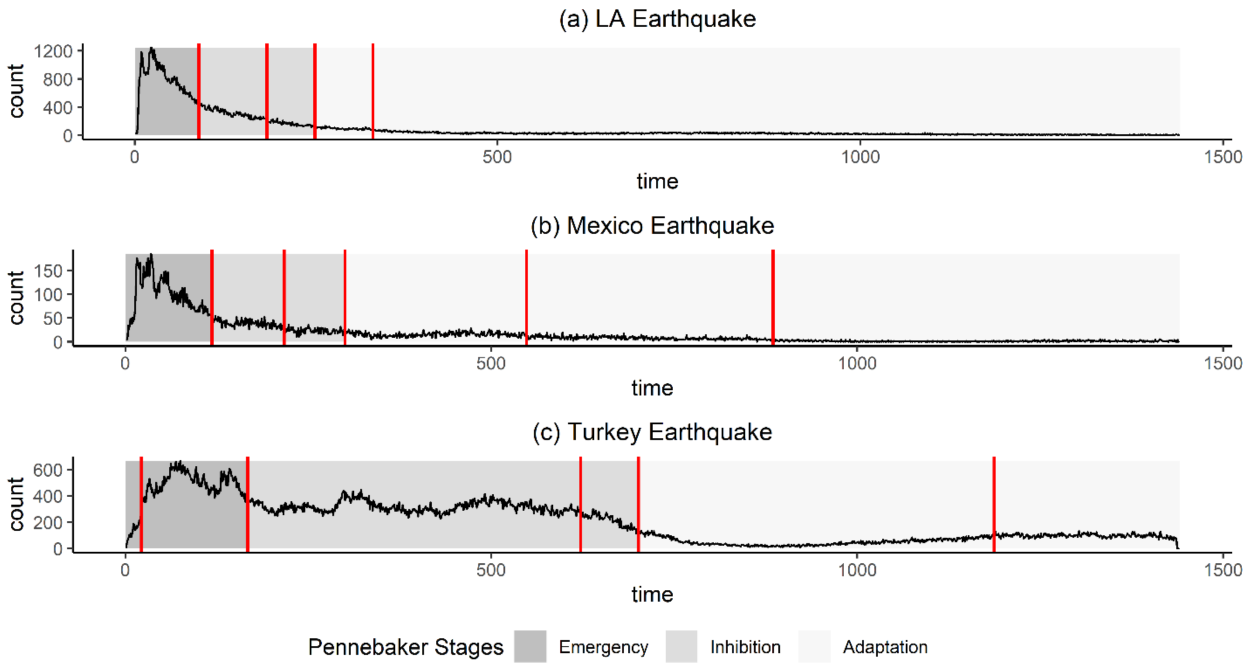

Figure 3.1 Changepoint analysis and Pennebaker's model

At first sight, changepoints for the case of LA and Mexico line up quite nicely, while the case of Turkey seems to differ, a closer look suggests that this difference is not in intensity but rather in the length of the stages. Figure 3.2 shows that the drop in the number of tweets from the average of the emergency stage to the average of the consecutive stage is between 30 - 60%, with a decline of another 32-48 % from the second to the third stage, and another 70-80% from the third to the fourth stage. While the progression of the Turkish case is still distinct from the strong alignment of the LA and Mexico case, the general tendency corroborates Pennebaker's proposal.

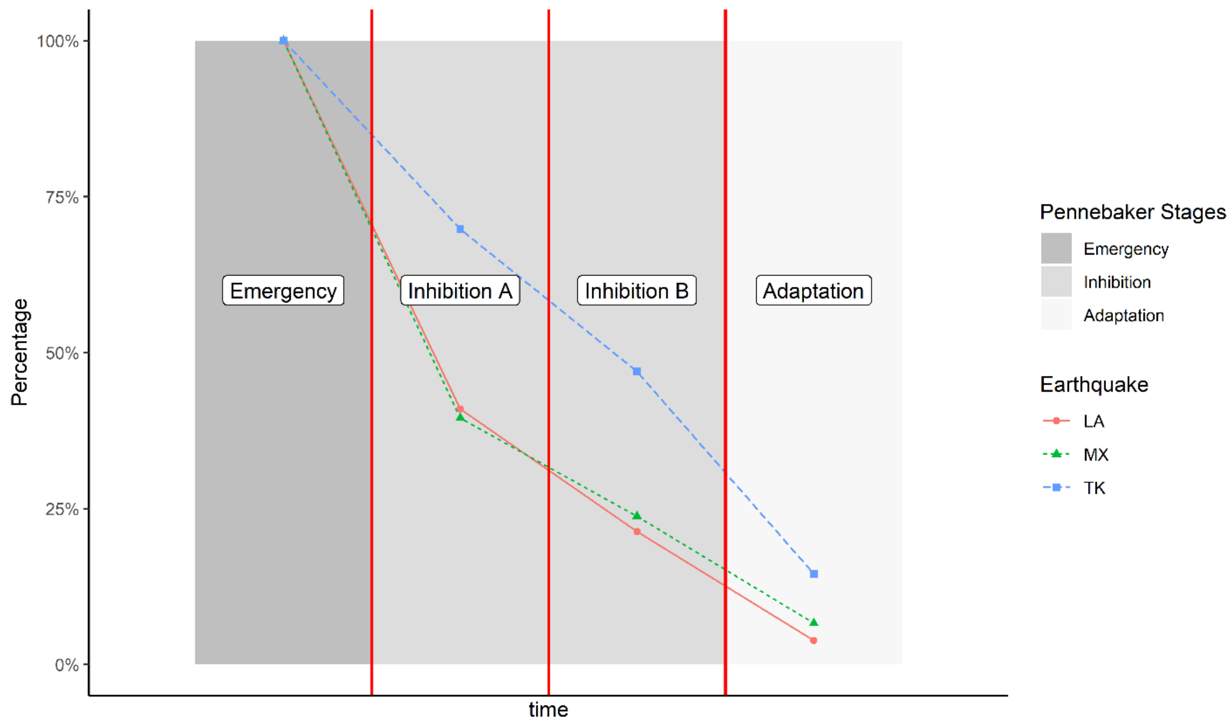

Figure 3.2 Percentage of reduction in the average number of tweets between consecutive stages

Methodologically, all replications suggest a pattern with some variation, especially concerning the length of the stages. Therefore, for this work's subsequent analysis, the stages are divided into emergency, inhibition A, inhibition B, and adaptation (see labels in Figure 3.2).

The changepoint analysis reveals that information sharing on social media in the aftermath of catastrophic events resembles Pennebaker's model, with rapidly increasing beginning and consecutively decreasing communication intensity. However, while all three cases show similar patterns in terms of intensity, the data suggest that these stages do not necessarily have the same length. Still, it is plausible to differentiate them in terms of their average differences and variability between stages.

3.4.2 RQ2 Stage Model of Communicated Emotions

Differential (ANOVA) and relational analysis of emotions (clustering) were conducted within the identified stages to analyze how emotions change over time in the aftermath of a traumatic event. The first step involved identifying the significance of each emotion by calculating the percentage they constitute in each stage and assessing their average similarities. Secondly, emotions were grouped into clusters based on their similarity, utilizing the autocorrelation function (ACF).

Relative percentages for each emotion in the stages of the social sharing process displayed in Figure 3.3 indicate that sadness and interest are predominant in all cases. Furthermore, it was noted that positive expressions account for an average of 33% when combining both positive and negative emotions.

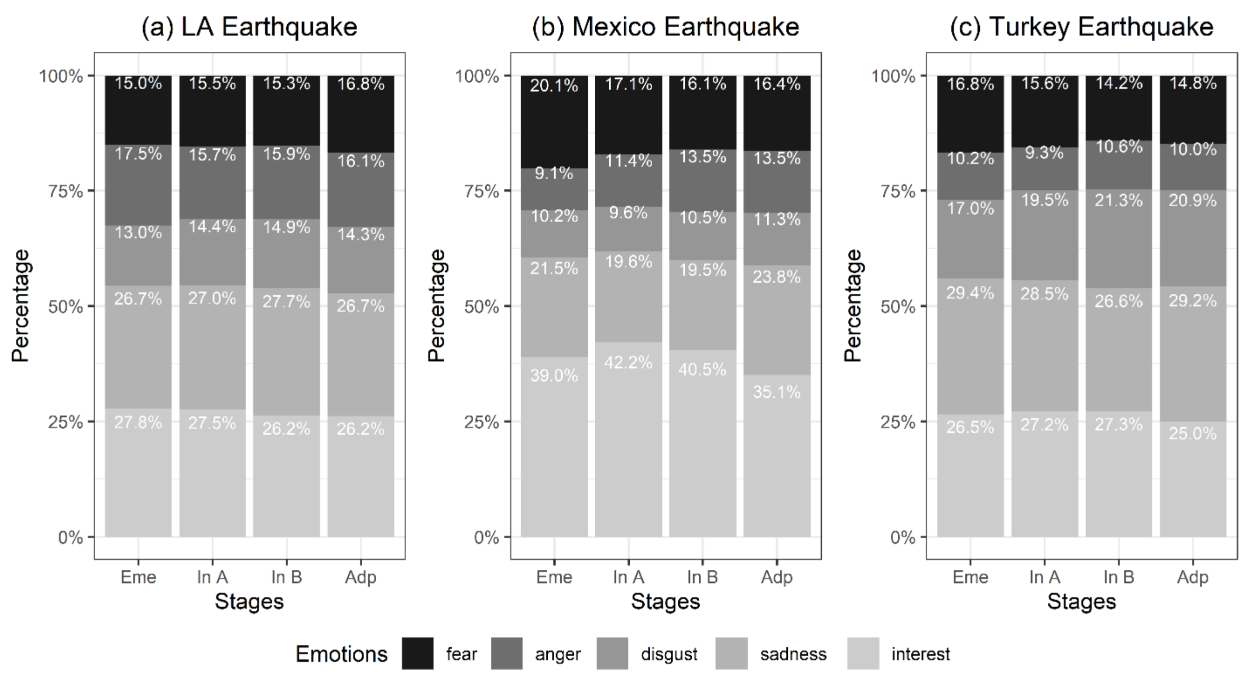

Figure 3.3 Proportion of emotions by stages

In Figure 3.4, the ANOVA’s post-hoc Tukey HSD test for pairwise comparisons reveals that sadness and interest have a statistically equal mean for the LA earthquake in all stages.

Moreover, the LA case shows no significant differences between anger and fear across the process, disgust and fear during the first three stages, and disgust and anger for the final three stages. Considering the previous description, the LA case can be characterized by having two groups of emotions with similar mean: sadness and interest; and fear, anger, and disgust. In the case of Mexico, the means of disgust and anger are not statistically different among all stages. Sadness and fear are not different at the beginning. The same happened for fear and anger in the last two stages. For Mexico, fear, anger, and disgust are similar, while interest is not similar to any other emotion. The case of Turkey only shows two instances in which emotions are not statistically different, disgust and fear in the initial stage and sadness and interest in the inhibition B stage. Overall, the descriptive analysis shows a commonality differentiating the most and less expressed emotions. Sadness and interest show similar mean levels during all the process, and they are the most expressed emotions. While fear, anger, and disgust are expressed less; also, these last emotions present occasional similarities in their means.

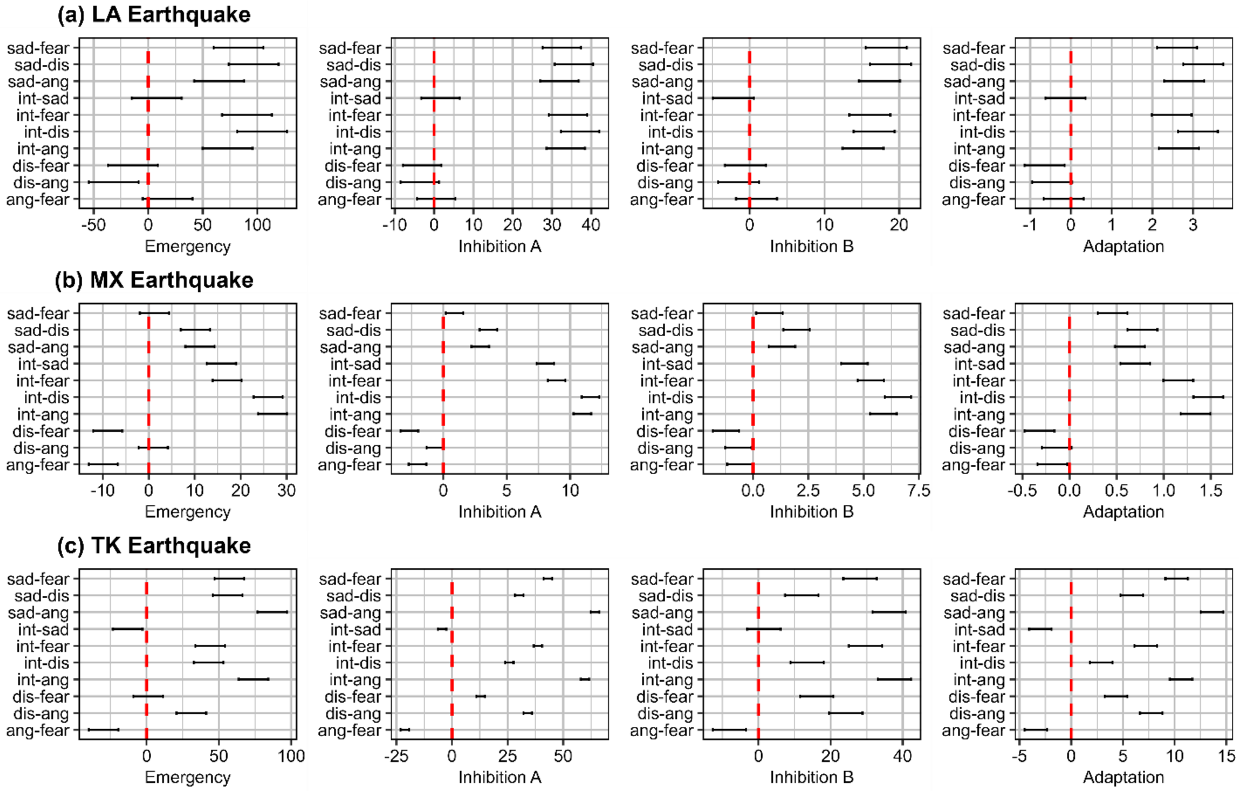

Figure 3.4 Tukey HSD test with a pairwise comparison of emotion means within stages for the three earthquakes.

The previous analysis gives an initial understanding of what emotions are more relevant on a relative scale. Given the nature of time series, the analysis can also incorporate information of the time structure. The ACF is a measure that helps to understand how the present value of a time series is related to its past values. To incorporate information of the time structure, hierarchical clustering is used to group emotions based on their ACFs.

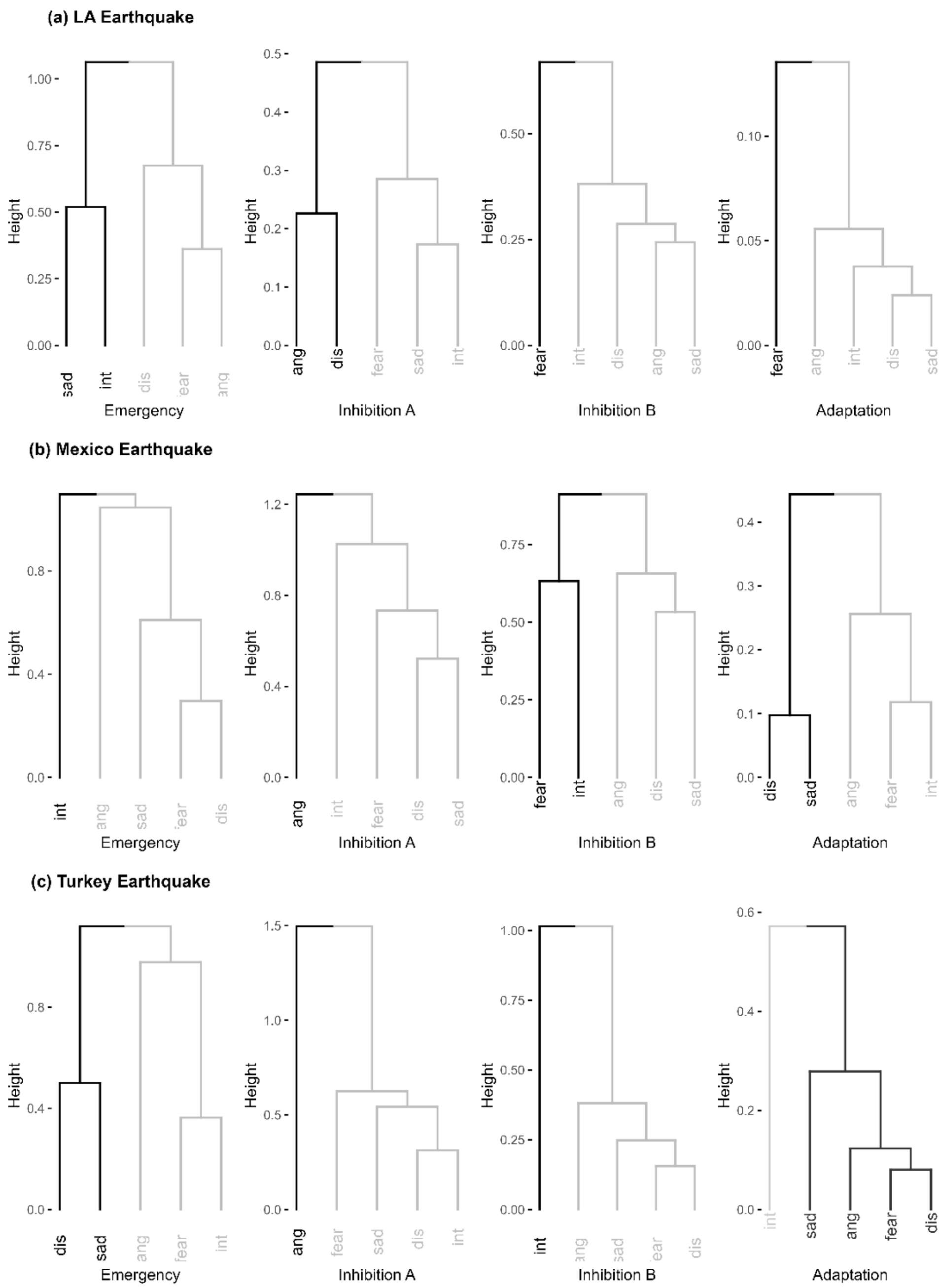

Figure 3.5 Hierarchical clustering of emotions by stage. Black and grey colors represent different clusters. The dissimilarity measure was based on ACF, and the optimal number of clusters ($k = 2$) was determined using the silhouette coefficient.

Figure 3.5 presents the results of the hierarchical clustering method. In the LA earthquake, emotions representing the highest percentages (sadness, interest) are closely grouped during the emergency stage. Later, they stay part of the same cluster, but their association also includes anger and disgust. Anger forms groups with all emotions in different stages through the process. In the case of fear, it becomes a separate branch in the final two stages of the process. Disgust is initially associated with fear and anger and later with sadness. Compared with the previous analysis, it can be observed that the relationship between sadness and interest also has a component of autocorrelation in time. In contrast, fear is a more independent emotion that does not cluster with others during inhibition B and adaptation stages. This last result shows that the emotional expressions are not focused on alarming feelings in a geographical area known for facing earthquakes.

The case of Mexico also shows a close relationship between sadness and disgust, grouping them close during the inhibition and adaptation stages of the process. Moreover, they create a separate cluster in the adaptation period, which is the longest in extension. Interest, the emotion most expressed according to the descriptive analysis, evolves from an isolated cluster to an association with fear. Looking at the ANOVA analysis, it can be noticed that, even though interest was significantly different in terms of mean, it develops associations with other emotions when ACF is considered. For the review of sadness, it can be grouped with disgust toward the end of the process. The sadness-disgust relationship was also observed in the LA case in the adaptation stage.

Lastly, for the Turkey earthquake, similar to Mexico, disgust and sadness are part of the same cluster through the process but not always being the most similar emotions. Interest, important in terms of mean, isolates in a branch of the dendrogram during the two final stages forming its own cluster. In the final stages, a separation between positive and negative emotions can indicate differences in emotional expression between cases of places used to receive earthquakes, like LA and Mexico and other areas where these events are less common.

Overall, the hierarchical clustering results reveal that general patterns across stages are complex to define. However, sadness and disgust show a significant association across all the cases, which is consistent with the share of the emotion they represent in the total. An interesting contrast is that while interest is a more isolated emotion in the aftermath of the Turkey earthquake, it has more significant associations with other emotions in the LA and Mexico cases. On the contrary, fear, more separated in the LA case, forms different clusters in the Turkey case.

3.4.3 RQ3 Chain of Emotional Stages

The relationship X → Y represents the shortest possible sequence in which an emotion X influences the expression of emotion Y. When this predictive relationship does not exist; it can be assumed that emotion Y is better explained/predicted only by its past. To establish a chain of emotions in Pennebaker's work, it is necessary to find a sequence that evolves through the stages in the model. I studied the time series of emotions adjusting vector autoregressive models (VAR) for each one of the stages then a Granger causality tests was computed to determine the relationships. Table 3.1 shows the statistically significant results (for details about all Granger causality tests results, refer to the Appendix A)

Table 3.1.

Granger causality tests results.

Case	Emergency	Inhibition A	Inhibition B	Adaptation
LA	Disgust → Fear Disgust → Sadness Interest → Sadness	Interest → Anger	Fear → Disgust Fear → Sadness Disgust → Anger Sadness → Fear Interest → Sadness	Sadness → Disgust Interest → Fear Interest → Anger Interest → Disgust Interest → Sadness
Mexico	Fear → Disgust Fear → Interest Sadness → Anger Interest → Sadness	Interest → Fear		Fear → Anger Sadness → Anger Sadness → Disgust Interest → Fear Interest → Anger Interest → Disgust
Turkey		Fear → Interest		Disgust → Anger Disgust → Sadness Sadness → Fear Sadness → Anger Sadness → Disgust

Note: Only significant results displayed ($p<.05$). Notation X → Y represents X Granger-causes Y

Granger causality tests do not show a common pattern among the three cases; thus, it is not possible to determine the existence of a chain of emotions. Another outcome is that the emotion that predicts others more frequently is interest in the LA and Mexico earthquakes, whereas, for Turkey, the most predictive emotion is sadness. These results match the ACF clustering analysis where interest becomes isolated in the Turkey case. On the other hand, the emotion that others predict on more occasions is sadness in the case of LA, while anger appears forecasted more for Mexico and Turkey. Overall, emotions with low arousal levels (sadness, disgust, interest), regardless of their valence, are the most relevant to predict other emotions. Conversely, on most occasions, the predicted emotions present high arousal levels (anger, fear). Only two sequences of three emotions are present through different stages of the social sharing process fear → sadness → disgust in the two final stages of the LA case, and fear → interest → fear in the initial stages of Mexico. Also, the relationships between emotions appear more frequently in the adaptation phase, predicted primarily by interest and sadness.

3.5 Discussion

3.5.1 New Data in Old Theoretical Bottles

Our findings demonstrate that the rate of talking in Pennebaker's offline model can be extended to social media. Moreover, this extension was made by linking the change between stages to structural changes in time series data. I also noted that the duration of the emergency, inhibition, and adaptation phases was different for each case. Still, the stages were identifiable, which shows that what matters is the change in intensity between them instead of identifying a fixed period. This outcome follows similar results of previous analyses about stage models at the personal level. For example, studying people who faced the death of a spouse, child, or other tragedies, Wortman and Silber (1989) determined that only about 30% of the participants evolved their trauma according to stage models, while most present variations from the theoretical models. The same authors reconfirmed these results years later when they revisited their conclusions (Wortman & Silver, 2001).

In the case of Turkey, it is shown that the inhibition phases were more prolonged than in the other cases; looking in more detail, it can be noticed that the amount of activity during the inhibition stage generates a surplus compared to the other cases. A possible explanation could be that LA and Mexico, because of their closeness to the Pacific and Cocos tectonic plates, people are more used to experiencing earthquakes; therefore, they tend to talk less about them. In contrast, Turkey is part of Europe, which does not experience earthquakes often. In fact, in the datasets of LA and Mexico, we find tweets mainly in English and Spanish, but for Turkey, in addition to English and Spanish, we also get Latvian, Romanian, Portuguese, French, and, obviously, Turkish which shows a broad geographical interest within Europe to talk about the event. Another explanation might be the saturation of the network. Using the number of retweets as a proxy for information saturation, a post-hoc analysis showed that the average number of retweets for the Turkey case during the stage of inhibition A and B together is (M_{TK} = 11.22), while LA and Mexico have means of (M_{LA} = 38.25) and (M_{MX} = 17.02), respectively.

The emphasis on replicating the results showed deviance for the LA and Mexico pattern in the case of Turkey. While the analysis of three cases seems helpful in terms of replication, it is important to note that it is still far from being representative in terms of statistical regularity; therefore, stages of different time lengths should be expected. The addition of dozen future cases might lead to the emergence of a larger picture, taking this case replication study to large-scale statistical regularity.

3.5.2 What Emotions Tell Us

The study of emotions presents interesting outcomes. Interest and sadness are the most expressed emotions in all cases across the stages of Pennebaker's model. Considering the two-dimensional decomposition of emotions in their fundamental arousal and valence components (Russell & Barrett, 1999), sadness and disgust express negative valence with low arousal, fear and anger transmit negative valence with high arousal, and interest conveys positive valence with low arousal. The analysis of interest and sadness shows that a low arousal level is relevant in social communication in the aftermath of earthquakes, regardless of valence. Moreover, interest and sadness are good predictors of other emotions, especially in the model's adaptation phase. A possible explanation for this situation is that more active emotions, such as anger and fear, are more intense right after earthquake shocks, and subsequently, even though they diminish their intensity, they can be predicted by less active emotions. This prediction might come out of frustration in the population after expressing sadness and interest for an extended interval. In line with this rationale, it has been shown that emotions like fear are relevant at the initial stages of a natural disaster (Spence et al., 2015). At the same time, sadness typically presents messages of compassion that attract either positive-compassionate or angry responses (Kušen & Strembeck, 2021a).

The presence of positive emotions in the aftermath of catastrophic events has been associated with demonstrations of kindness, prayers, gratitude, and hero-praising, among others (Kušen & Strembeck, 2021b, 2021a; W. Liu et al., 2018). There were similar expressions in this dataset, for example, LA: “No damage, here. You all good? #earthquake #EarthquakeLA #californiaearthquake”, MX: “Life puts us right moments of tension to value and enjoy those moments of happiness, tranquility, and well-being #sismocdmx #CDMX #sismo, or TK:” For those who cannot enter their house, free soup will be served in the garden of BUENAS BISTRO in Bornova during the night #earthquake #izmir #canimizmir Aegean Sea.” However, comparing the dynamic of interest using the cluster and Granger causality analyses, I notice that in the case of Turkey, interest evolves without grouping or predicting other emotions. This finding reinforces that positive feedback loops exist in social conversations about critical topics (Kušen & Strembeck, 2021a; Wang & Wei, 2020).

In the broader context of crisis communication, this analysis can be inserted in the initial stage of a crisis. It can shed light on actions to implement during this period. For example, we observe that after a disaster occurs, Twitter trending discussions are intense. Still, they tend to disappear fast, a circumstance that disaster management authorities should consider if one of their goals is to spread information through this platform. Regarding emotions, in the last stages of the process, sadness and interest are predictors of emotions such as fear or anger. I argue that these emotional expressions hours after the main event can result from frustration. Then, as the CERC model proposes, rapid communicational interventions should be established to reduce uncertainty and address this kind of emotional turmoil (Reynolds & Seeger, 2005) because, as research suggests, formal leaders are relevant to help people interpret disruptive events (Seeger et al., 2002).

3.5.3 Complementary Methods

Regarding the methodological analysis, asking for more restrictions on the level of relationship between emotions generates a better comprehension of the phenomenon, but with some obstacles.

Initially, using the ANOVA and post-hoc test of pairwise comparisons to evaluate general statistics of emotions gave an initial descriptive approach to understanding the data. Later, using the method of hierarchical clustering with ACF as a measure of dissimilarity presented a straightforward procedure to generate associations between emotions without the need to verify assumptions. However, because time structures are complex, the clustering results cannot reveal how the correlation between lagged versions of the time series, including information from each emotion's past, represents interactions between them. Finally, a more detailed result was obtained using VAR models to test Granger causal structures. Yet, as with other statistical models, the complication lies in adjusting a stable model that verifies the assumptions needed to establish correct statistical inferences. For example, the analysis of residuals for the LA and Mexico cases in the adaptation phase shows a slight deviation from normality, but the adjusted model was stable. By mixing classic differential analysis, model-free clustering, and model-based analyses, this study is a good example of complementary methodologies.

3.5.4 Limitations

There are also limitations in this study. First, information was collected using the most relevant hashtags about the events; hence, any related information not containing the hashtag was missed. This approach did not capture the full extent of the conversation on social media, omitting information linked to the event. Additionally, the mechanism behind Twitter's generation of trending topics remains inaccessible, making it impossible to discern whether posts about the issue were only popular or they had genuine concern about the issue. Second, Pennebaker’s model is based on evidence from individuals sharing their experiences. In social media environments, it is acknowledged that not only humans but also automated accounts (bots) are behind user profiles, publishing content. Since bots were not filtered out, the data is partly contaminated with information produced by them. However, when accessing the hashtag interface on Twitter, users cannot easily differentiate between content updated by people or by bots. Third, to assess emotions in the collected data, NLU from IBM Watson, a Machine Learning as a Service (MLaaS) tool, was used. As MLaaS is provided by cloud computing providers, NLU is not open-source, thus the workings of it remain unknown. Fourth, unlike other natural disasters, earthquakes are followed by a series of aftershocks. The study did not include a time series for these aftershocks, which could have provided insights into the nuances of different dynamics throughout the process.

3.6 Supplemental online material

An online repository with supplemental materials is available at https://osf.io/4fne5. The repository contains supplementary information, databases, and code for analysis.

Chapter 4: Lean-back and Lean-forward Online Behaviors: The Role of Emotions in Passive Versus Proactive Information Diffusion of Social Media Content. [2]

4.1 Introduction

A relevant characteristic of social media platforms is that they allow users to easily share content by reposting or forwarding information. For example, retweets make up almost half of all posts (46%) from more frequent tweeters on the microblogging platform Twitter and more than one quarter (26%) of those from less active tweeters (Odabaş, 2022). This digital innovation is one of the main drivers of the success of social media. According to the Pew Research Center (2021), 72% of the adult population in the US declare they ever use social media sites. As such, this easy and convenient way of sharing information has reshaped, among other activities, the way people consume news (Mitchelstein & Boczkowski, 2010), chat with friends (Valkenburg & Peter, 2009), buy goods (Chawla et al., 2015), or find romantic partners (Hobbs et al., 2017).

Regarding online information sharing, the literature on news consumption distinguishes between two modes of engaging with content: lean-back and lean-forward (Park & Kaye, 2018; Picone, 2007). A lean-back behavior is related to situations where users spread information by reposting content generated by others without modifications. On the other hand, lean-forward behavior considers a more demanding task in which users change, to some extent, the content they have been exposed to before reposting it. In essence, both modes have existed to some degree since humanity shared content around the campfire in front of prehistoric caves and are firmly embedded in academic citation practices that distinguish between direct and indirect quotations. The ease of digital copy-pasting and the massiveness of digital networks have

[2] This chapter is an adaptation of the article Flores, P. M., & Hilbert, M. (2023). Lean-back and lean-forward online behaviors: The role of emotions in passive versus proactive information diffusion of social media content. Computers in Human Behavior, 147, 107841. https://doi.org/10.1016/j.chb.2023.107841

facilitated information sharing processes and, additionally, have left a digital footprint behind that allows us to study this communication mechanism (Parks, 2014).

Previous research in social media has shown that information sharing is driven by a combination of cognitive and affective factors (Kim & Yang, 2017). Without disregarding the role of cognitive differences, this work focuses on the affective dimension to study the difference between lean behaviors. The interest in the affective dimension lies in the fact that emotions have been shown to play an important role in generating more engagement in information sharing and producing feedback within online communities (Berger & Milkman, 2012; W. J. Brady et al., 2017; Kramer et al., 2014; Stieglitz & Dang-Xuan, 2013).

To understand the differences in emotional responses associated with lean-back and lean-forward behaviors, this study analyzed six case studies chosen from widely discussed topics on Twitter. These included two cases each of political affairs, natural disasters, and sporting events. Natural Language Processing (NLP) techiques were employed to assess the affective dimensions in the text of tweets shared during information cascades. Finally, lean-back and lean-forward messages were compared via statistical tests and structural models.

This work aims to contribute to the current studies of human online interactions in various aspects. First, extending the communicational application of lean-back and lean-forward concepts that usually constrained their use to online news consumption and production. Second, extensive research on online emotional contagion in information cascades analyzes how individuals that perceive emotions in messages they receive later generate content with a similar emotional tone. Typically, in the content generation step, researchers have analyzed emotions generated by either users replying (Chmiel et al., 2011; Dang-Xuan & Stieglitz, 2012; Goldenberg et al., 2020) or further forwarding previous content (Alvarez et al., 2015; W. J.

Brady et al., 2017). This study recognizes that lean behaviors coexist within information cascades; therefore, it seeks to fill the gap related to the communication dynamic between lean-back and lean-forward messages. Moreover, by analyzing the role of emotions, this work reviews the extent to which the inclusion of lean-forward expressions introduces changes in the emotional tone of the discussion. Third, considering that lean-forward behavior is a more demanding task for users (content creation), it also sheds light on the resulting emotions of users that show a more significant engagement in online interactions.

4.2. Literature Review

4.2.1 Active Sharing Behaviors in Social Media.

Studies about news consumption have analyzed the spectrum of active sharing behaviors online. Park and Kaye (2018) distinguish between two types of active behaviors: lean-back and lean-forward. Lean-back refers to actions that do not require much information from users, such as highlighting or forwarding information; generally, those online actions require clicking one button on social media applications. On the contrary, for lean-forward actions, users create content by writing, adding, or editing information they were exposed to before sharing it again. It is important to notice that both lean behaviors vary within a spectrum of actions. For example, while lean-back behavior can include rating, tagging, or sharing information, lean-forward can consist of commenting, completing, and even producing complete pieces of news (Picone, 2007).

From a cognitive perspective, depending on the action performed, behaviors in social media require different amounts of cognitive effort (C. Kim & Yang, 2017), as individuals use more cognitive energy for creating than consuming information (Piolat et al., 2005). The cognitive dimension of behaviors on social media has also shown an association with affection. In a study by Kim and Yang (2017), the authors determined different drivers for actions on social media. The study concluded that liking content is an affectively driven action, commenting is cognitively guided, and sharing is a combination of affective and cognitive factors.

This work focuses on participative behaviors to understand the differences between lean-back and lean-forward sharing behaviors in the affective dimension. The reason to study these two behaviors is their fundamental role in the propagation of information by a sequence of user-generated content known as information cascades (Zhou et al., 2021).

4.2.2 Emotions and Online Information Sharing.

The literature on social media has identified that emotions act as drivers for information diffusion processes (Berger & Milkman, 2012; W. J. Brady et al., 2017; Hansen et al., 2011; Stieglitz & Dang-Xuan, 2013). They have been shown to be contagious, spreading via users' interaction on social media platforms (Coviello et al., 2014; Ferrara & Yang, 2015; Goldenberg & Gross, 2020; Kramer et al., 2014), and relevant for attention and engagement (Nelson-Field et al., 2013; Yu, 2014). These characteristics of emotions suggest that emotionally charged messages may lead to more cognitive involvement from people, resulting in a higher probability of sharing information (Luminet et al., 2000; Peters et al., 2009).

The study of emotions on social media has drawn conclusions using different approaches to assess emotions. A model that has generated many results has been the bi-dimensional classification of emotions based on arousal and valence. On the one hand, findings about the arousal dimension indicate that emotions eliciting high arousal levels produce higher levels of mobilization that increase information-sharing behavior regardless of whether they present positive or negative valence (Berger, 2011; Berger & Milkman, 2012). On the other hand, valence (positive, neutral, or negative) results are mixed and vary depending on the subject. For example, health information has shown that negative emotions produce more virality (Meng et al., 2018), while in false rumors, positive emotions allow them to reach more users (Pröllochs et al., 2021). In addition, the news case has proven to be conflictive with empirical results indicating that either positive (Heimbach & Hinz, 2016) or negative content (Hansen et al., 2011) generates virality. These findings show that higher arousal is consistent with more information sharing, but the valence type varies depending on the topic.

We suggest that individuals use different amounts of cognitive effort depending on the lean behavior they engage in online communication. Furthermore, as cognitive and affective factors play a combined role in online sharing behaviors (C. Kim & Yang, 2017), it should be expected that the affective dimension of lean behaviors also presents a difference. Operationalizing the affective dimension as the emotion conveyed in the online shared messages and initially considering a sentiment analysis used in the literature to refer to positive/negative emotion. We posit the following research question:

Research question (RQ1): How does the emotional valence (positive/negative) of online content differ when users generate content using lean-back versus lean-forward behavior?

In addition to analyzing sentiment, previous studies have assessed emotions in information sharing by classifying them into discrete categories such as basic emotions (Ekman, 1992) or Plutchik's emotions wheel (Plutchik, 1980). For example, Pröllochs et al. (2021) found that false rumors are more viral when containing words classified as trust, anticipation, or anger. In the case of news, Berger and Milkman (2012) showed that articles with content that evokes awe, anger, and anxiety are more shared. A replication of this study in Germany found the same result in the case of anger, but it did not find more virality for awe or anxiety-inducing content (Heimbach & Hinz, 2016). Similarly, Fan et al. (2016) showed that anger can spread faster than joy on social media. From a communication research perspective, the discrete emotion view incorporates the arousal and valence dimensions intrinsically, but it goes further by capturing elements that provide the distinction necessary to explain people's actions in more detail (Nabi, 2010). We analyze the following question to understand the nuances that categorical emotions incorporate into lean behaviors.

Research question (RQ2): How do categorical emotions of online content differ when users generate content using lean-back versus lean-forward behavior?

4.2.3 Lean Mechanisms in Emotions Sharing.

Online information cascades are formed by a propagation sequence of user-generated content (Zhou et al., 2021). This dynamic process generates users to influence each other. Regarding emotions, the literature has shown that online interactions lead to emotional contagion (Coviello et al., 2014; Kramer et al., 2014). These contagion processes are driven by mechanisms of mimicry, category activation, and social appraisal (Goldenberg & Gross, 2020). Mimicry refers to the activation of synchronous behavior in receivers based on the emotional expressions they were exposed to (Hess & Fischer, 2014). Category activation is a mechanism in which the exposure to emotional expressions evokes an emotion category that later activates emotional processes (Peters & Kashima, 2015). Social appraisal occurs when individuals use the emotions of others as a guide for their appraisals, creating similar emotional experiences (Clément & Dukes, 2017).

When people interact, contagion mechanisms produce mutual influence between individuals, which may lead to reduced variability in emotions, triggering emotional consolidation at the collective level (von Scheve & Ismer, 2013). By focusing on lean behaviors within online information cascades, this study also seeks to understand the differences in emotional dynamics between lean-back and lean-forward interactions. Figure 4.1a presents the mechanism of online lean behaviors. The fundamental element in an information cascade that lean behaviors represent can be explained as a chain in which online users are (1) exposed to information → (2) perform a lean behavior → (3) share information. Subsequently, this "new" shared information becomes available to other users on the platform. In the case of lean-back behavior, the information a user was exposed to is the same as the information the user shares afterward, while for lean-forward behavior, the information shared introduces novel data. Therefore, in the case of emotions, lean-forward messages should introduce variability in the emotional intensity of the messages compared to lean-back content. To understand the dynamic previously explained, we analyze the question.

Research question (RQ3): Do emotions conveyed in lean-forward messages decrease or increase the variability of emotions compared to lean-back messages?

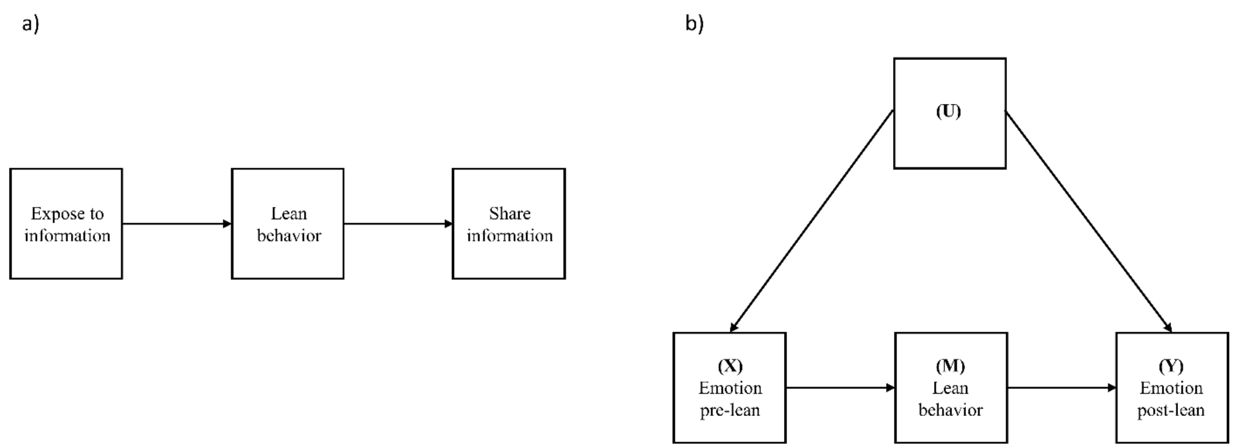

Figure 4.1 (a) Lean mechanism for information sharing. (b) emotional dynamics of lean behaviors.

From an emotion dynamics perspective, the diffusion of information via lean-back behavior will spread information through the network with the same emotion, so it is possible to know with total confidence what emotions are part of the contagion process. On the other hand, lean-forward messages can introduce different emotions in the information cascade; therefore, we cannot know beforehand how these new emotions alter the information cascade. Yet, as the lean-forward messages are associated with previous information, it seems reasonable to use that information to make inferences about the new emotions.

To elucidate the emotional dynamics of lean behaviors, the mechanism of Figure 4.1b is proposed. Here, the variable X represents the emotion individuals are exposed to (pre), M either lean-back or lean-forward behavior, Y the emotion conveyed in the messages individuals spread online (post), and U accounts for unmeasured confounding variables between X and Y. The rationale to incorporate variable U is that assuming a short timespan between being exposed (X) and sharing content (Y) for a user taking part in an information cascade, we consider that unmeasurable variables that can affect the relationship between pre and post emotions do not affect the lean behavior directly. In other words, the decision to share information online is based on the emotional appraisal of the content users are exposed to. In particular, the model in Figure 4.1b respects the conditions for the front-door criterion in Structural Causal Modeling (SCM) (Pearl & Mackenzie, 2018). Finally, this model allows us to calculate the influence (cause) of the conveyed emotion X on the emotion Y. We analyze the question:

Research question (RQ4): How do previous emotions in information cascades influence the new emotions incorporated in the discussion via lean-forward messages?

4.3. Method

This study uses social media data, computational tools for text assessment, and different statistical analyses to answer the research questions. Twitter was chosen for data collection on six independent events occurring between 2019 and 2022. These events are categorized by their topics into two political discussions, two natural disasters, and two sporting events. The inclusion of multiple cases aims to address the issue of replication crisis (R. A. Klein et al., 2014; Open Science Collaboration, 2015). The process of coding to assess emotions was conducted using NLP tools.

Twitter allows to operationalize the concepts of lean-back and lean-forward behaviors by using, as a proxy, users' options for spreading information within the platform. We consider a lean-back behavior when users spread information by reposting content generated by others; generally, performing that action only requires clicking one button. In the case of Twitter, the retweet feature spreads information within the network in a lean-back fashion. For lean-forward behavior, users' actions are more demanding because they require creating or modifying information by interacting with the content they have been exposed to. The feature we use here is quote tweets which allow users to add more content to the platform by complementing previous tweets and inserting more information; this new information must be produced by the user who quotes.

4.3.1 Data Collection

Tweets were collected from six independent events that generated information cascades. Two political discussions, the second day of hearings for the nomination of Judge Amy Coney Barrett on October 13, 2020, and Judge Ketanji Brown Jackson on March 22, 2022, both events started at 9:00 am (UTC-4) on their respective dates. Two natural disasters, the earthquake that struck the Southern California area on July 5, 2019, at 8:19 pm (UTC-7), and the earthquake of the Kermadec Islands in New Zealand on March 5, 2021, at 8:28 am (UTC+13). Finally, two sporting cases, the NBA final game of the championship for two consecutive seasons on October 11, 2020, at 7:30 pm (UTC-4), and July 20, 2021, at 9:00 pm (UTC-4).

The data collection was performed using Twitter API 2.0 for academic research, allowing access to the platform's historical public data. Based on the historical archives from Twitter (*Export Public Twitter Data*, 2022; *Twitter Trending Archive*, 2022), we selected the most relevant trending topic related to the event in the country in which the event took place. This selection generated the keywords "Barrett" and "Judge Jackson" for the political cases; "#EarthquakeLA" for the earthquake in Southern California, "Kermadec islands" and "#eqnz" for the earthquake in New Zealand; and "#NBAFinals" for the sporting events. We used the most relevant trending topic for each case because they give us the larger information exchange in the platform. The variability of keywords (use of hashtags and nouns) is justified because Twitter organically generates its trending topics. We included a boolean combination of keywords in the search query for the earthquake in New Zealand because the most relevant trending topic, "#eqnz," corresponds to a live earthquake monitoring hashtag in New Zealand (https://eqnz.nz). Therefore, to ensure we collected tweets related to the event under analysis, we constrained the search to tweets that included "Kermadec islands."

Based on the information provided by the API, we removed non-English tweets and constrained the analysis timeframe to eight hours to perform the comparison. Then, because of our interest in comparing the basic mechanism of lean behaviors, we eliminated all the duplicated cases in the dataset. Finally, we classified the remaining tweets in the dataset as lean-back (retweet) or lean-forward (quote tweet) behavior based on the categorization provided by the Twitter API. After this process, the resulting quantities were $N_{JB} = 23{,}228$ and $N_{JJ} = 5{,}761$ unique tweets for Judge Barrett (JB) and Judge Jackson (JJ) cases, $N_{LA} = 3{,}564$, and $N_{NZ} = 1{,}139$ unique tweets for the Southern California (LA) and New Zealand (NZ) earthquakes, and $N_{N20} = 7{,}994$ and $N_{N21} = 6{,}445$ unique tweets for NBA 2020 (N20) and NBA 2021 (N21) finals.

A second data collection was performed for RQ3 and RQ4. This collection aimed to gather the tweets referenced in the first data collection as RQ3 and RQ4 focused on understanding the relationship of emotions in messages that triggered lean-forward behaviors and emotions in resulting messages following a lean-forward response. Using all the IDs of the quoted tweets obtained in the first data collection, new requests to the Twitter API were made. For the second data collection, even though the academic track of the Twitter API has full access to the information of the platform, we did not collect tweets for all the IDs requested. We obtained $N_{JB*} = 2{,}273$, $N_{JJ*} = 206$, $N_{LA*} = 387$, $N_{NZ*} = 52$, $N_{N20*} = 1{,}306$; and $N_{N21*} = 517$ tweets, which on average represents 34% of the IDs requested. Users deleting tweets or changing their accounts from public to private are examples that can explain why part of the information was not retrievable.

4.3.2 Emotion Coding

To assess the overall valence and categorical emotions expressed in the tweets, this study used the IBM Watson Natural Language Understanding (NLU) tool, following the same assessment described in Chapter 3. For detailed information on how this tool evaluates valence and emotions, refer to Section 3.3.2.

To test the validity of the emotional assessment completed with NLU, its results were compared against tweets manually coded. The manual coding process was conducted by two trained coders who had to choose one of the five emotions and valence (positive/negative) present in a list of tweets. Based on Ekman and Cordaro (2011), definitions of the emotions were adapted and given to the coders. Whenever more than one of the emotions was present, the primary emotion was determined by the longest one in the text. Next, the intercoder reliability was calculated using a random sample of 50 tweets, obtaining Krippendorff's α values of 0.87

for valence, 0.85 for fear, 0.70 for anger, 0.72 for disgust, 0.75 for sadness, and 0.91 for joy—all of them over the cutoff value of 0.67 (Krippendorff, 2004, p. 245). Finally, the set of reliable coded data was used to determine the precision, recall, and F1 scores of the emotional classification of NLU. We obtained valence (precision: 0.71, recall: 0.63, F1: 0.67), fear (precision: 0.69, recall: 0.61, F1: 0.65), anger (precision: 0.82, recall: 0.75, F1: 0.78), disgust (precision: 0.83, recall: 0.79, F1: 0.81), sadness (precision: 0.65, recall: 0.59, F1: 0.62), and joy (precision: 0.53, recall: 0.67, F1: 0.60).

The valence and emotion assessment results returned a few errors from NLU; therefore, those tweets were eliminated from the final analysis. The number of errors were $N_{JB,e} = 17$ and $N_{JJ,e} = 4$ for the JB and JJ cases, $N_{LA,e} = 5$ and $N_{NZ,e} = 0$ for the LA and NZ cases, and $N_{N20,e} = 48$ and $N_{N21,e} = 33$ for the N20 and N21 cases.

4.3.3 Analytical Procedure

To analyze RQ1, we compared the valence of tweets between lean behaviors using *t*-tests and effect sizes. As *t*-tests statistics can present small differences as significant with big samples, we computed effect sizes, which is considered good practice for studies with large samples (Khalilzadeh & Tasci, 2017). We also reviewed the similarities between the probability distributions of emotional valence for lean-back and lean-forward to check if the *t*-tests were performed between unbalanced distributions.

In the case of RQ2, the same statistical analysis implemented in RQ1 was performed, comparing the differences in fear, anger, disgust, sadness, and joy between lean behaviors. Over again, *t*-tests, effect sizes, and comparisons of probability distribution were computed.

To study RQ3, the first and second data collections were used to construct a database with a temporal structure containing the tweets that triggered lean behavior (pre), the lean behavior, and tweets shared into the information cascade after the lean behavior (post). For lean-forward behavior (quote tweets), we extracted emotion pre from the text in the tweets of the second data collection and the emotion post from the text in the first data collection. In the case of lean-back behavior (retweets), pre and post tweets texts are the same; therefore, emotions pre and post were replicated. The assessment of emotion was completed using the NLU system described in the previous section.

To perform the statistical analyses of RQ3 and RQ4, the following measures were used for the variables in Figure 4.1:

- X: the level of emotion in the pre lean behavior tweet text assessed by NLU.
- M: a dichotomic variable, taking value 0 for lean-back and 1 for lean-forward behavior.
- Y: the level of emotion in the post lean behavior tweet text assessed by NLU.

From the number of tweets retrieved in the second data collection, the database constructed was unbalanced, containing a majority of lean-back messages in each one of the cases. Therefore, we decided to pull balanced samples from the new database to improve the inference in the comparisons between lean behaviors. To do so, we bootstrapped 30 samples with 400 messages each for every case analyzed. The benefit of this resampling process is to derive a better estimate for the statistical analysis as it does not assume any underlying data distribution.

The last step to answer RQ3 was comparing the absolute value of the difference of the means between pre lean emotions ($|\overline{X_{LF}} - \overline{X_{LB}}|$) with the absolute value of the difference of the means between post lean emotions ($|\overline{Y_{LF}} - \overline{Y_{LB}}|$). As the variables X_{LB} and Y_{LB} have the same level of emotion, we use the notation $\overline{LB} = \overline{X_{LB}} = \overline{Y_{LB}}$. Convergence towards lean-back emotions is defined as the scenario where the absolute difference in the mean emotions after lean behavior ($|\overline{Y_{LF}} - \overline{LB}|$) is smaller than the absolute difference in the mean emotions before lean behavior ($|\overline{X_{LF}} - \overline{LB}|$).

Finally, to analyze RQ4, we fitted the model in Figure 4.1b to the same bootstrapped samples of RQ3. The model in Figure 4.1b is, in essence, a path model that respects the front-door criterion of SCM (for details, Pearl & Mackenzie, 2018); therefore, we adjusted a linear model. To compute the effect of pre lean-forward emotions X on post lean-forward emotions Y, we multiplied the effect of X on M times the effect of M on Y. For example, the effect of fear → anger can be calculated as (fear → M)$*$(M → anger). As we measured the level of five emotions, we have five emotion variables X and five emotion variables Y; thus, the final number of combinations that present the effect of one emotion on another is 25.

4.4. Results

The complete analysis of the six cases includes 13,014 lean-forward messages (quoted tweets) divided into $N_{JB, LF}$ = 5,414, $N_{JJ, LF}$ = 1,770, $N_{LA, LF}$ = 865, $N_{NZ, LF}$ = 160, $N_{N20, LF}$ = 2,740, and $N_{N21, LF}$ = 2,068; and 31,114 lean-back messages (retweets) divided into $N_{JB, LB}$ = 17,814, $N_{JJ, LB}$ = 3,991, $N_{LA, LB}$ = 2,699, $N_{NZ, LB}$ = 979, $N_{N20, LB}$ = 5,254, and $N_{N21, LB}$ = 4,377. On average, the ratio of lean-forward to lean-back messages is 0.37. Considering that a large sample size typically guarantees statistical significance, even with small differences, we incorporate the measure of effect sizes using Cohen's *d*. The rule of thumb suggested by Cohen (1988) says that an effect size of 0.2 is considered small, 0.5 medium, and 0.8 large.

4.4.1 RQ 1 Emotional Valence Difference

For RQ1, the differences in the emotional valence between lean-forward and lean-back messages were tested. The statistical analysis reveals that the difference in emotional valence between lean-forward ($M_{JJ, LF}$ = -0.21, $SD_{JJ, LF}$ = 0.60) and lean-back ($M_{JJ, LB}$ = -0.19, $SD_{JJ, LB}$ = 0.60) for JJ is non-significant (t (3,356.1) = -0.96, p = .338) with an effect size of d = -0.03, 95% CI [-0.08, 0.03]. In the JB case, the test reports a significant difference (t (8,731.5) = 2.18, p = .029) between lean-forward ($M_{JB, LF}$ = -0.25, $SD_{JB, LF}$ = 0.55) and lean-back messages ($M_{JB, LB}$ = -0.26, $SD_{JB, LB}$ = 0.54) but with no effect size (d = 0.03, 95% CI [0.00, 0.06]). For the data from earthquakes, the comparison LA lean-forward ($M_{LA, LF}$ = -0.11, $SD_{LA, LF}$ = 0.55) and lean-back ($M_{LA, LB}$ = -0.27, $SD_{LA, LB}$ = 0.54) is significant (t (1,502.8) = 2.18, p < .001) with a small to medium effect size (d = 0.28, 95% CI [0.21, 0.36]). At the same time, NZ is non-significant (t (192.7) = 1.22, p = .225) with no effect size (d = 0.12, 95% CI [-0.04, 0.29]) between lean-forward ($M_{NZ, LF}$ = -0.20, $SD_{NZ, LF}$ = 0.56) and lean-back ($M_{NZ, LB}$ = -0.26, $SD_{NZ, LB}$ = 0.44). In the case of sporting events, both cases present significant differences. N20 (t (5,800.4) = 6.91, p < .001) with lean-forward ($M_{N20, LF}$ = 0.24, $SD_{N20, L\text{-}F}$ = 0.61) versus lean-back ($M_{N20, LB}$ = 0.13, $SD_{N20, LB}$ = 0.64), and N21 (t (4,367) = 11.92, p < .001), lean-forward ($M_{N21, LF}$ = 0.29, $SD_{N21, LF}$ = 0.61) and lean-back messages ($M_{N21, LB}$ = 0.10, $SD_{N21, LB}$ = 0.66). Regarding effect sizes, N20 is not relevant (d = 0.16, 95% CI [0.11, 0.21]). Meanwhile, N21's result is the most substantial of the six comparisons (d = 0.31, 95% CI [0.26, 0.36]). In most cases, lean-forward messages display a more positive valence (JB, LA, NZ, N20, and N21). However, effect sizes are relevant only in the LA and N21 cases (see Figure 4.2).

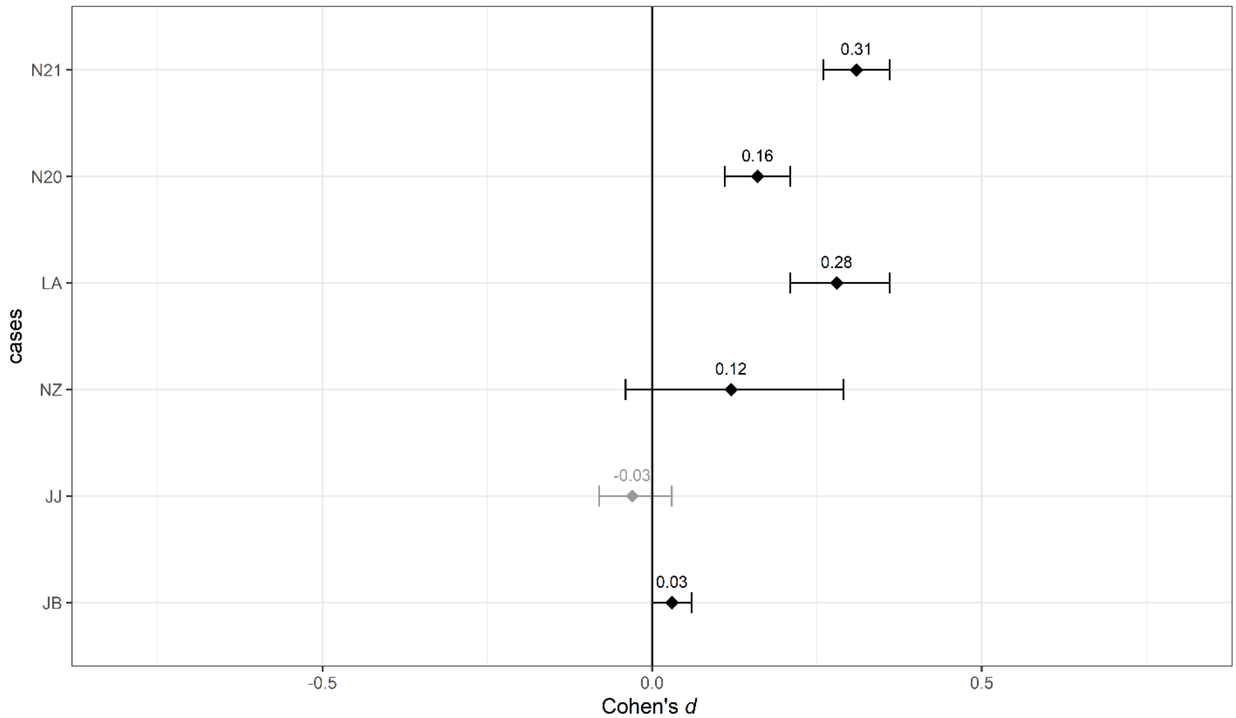

Figure 4.2. Cohen's d effect sizes and confidence intervals comparing mean valence level for all cases. According to the rule of thumb suggested by Cohen (1988) for effect sizes: 0.2 is small, 0.5 is medium, and 0.8 is large.

From our procedure to classify tweets in lean-back and lean-forward behavior, it can be noticed that nothing prevents a quote tweet (lean-forward) from being retweeted (lean-back) later within an information cascade. In the previously described scenario, a piece of information appears with both behaviors producing duplications. To address the duplication issue, we conducted a robustness check showing that the duplicated tweets are a small number and their presence does not change significantly the results presented here.

4.4.2 RQ 2 Categorical Emotions Difference

To analyze RQ2, we evaluated the mean level of emotional differences between lean behaviors for fear, anger, disgust, sadness, and joy. The results in Figure 4.3 present the effect sizes of the comparison of emotions mean levels for lean behaviors. We observe that effect sizes are consistent in sign and magnitude within the same topic (political, natural disaster, or sports). Analyzing natural disasters and sports events jointly (3c-f), it can be noticed that the sign of the effects is the same for all emotions. Fear and joy do not differ between lean behaviors showing smaller effect sizes. On the contrary, anger, disgust, and sadness present small to medium effect sizes on average. For the political cases (3a-b), sadness and joy show non-significant effect sizes, while disgust, anger, and fear display medium to large effects. Another interesting observation is that disgust and anger have consistent signs across the six cases, with disgust being more intense in lean-back messages and anger in lean-forward. They also present small to large effect sizes except for anger in N21.

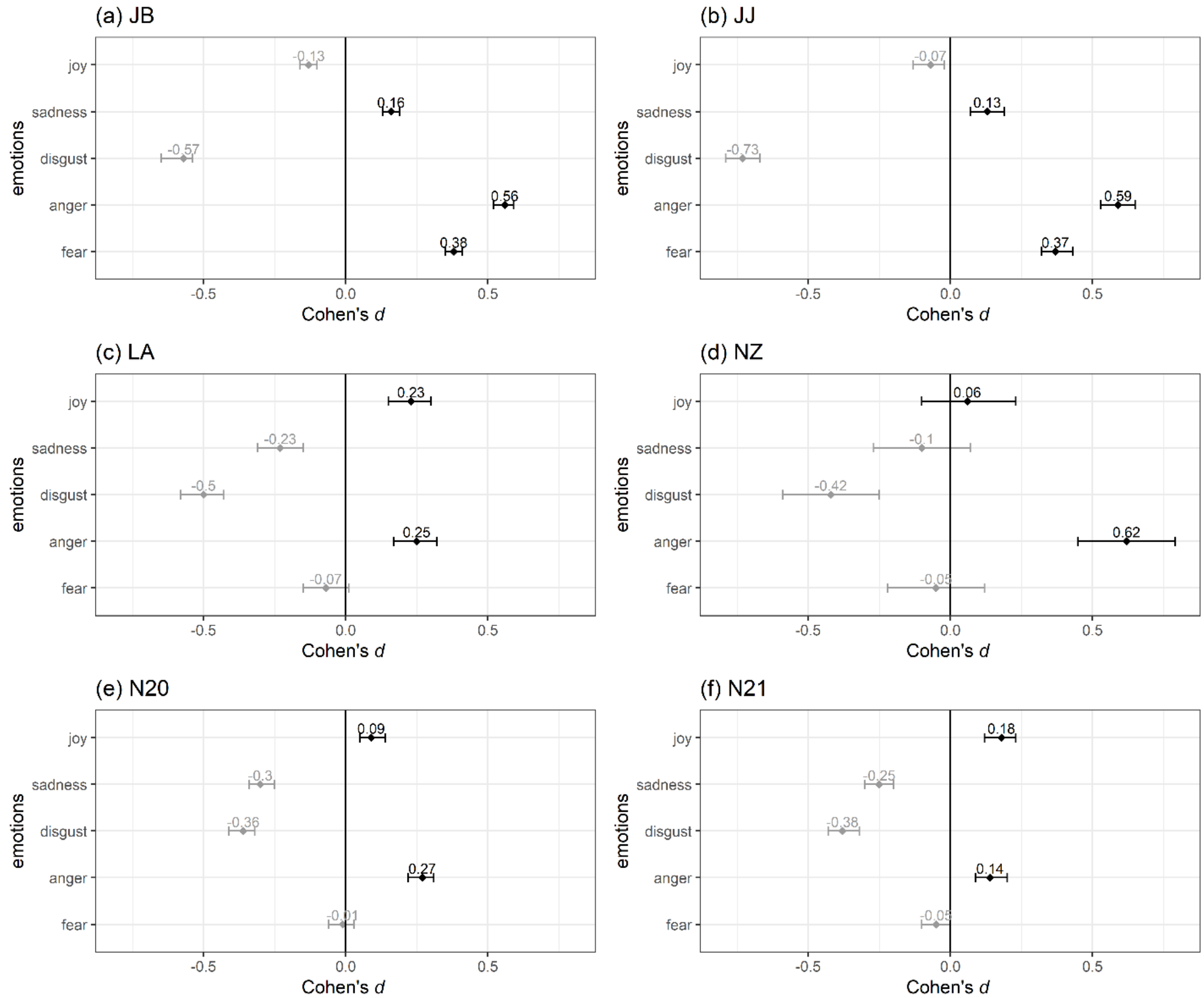

Figure 4.3 Cohen's d effect sizes and confidence intervals comparing mean emotions level. JB & JJ: political; LA & NZ: earthquakes; N20 & N21: sports. Results in color gray (negative values) show an emotional level higher for lean-back. Conversely, black (positive values) shows a higher emotional level for lean-forward behavior. Details of CIs in Appendix B (Table B1)

4.4.3 RQ3 Variability Introduced by Lean-forward Messages

Considering the similarities in the analysis of the emotions within topics in RQ2, we performed an aggregate analysis for RQ3 by type of event. The results in Table 4.1 show that when we compare the absolute value of the difference between the mean emotions expressed in quoted tweets ($\overline{X_{LF}}$) and retweets ($\overline{LB}$) versus the absolute value of the difference between the mean of emotions in quote tweets ($\overline{Y_{LF}}$) and retweets ($\overline{LB}$) in nine out of the fifteen comparisons, the resulting emotions of the lean-forward messages converge to the emotions expressed via lean-back messages. We find convergence in the sense that the absolute difference of post lean emotions ($|\overline{Y_{LF}} - \overline{LB}|$) is smaller than the absolute difference between pre lean emotions ($|\overline{X_{LF}} - \overline{LB}|$); therefore, the absolute distance of emotional levels decreases after lean-forward messages. Furthermore, convergence holds when we average the differences across all the emotions. Disgust and joy converge consistently to the emotions of lean-back messages, while sadness diverges. Anger and fear alternate their convergence to lean-back messages depending on the topic (for details, see Figure B1 in Appendix B).

Table 4.1

Means and absolute differences of emotion levels expressed in lean-back and lean-forward messages.

Topic	Emotion	$\overline{X_{LF}}$	$\overline{Y_{LF}}$	$\overline{LB}$	$\lvert\overline{X_{LF}} - \overline{LB}\rvert$	$\lvert\overline{Y_{LF}} - \overline{LB}\rvert$
Politics	fear	0.074	0.077	0.057	0.017	0.020
	anger	0.088	0.107	0.066	0.022	0.040
	disgust	0.132	0.139	0.243	0.111	**0.104**
	sadness	0.212	0.229	0.204	0.009	0.025
	joy	0.248	0.261	0.287	0.039	**0.026**
Earthquake	fear	0.218	0.170	0.186	0.031	**0.017**
	anger	0.058	0.069	0.052	0.006	0.017
	disgust	0.036	0.046	0.076	0.041	**0.030**
	sadness	0.243	0.211	0.244	0.001	0.032
	joy	0.271	0.375	0.334	0.064	**0.041**
Sports	fear	0.071	0.061	0.066	0.006	**0.005**
	anger	0.073	0.071	0.058	0.015	**0.012**
	disgust	0.062	0.095	0.124	0.062	**0.028**
	sadness	0.220	0.199	0.236	0.015	0.037
	joy	0.412	0.484	0.453	0.042	**0.030**

Note. The numbers in bold show the cases in which the difference $\left|\overline{Y_{LF}} - \overline{LB}\right|$ is smaller than $\left|\overline{X_{LF}} - \overline{LB}\right|$. In those cases, the resulting emotion in the content of lean-forward messages converges with the emotion in lean-back messages.

4.4.4 RQ4 Influence of Lean-forward Emotions

For each case, the results of the SCM for RQ4 contain five estimates for pre lean-forward emotions on lean-forward behavior ($X \rightarrow$ M), five estimates for lean-forward behavior on emotions ($M \rightarrow$ Y), and 25 effects of pre lean-forward emotions on post lean-forward emotions ($X \rightarrow$ Y) computed as the multiplication between ($X \rightarrow$ M) and ($M \rightarrow$ Y). For details about all the SCM estimates, see Table B2 in the appendix.

Figure 4.4 presents the significant effects of emotions in quoted tweets on emotions expressed in lean-forward tweets resulting from the analysis of the SCM (Figure 4.1). To obtain the appropriate significance levels of the estimates for a familywise $\alpha = .05$ in the SCM, we performed an adjusted Bonferroni correction for structural models (Smith & Cribbie, 2013). The adjusted Bonferroni correction results required setting a significance level of .008 for each estimate in the model.

The answer to RQ4 shows that most of the effects $X \rightarrow$ Y are non-significant. Nevertheless, from the emotions with significant effects, disgust provokes a consistent increment of itself in all the cases, which means that the resulting content of lean-forward behavior will express a higher level of disgust. Furthermore, for information cascades about political topics, we also found that anger decreases the level of disgust.

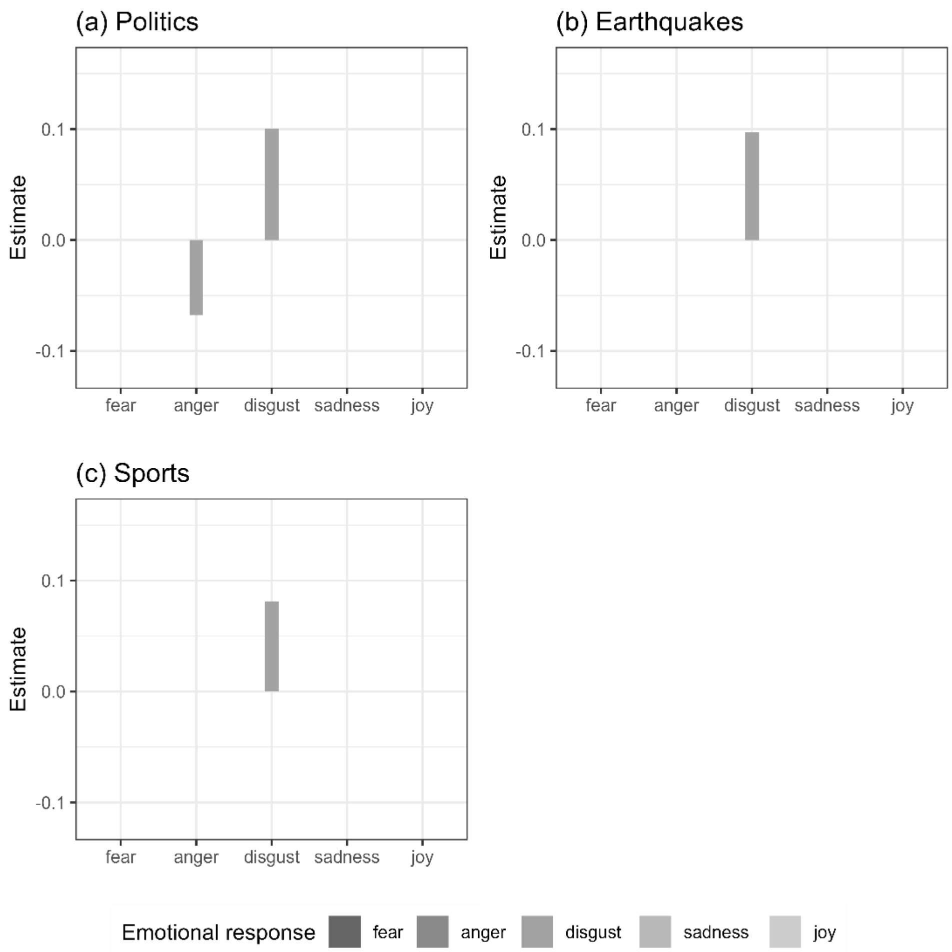

Figure 4.4 Significant effects of lean-forward behavior using front-door criterion. The emotion on the x-axis causes the emotion represented by shaded bars. The total effect of the response corresponds to the height of the bars for each emotion according to the color of the legend. Only significant results are displayed (p < .008).

In summary, the results for RQ1 show that when we focus on the valence of emotions within the negative/positive spectrum, even though we found evidence that lean-forward messages tend to be more positive, it is not possible to establish clear significant differences between lean behaviors. The assessment of RQ2 using categorical emotions shows differences based on the topics discussed (politics versus natural disasters and sports). Still, disgust and anger have consistent size effects in all the cases, with disgust being more intense in lean-back messages and anger in lean-forward. In the case of RQ3, we observe that, on average, emotions in lean-forward behavior tend to reduce the variability to the level of emotions compared to lean-back content. Finally, for influential effects, we found that disgust is the emotion that produces the most relevant changes in other emotions.

4.5. Discussion

4.5.1 Lean Behaviors and Emotions.

Our initial findings suggest that the positive/negative emotional valence analysis does not provide clear evidence of differences between lean-back and lean-forward behaviors. An explanation for these results could be that the categorical assessment of valence only captures a portion of the emotional richness embedded in online expressions. The apparent lack of fine-tuning in the valence assessment would also justify why previous literature shows mixed results for virality when measuring emotional valence, for example, in the spread of online news (see Hansen et al., 2011; Heimbach & Hinz, 2016). Therefore, using a more detailed framework to analyze conveyed emotions on social media seems necessary. Previously, we mentioned that one of the advantages of discrete emotions is that they intrinsically incorporate valence and arousal dimensions. In a study by Russell and Barret (1999), the authors identified the degree of pleasantness (valence) and arousal as independent dimensions of core affect; thus, they proposed a bi-dimensional cartesian plane to position categorical emotions based on assessing those two fundamental dimensions. Combining the results of RQ1 and RQ2, we observe that incorporating five basic emotions in the analysis gives us more nuances about users' expressions. For example, even though the effect size of valence for the difference between lean behaviors is small, disgust significantly differs when comparing lean behaviors. These findings suggest that the arousal dimension may be more relevant than valence to unveiling the differences between lean behaviors. Moreover, we observe that for earthquakes and sporting events, the results are entirely consistent, while in the case of political discussions, the effect of fear is significant in favor of lean-forward messages, a result not observed in other cases. Therefore, differences between lean behaviors can also be linked to the topic in discussion.

The analysis of basic emotions gives us more information about the negative ones (fear, anger, disgust, sadness) compared to only one positive (joy). We observe that when the effect of fear is significant, the emotional expression is higher for lean-forward behavior. Also, disgust and anger are more intensely expressed in lean-back and lean-forward behavior. Still, on average, the amount of fear, disgust, and anger in the information cascade is small compared to sadness (details in Figure B1 of the appendix), suggesting no relationship between how much emotion is expressed and the difference between lean behaviors. Therefore, the difference is better explained by the type of emotion. According to the revised definitions of Ekman and Cordaro (2011), fear is the answer to a threat that activates impulses to free or flee; anger encompasses the response to interference with goals people care about; disgust is a repulsion provoked, among other things, by offensive ideas; sadness is a resigned response to the loss of meaningful objects or people; and joy refers to feelings that are enjoyed, sought by the person. With these definitions, disgust appears as an emotion with a less active response than anger and fear; moreover, considering Russell and Barret's (1999) valence-arousal plane, the case is the same, with fear and anger exhibiting a higher arousal. Connecting the emotional difference between lean behaviors and the arousal dimension of emotions, we obtain that a behavior demanding more engagement and cognitive activity, such as lean-forward, also expresses emotions with higher arousal; thus, creating content seems to entail the expression of active emotional states.

4.5.2 Emotional Contagion

From the review of the dynamics between pre and post lean-forward behaviors, our findings suggest that, on average, the level of emotion in the post-lean-forward messages reduces the emotional variability with respect to the lean-back content. These results are also consistent with most of the causal effects calculated in the analysis of RQ4 (the only exception is anger decreasing disgust for political topics). Reducing variability produces a convergence in the emotional level of messages between lean behaviors. This convergence can be explained by the process of emotional contagion, which via mechanisms of mimicry, category activation, and social appraisal, synchronizes and creates similar emotional experiences (Goldenberg & Gross, 2020). The data collection shows that the information was predominantly spread via lean-back behavior (63%); thus, from its majority position, lean-back messages seem to influence lean-forward responses so that the level of emotions becomes similar. In other words, the coexistence of lean behaviors within information cascades triggers an emergent synchronization of the emotional tone in the online discussion.

From the studied events, online political discussions present deviations from other cases. For political information cascades, fear appears with a significant difference between lean behaviors; in three out of five emotions, there is no emotional convergence between lean behaviors, and a significant causal effect increases the variability of disgust. Previous research has shown that political discussions are polarized and uncivil (Armaly & Enders, 2021; Y. Kim & Kim, 2019; Yarchi et al., 2021); therefore, it should be expected that a spiral of emotions plays an important role in information cascades. These results are also consistent with Del Vicario et al. (2016) findings, which showed that when polarized groups dominate online discussions, the variability in emotions may increase instead of decrease. In the context of emotion contagion, political discussions are more polarized and do not necessarily converge emotionally. Instead, these online interactions seem to produce complimentary emotions. An interesting derivation of these conclusions will be to analyze if a polarized social media structure with a polarized information cascades produces emotion contagion locally but not globally.

Another interesting result from the causal effects is how disgust increases joy in earthquake cases when considering a significant level of 0.01 (mathematically similar to the 0.008 resulting from the familywise Bonferroni correction). As joy is the only positive basic emotion of the theoretical framework, the NLP system does not discriminate between variations of positive expressions. Previous research has shown that in the aftermath of terrorist attacks, individuals can change from negative to positive expressions of comfort and support (Garcia & Rimé, 2019). Looking at the dataset, we found that tweets marked with high levels of joy have messages such as: "Keep calm, stay safe #EarthquakeLA," "Read up, the science will keep you calm! #EarthquakeLA #earthquakecalifornia", and "How lucky are our mates in Timaru etc!? Seriously though, stay safe people #eqnz". Considering these previous examples and the shocking nature of terrorist attacks or earthquakes, it is possible to propose that the NLP might have detected comfort or support instead of joy.

4.5.3 Limitations

This study also presents limitations. First, the analysis of positive emotions is constrained by the lack of agreement on what emotions, besides joy/happiness, should be included as positive categories. For example, some authors include interest/seeking (Izard, 2011; Levenson, 2011), contempt (Ekman & Cordaro, 2011; Izard, 2011), or love (Levenson, 2011). However, these categorizations do not incorporate a similar number of positive and negative emotions producing an unbalanced distribution of discrete categories with opposite valence that may overestimate the presence of joy against other negative emotions.

Second, the data collection process produced unbalanced databases with a high proportion of retweets compared to quote tweets. Even though the data collection results are a condition of the communication dynamic studied, we checked the results of RQ1 and RQ2 for robustness (available in Supplemental Information) and used a bootstrapping technique to analyze RQ3 and RQ4 to improve our statistical inferences. However, our second data collection was not optimal. Therefore, we assume that the exponential decay of available information using the Twitter API detected by Pfeffer et al. (2022) plays a role in 34% of data retrieval.

Third, the collection of six cases seeks to evaluate the generalizability of online lean behaviors in different scenarios. However, we recognize that some of the events occur in different circumstances that affect the extent to which people participate in online discussions and express emotions. For example, in earthquake cases, people from the United States and New Zealand can present cultural differences regarding how they face natural disasters. In fact, as we analyzed the most relevant trending topic for each case, we noted that in New Zealand's earthquake, an institutionally established monitoring system created the trending hashtag #eqnz.

4.6 Supplemental online material

An online repository with supplemental materials is available at https://osf.io/unxj2. The repository contains supplementary information, databases, and code for analysis.

Chapter 5: The Mood-Emotion-Content Nexus: Analyzing the Influence of Affective Factors on the Spread of Misinformation in Short Videos

5.1. Introduction

In the contemporary digital landscape, social media platforms play a crucial role in spreading information by connecting millions of users worldwide. The Reuters Institute Digital News Report (Newman et al., 2023) highlights this trend, noting that 30% of users across 45 countries consume news via social media, surpassing the 22% who access news directly from news outlets' websites. This shift in the way individuals access information underscores the relevance of social media in information distribution but also brings challenges, particularly in misinformation spreading.

Research on misinformation in social media has noted the relevant role of emotions in believing and sharing misinformation (Greenstein & Franklin, 2020; Martel et al., 2020; Pröllochs et al., 2021). Studies have shown that emotions, particularly negative and high-arousal ones such as anger or anxiety, are key drivers in the spread of false information (Vosoughi et al., 2018). It has been argued that the underlying mechanisms that explain this connection between negative emotions and information sharing are related to negativity bias, motivated reasoning, and affective polarization (Weeks, 2023). It seems relevant to remark that the literature has often segmented its focus on the emotional content of the information (Pröllochs et al., 2021; Vosoughi et al., 2018) or the affective states of the individuals exposed to misinformation (Greenstein & Franklin, 2020; Horner et al., 2021; Martel et al., 2020), rarely considering both simultaneously.

Another relevant aspect of the current literature on misinformation is its primary focus on textual misinformation, despite the increasing consumption of visual content, such as images, memes, and videos, in online communication. Recent studies have begun to address this gap by incorporating visual analysis in misinformation research (Qian et al., 2023; Yang et al., 2023). However, the exploration of visual misinformation remains underrepresented over the last decade compared to its textual counterpart (Peng et al., 2023). The current state of the study of visual misinformation appears inconsistent with the behavioral trends of people spending less time reading (*Time Spent Reading*, 2019) and engaging more with visual content on platforms like YouTube or TikTok, which have gained traction over traditional text-based platforms (Newman et al., 2023).

Considering the state of the research in visual misinformation and emotions, this study aims to contribute to the literature by analyzing a mechanism that simultaneously incorporates the effects of the content on individuals' experiences of emotion when exposed to misinformation delivered via short social media-like videos. Specifically, the study analyzes whether it is the context (mood), the content (credibility), or the effect (emotions) that primarily drives the dissemination of misinformation. The objective is to determine whether the propensity of individuals to disseminate short misinformation videos online is predominantly influenced by their prevailing mood or by the emotions elicited during video consumption. Moreover, this work explores whether the credibility of the information shown in videos affects the extent to which people share that information on social media. Additionally, we investigate how the emotional experiences of individuals who share misinformation relate to the level of visibility (affordance) they select to share the content.

The overall contribution of this work is threefold. First, it extends research on visual misinformation, which appears limited compared to the evolving trends in online information consumption. Second, by examining the mood and emotions experienced after exposure to misinformation videos, we propose a mechanism to understand the interplay between content and individuals' emotions. Third, in light of the emerging research on technological affordances and emotion (E. L. Cohen & Myrick, 2023), we seek to deepen our understanding of the role of visibility in sharing information, specifically within the context of short video misinformation.

5.2. Literature review

5.2.1 Visual Misinformation

Visual misinformation, which involves spreading false or misleading information through visual formats such as images, memes, or videos, has emerged as a growing area of interest in recent years. However, despite its increasing relevance, the study of visual misinformation has been notably underrepresented in the literature compared to text-based misinformation. Peng et al. (2023) conducted a review of articles from flagship political communication journals, leading communication journals, and highly cited interdisciplinary journals, revealing a significant disparity in the prevalence of research on visual misinformation compared to text-based misinformation over the past decade. Several factors contribute to the scarcity of research on visual misinformation. Brennen et al. (2021) highlight the methodological challenges associated with visual communication research, noting that visual data, such as images and videos, are more complex to collect, store, and analyze at scale compared to textual data. Furthermore, Pearce et al. . (2020) point out that existing analytical tools for social media analysis are primarily designed for text-based content, making studying visual misinformation more challenging.

As the landscape of media consumption evolves, with platforms based on visual content, such as YouTube and TikTok, increasingly outpacing text-based platforms in user engagement (Newman et al., 2023), the need for more focused research on visual misinformation has become increasingly apparent. Communication scholars have emphasized the importance of conducting more studies in this area (Heley et al., 2022) and have proposed theoretical frameworks and research agendas to facilitate such investigations (Hemsley & Snyder, 2018; Peng et al., 2023).

The current literature on visual misinformation, while scarce, spans a wide range of subjects. Hameleers et al. (2020) studied the credibility of textual versus multimodal (text plus visual) misinformation, finding that in its multimodal form, misinformation appears more credible, regardless of the source. In the context of the COVID-19 pandemic, Brennen et al. (2021) discovered that more than half of the visual pieces serve as evidence for false claims instead of being manipulated, a phenomenon known as “cheap fakes.” Qian et al. (2023) explored the impact of a media literacy intervention on the intention to use reverse search tools to check cheap-fake misinformation images, finding that while the intervention increased the intention to use these tools, it did not affect credibility judgments or misinformation discernment. Studies on WhatsApp have revealed that public groups in Brazil and India share a significant portion of image misinformation even after it has been fact-checked (Reis et al., 2020), and an analysis of 1.6 million images from public WhatsApp groups in India found a high prevalence of misinformation (Garimella & Eckles, 2020). In the case of Facebook, Yang et al. (2023) showed that 23% of images in U.S. public groups present misinformation, with right-wing leaning images being 5 to 8 times more likely to misinform, displaying a partisan asymmetry.

Despite the growing body of research on visual misinformation, to the best of our knowledge, there is a gap in the literature concerning the study of interactions between affective states and misinformation. Given the established role of emotions in shaping personal cognitive information understanding and interactive social behaviors of individuals (Forgas, 2008), it seems relevant to address research in that direction.

5.2.2 Emotions and Online (Mis)Information Sharing.

The literature on online information sharing has consistently highlighted the role of emotions as fundamental drivers in the diffusion of information across platforms (Berger & Milkman, 2012; W. J. Brady et al., 2017; Hansen et al., 2011; Stieglitz & Dang-Xuan, 2013). Emotions have been demonstrated to possess the capacity to spread through user interactions, facilitating the viral spread of content (Coviello et al., 2014; Ferrara & Yang, 2015; Goldenberg & Gross, 2020; Kramer et al., 2014). Furthermore, emotions play a crucial role in capturing attention and fostering the engagement of individuals with content (Nelson-Field et al., 2013; Yu, 2014). These attributes of emotions imply that messages with high emotional content are likely to engage individuals on a deeper cognitive level, thereby increasing the likelihood of the information being shared (Luminet et al., 2000; Peters et al., 2009). Moreover, the emotional contagion effect suggests that the emotional tone of a message, whether positive or negative, can significantly influence its spread, impacting not only the reach of the information but also the emotional state of the audience. Thus, understanding the emotional dynamics of online interactions provides crucial insights into information dissemination mechanisms and the potential for influencing public opinion and behavior.

In examining the relationship between misinformation and emotions, scholarly research has utilized both dimensional (valence-arousal) and categorical approaches to study emotions. The dimensional approach, which classifies emotions based on their valence (positive or negative) and arousal (high or low), has produced mixed findings. For instance, Pröllochs et al. (2021) found that false rumors are more likely to become viral if they contain a higher proportion of positive sentiment terms. In contrast, other studies have indicated that the more extended discussions of false information are prolonged, the more negative the expression of sentiment (Zollo et al., 2015), users posting in conspiracy theory forums exhibit more negative and emotional language even before participating in such forums (C. Klein et al., 2019), and individuals with anti-vaccination beliefs gravitate towards forums characterized by more negative sentiments (Faasse et al., 2016). Offering a more neutral perspective, Martel et al. (2020) found that reliance on either positive or negative emotions can increase susceptibility to fake news. On the other hand, the categorical approach to emotions has generated its most substantial results around anger and anxiety. In the case of anger, it has been found that increases the susceptibility to misinformation (Greenstein & Franklin, 2020), helps fake news to become viral online (Chuai & Zhao, 2022), makes more likely for individuals process false political information (Weeks, 2015), produces negative impact towards vaccination attitude when exposed to conspiracy misinformation (Featherstone & Zhang, 2020), and facilitates the recall of health misinformation (Lee et al., 2023). As for anxiety, its association with uncertainty increases individuals' propensity to accept rumors as a means to alleviate their anxious-uncertainty state (DiFonzo, 2008). Empirically, anger has been associated with belief in falsehoods (Martel et al., 2020) and has a documented role in influencing the belief in and dissemination of misinformation during crises such as the COVID pandemic (De Coninck et al., 2021; Freiling et al., 2023).

An important aspect of the previous literature is its focus on emotions. Yet, this emphasis overlooks another crucial aspect of affect that can give a better context to misinformation sharing: mood. Unlike emotions, which are intense and typically triggered by specific events, moods represent more general and prolonged emotional states that can last longer and influence behavior (Gross, 2015). Given that existing research on emotions and misinformation sharing tends to emphasize the role of negative emotions and the gap in the literature with its lack of analysis of contextual moods, this study explores the relationship between mood, emotions, and misinformation, analyzing the following hypothesis.

H1a: The intensity of positive and negative moods is positively associated with more content sharing. The effect of negative mood will be greater than the effect of positive mood.

Research about emotions and misinformation typically assesses emotions by analyzing the content individuals are exposed to (Pröllochs et al., 2021; Vosoughi et al., 2018) or evaluating the emotional experiences of the individuals exposed to misinformation (Greenstein & Franklin, 2020, 2020; Horner et al., 2021). Notably, there is a significant gap in the literature regarding the concurrent analysis of both mood and emotions experienced by individuals in relation to misinformation, with the study by Lühring et al. (2023) being a rare exception. Given this gap, we want to extend the analysis of this mechanism by assessing the following hypothesis:

H1b: The intensity of positive and negative moods and the strength of emotions experienced are simultaneously and positively associated with more content sharing.

Past research indicates that individuals often face difficulty distinguishing between truth and falsehood. Bond and DePaulo (2006) found that people's accuracy in discerning lies from truths averages 54%, which is slightly better than chance. The literature on misinformation suggests that several mechanisms, including negativity bias, motivated reasoning, and the effects of group identity and affective polarization, can influence how individuals interact with information online (Weeks, 2023). Efforts to correct misperceptions after exposure to misinformation have produced inconsistent outcomes, displaying both positive and negative effects following correction attempts (Walter & Murphy, 2018). Moreover, there is a tendency for individuals to resist rejecting misinformation, and correction efforts may paradoxically reinforce belief in false information (Nyhan & Reifler, 2015). In the context of social media, where users do not necessarily follow only reliable sources of information, it can be expected that they encounter a mix of more and less credible information. Under such circumstances, the perceived credibility of content, along with the contextual mood and emotions experienced by users, plays a critical role in influencing their decision to share information. Considering the impact of content credibility, we posit that user behavior related to sharing content will differ based on the credibility level of the content and the emotions it elicits. We propose the following hypothesis: (Figure 1 illustrates the mechanism of the study's hypotheses).

H2: The experimental condition created by the distinction between high and low levels of credibility on content sharing will be statistically significant, and more credible information will be positively correlated with content sharing.

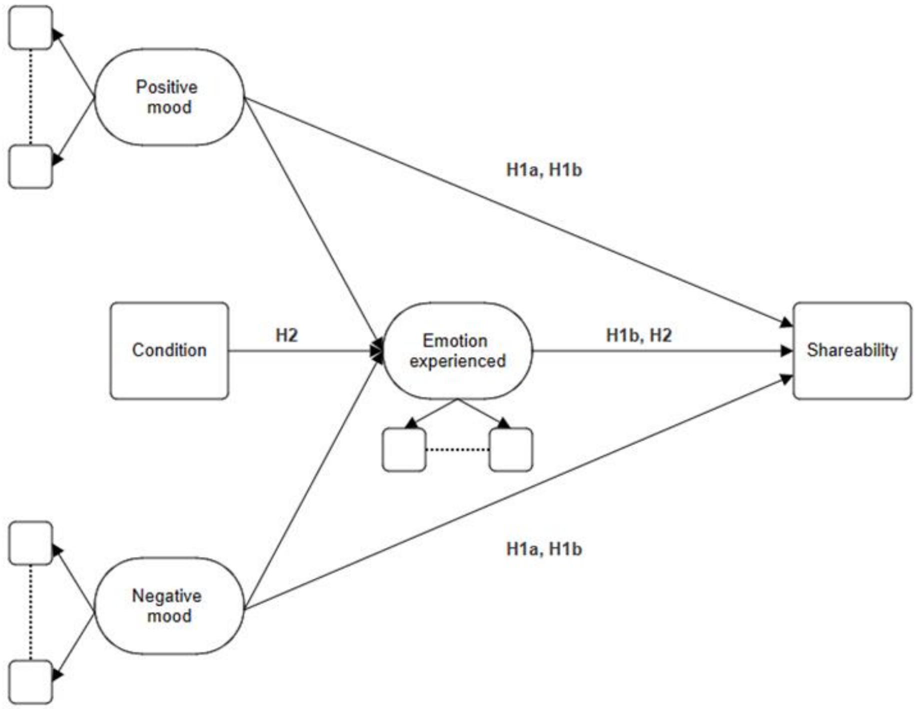

Figure 5.1 Structural model for the influence of mood and emotions in content sharing

Another relevant aspect of online content sharing is to analyze how current technology allows users to spread information and its relationship with mood and emotions. To conduct the analysis, this work relies on the concept of technological affordances which refers to any capacity or feature of technology that shapes how users use it (Fox & McEwan, 2017; Rice et al., 2017). The relevance of affordances for information sharing is that they can constrain or enable the process. For example, the affordance of visibility can shape norms of emotional expressions online by determining the appropriateness of certain expressions (E. L. Cohen & Myrick, 2023). Studies have shown that users tend to post positive rather than negative emotions on social media (Reinecke & Trepte, 2014). Negative emotions, perceived as more intimate, are considered less appropriate for high-visibility areas such as social media feeds (Bazarova & Choi, 2014). Furthermore, the affordance of interactivity has also been associated with emotional information sharing. Berger and Milkman (2012) found that articles inducing higher arousal levels are more likely to be shared by readers using website forwarding features.

In this study, we focus on the affordance of visibility to analyze the relationship between moods and emotions and information sharing. Visibility is understood as the extent to which media messages can be seen, reached, or accessed by other users (Treem et al., 2020). The rationale for this analysis considers that in current social media platforms, there is a wide range of visibility levels, from low-visibility 1-on-1 direct messages, such as texts or emails, to highly visible, publicly available messages on social media feeds that can be potentially accessed by any person with an internet connection. Given this context, the following research question is analyzed:

RQ: What is the relationship between affective states (mood) and emotions experienced with the level of visibility people choose to share misinformation?

5.3 Method

5.3.1 Study design

This study was preregistered in OSF. We followed all steps outlined in the preregistration available at https://osf.io/c63fv, except where noted. It consists of two different surveys. In the first survey using collective assessment, we determined the level of credibility of videos with misinformation. We asked participants about the accuracy of the information on social media videos that have gained enough popularity to be evaluated for their truthfulness by fact-checking websites such as Politifact.com and Snopes.com. Following the previous procedure, we ensure that our selection of perceived credibility is based on a collective assessment. From this process, we extracted the videos to create the conditions of this project's primary survey.

The second survey is designed as a between-subjects survey experiment using Qualtrics. We used a single-factor design with random assignment of the participants to one of two groups (videos with high and low credibility). The selection of videos for the low and high levels of credibility will be based on an initial survey.

5.3.2 Stimuli selection

The selection of the stimuli was based on the results of the first survey. To create the initial survey, we collected 13 misinformation videos posted on TikTok that Politifact.com or Snopes.com fact-checked. This collection process spanned from August to October of 2023.

Using the collection of misinformation videos, we elaborated an online survey in Qualtrics to assess the level of credibility of each one of the videos with a Likert scale of six options (1 = Definitely false; 6 = Definitely true). Participants were recruited from the specialized online platform SurveySwap.io (N=84, 57.3% female), with the median and mean ages falling within the 45-59 year age group. Participants received compensation of 30 survey credits, the standard currency within the SurveySwap environment. Eligibility criteria required participants to be at least 18 years of age and residents of the U.S.

To complete the survey, participants answered the question of the level of credibility for each video. For the integrity of responses, videos were presented in random sequence, accompanied by an attention check question following each video. Failure of any attention check resulted in termination of participation. Additionally, we incorporated two control questions related to the U.S. to confirm the participants’ residency status. Incorrect responses, or those taking longer than 15 seconds (to preclude the possibility of participants searching for answers online), led to termination of participation. Participants were asked about demographics after answering all the questions about the videos.

For the final selection of videos, as outlined in our preregistration document, we distinguished videos with low and high credibility levels based on the survey results. We received 84 quality responses, all accurately completing 15 attention checks. For analyzing the results, we excluded outliers determined by the completion time (lower bound = $Q1 - 1.5 * IQR$; upper bound = $Q3 + 1.5 * IQR$). This process resulted in 76 valid responses.

From the valid responses, we identified two groups of four videos (lower and higher credibility). For the final selection within each group, we conducted linear regressions with the level of credibility as the dependent variable, controlling for demographic factors (age, sex, education, income, political leaning) and discarded videos where these variables were significant predictors. Additionally, we excluded videos related to the conflict between Israel and Palestine due to changes in the conflict dynamics since the video collection phase. From the remaining videos in each group, we selected a combination of two with a similar time length for low and high credibility conditions. We then conducted pairwise comparisons between the mean credibility values of the selected videos to ensure that the two groups were significantly different. For detailed information about this comparison, refer to Figure C1 in Appendix C.

5.3.3 Sample and Procedure

Participants for the main survey experiment were also recruited via SurveySwap.io (N=793, 60.5% female, with the median and mean ages falling within the 30-44 age group). Their participation was compensated with 30 survey credits. Eligibility criteria required participants to be at least 18 years of age and residents of the U.S.

To complete the survey, participants were first asked to describe their current mood using the Positive and Negative Affect Schedule (PANAS) questionnaire (Watson et al., 1988). Subsequently, they were randomly assigned to one of two experimental conditions: low credibility misinformation or high credibility misinformation. Participants received detailed instructions in both conditions and were asked to watch the videos attentively. On the same page as the videos, participants were prompted to report their emotional experiences during the viewing, utilizing the discrete emotions questionnaire developed by Harmon-Jones et al. (2016). Following the assessment of their emotions, the next page asked about the participants' likelihood of sharing the video with others via social media or messaging apps. If participants indicated a possibility to share, a follow-up question was presented, asking for specifics about where they intended to share the video. Each participant viewed two videos, which were presented in a random sequence. The survey concluded with a section collecting demographic information.

5.3.4 Measures

5.3.4.1 Positive and negative moods

Using the PANAS questionnaire (Watson et al., 1988), participants reported how they felt "today" (on the day they took the survey) about each one of the 20 items listed in the questionnaire. The PANAS questionnaire rates each item using a 5-point Likert-scale from 1 = not at all to 5 = extremely.

5.3.4.2 Emotion

Participants indicated the emotion experienced by answering the discrete emotion questionnaire (Harmon-Jones et al., 2016). The instrument measures four factors for each one of the following emotions: anger, disgust, fear, anxiety, sadness, and happiness. The measurement is done using a 7-point Likert-scale from 1 = not at all to 7 = an extreme amount. The order of the factors in the questionnaire was displayed randomly.

5.3.4.3 Shareability

Participants rated the likelihood of sharing the video with others via social media or messaging apps using a 4-point Likert-scale from 1 = very unlikely to 4 = very likely. In the case participants indicated the options 3 = somewhat likely or 4 = very likely, a follow-up multiple-choice question appeared, asking for specifics about where they intended to share the video (1-1 messages, group messages, private social network site, public social network site, other).

5.3.5 Attention check

To ensure the quality of the responses, our survey incorporated three attention checks. For the question regarding the emotion experienced while watching each video, we included "inattentive" and "unobservant" among the items listed. If participants rated either of these options between 4 = moderately and 7 = an extreme amount on the Likert scale, their participation was terminated. The third attention check involved a nonsensical question that required participants to select a specific color. Like the previous criteria, failure to choose the correct answer resulted in the participant being removed from the survey.

Furthermore, consistent with the initial survey conducted in this study, we included a control question to verify participants' residency status in the U.S. This question asked participants to identify a state that is not part of the contiguous United States, with Alaska being the only correct response listed as an alternative. Participants who answered incorrectly or took longer than 15 seconds to respond (to prevent the likelihood of searching for answers online) had their participation terminated.

5.3.6 Analytical procedure

Following exclusion criteria for the analyses outlined in the preregistration, participants who answered straight-lines for the PANAS or emotions questionnaire were removed. Similar to the analysis for the presurvey, outliers by completion time were also removed from the resulting group of respondents.

To analyze H1, the structural model presented in Figure 5.1 was adjusted for each of the six emotions in this study. Before adjusting the model, the reliability of the factors for PANAS and emotions was checked using Cronbach's α. In the case of H2, a linear mixed-effects model was used to determine whether sharing behavior varied significantly between the experimental conditions. Additionally, to assess the implications of the experimental conditions producing no difference in the sharing mechanism, a constrained version of the model in Figure 5.1 was adjusted and compared with the original model.

Positive and negative moods were calculated as aggregated values to adjust the model. These values were derived from the linear combination of factor scores obtained through a varimax rotation applied in a two-factor analysis of PANAS items. We then adjusted the structural model by categorizing experimental conditions into low credibility misinformation and high credibility misinformation. This adjustment considered the repeated measures of individuals exposed to two videos each. We configured a constrained model that required equal path coefficients for both conditions to examine the differences between the low and high credibility conditions. Using a chi-square difference test, this model was compared to the initial unconstrained model. To further validate the robustness of the analysis, we adjusted linear mixed-effects models. In these models, emotion scores were calculated as aggregated values. These values were derived from factor scores obtained through a varimax rotation applied in a six-factor analysis of the emotion items, as defined in Harmon-Jones et al.(2016).

For the analysis of visibility related to RQ, the dataset was refined to include only those instances where individuals opted to disseminate information. The visibility level was determined based on responses to how individuals would prefer to share the information. The options presented ordinally from lower to higher level of visibility were direct 1-on-1 messages (level 1), group messages (level 2), private social network sites (level 3), and public social network sites (level 4). In cases where respondents selected multiple sharing options, their data was duplicated across various rows to maintain the integrity of each choice. Among the participants, 14 selected the "other" option, and most indicated that they would prefer sharing information by talking to someone directly. These answers were excluded from the analysis due to the lack of online visibility. Subsequently, a linear structural model was adjusted to each of the six emotions to assess how positive mood, negative mood, and the respective emotion influence the level of visibility. This model considered repeated measures from individuals, grouped them by experimental conditions, and was evaluated against a constrained model to identify significant differences across conditions.

5.4. Results

After applying procedures to eliminate straight-line responses and outliers based on completion time, the filtered dataset contained 604 high-quality responses. This number meets the sample size requirement determined by the power analysis conducted during the preregistration phase. The participants were randomly assigned into two groups: 308 in the low credibility condition and 296 in the high credibility condition. These groups showed no significant differences in sex, age, education level, income, or political affiliation (for details, see Figure C2 in Appendix C). The reliability analysis for the positive and negative moods, measured using the PANAS, generated Cronbach's α values of .91 and .90, respectively. Regarding emotions, reliability measures were calculated separately for the two experimental conditions, resulting in Cronbach's α values of .94, .87, .92, .87, .70, and .92 for anger, disgust, fear, anxiety, sadness, and happiness, respectively, in the low credibility condition; and .95, .82, .93, .88, .67, and .92 for the same emotions in the high credibility condition. All emotions demonstrated high reliability levels except for sadness, which showed acceptable reliability.

5.4.1 Hypotheses

To test the effects of positive and negative moods and emotions on misinformation sharing for both experimental conditions proposed in H1 and H2, the structural linear model in Figure 5.1 was adjusted for each one of the emotions separately. The set of models presented good fit to the data for anger (CFI = .99, RMSEA = .03, SRMR = .01), disgust (CFI = .99, RMSEA = .05, SRMR = .02), fear (CFI = .99, RMSEA = .06, SRMR = .02), anxiety (CFI = .98, RMSEA = .06, SRMR = .02), and happiness (CFI = .98, RMSEA = .06, SRMR = .02), while sadness (CFI = .94, RMSEA = .07, SRMR = .04) showed an acceptable fit.

Figure 5.2 presents the significant regression estimates of the six models grouped by emotion. The analysis of the results reveals that hypothesis H1a is partially confirmed. Specifically, the coefficient estimates for the effect of positive and negative moods on sharing (pos → share, neg → share) present a positive correlation with content sharing in both experimental conditions (for details see Table C1, Appendix C). However, negative mood does not significantly influence sharing behavior for any of the emotions examined. This finding contradicts H1a's prediction that the impact of negative mood on sharing would be greater than the impact of positive mood. Interestingly, a closer examination of the model's complete mechanism reveals that negative mood significantly affects all negative emotions (neg → emo), suggesting that negative mood influences sharing behavior through the mediation of negative emotions. Regarding H1b, which aimed to determine whether moods and emotions simultaneously influence sharing behavior, Figure 5.2 shows that all emotions significantly affect misinformation sharing regardless of the experimental condition (emo → share), as does positive mood (pos → share). Nevertheless, the negative mood does not affect content sharing significantly (neg → share), indicating that H1b is not fully supported.

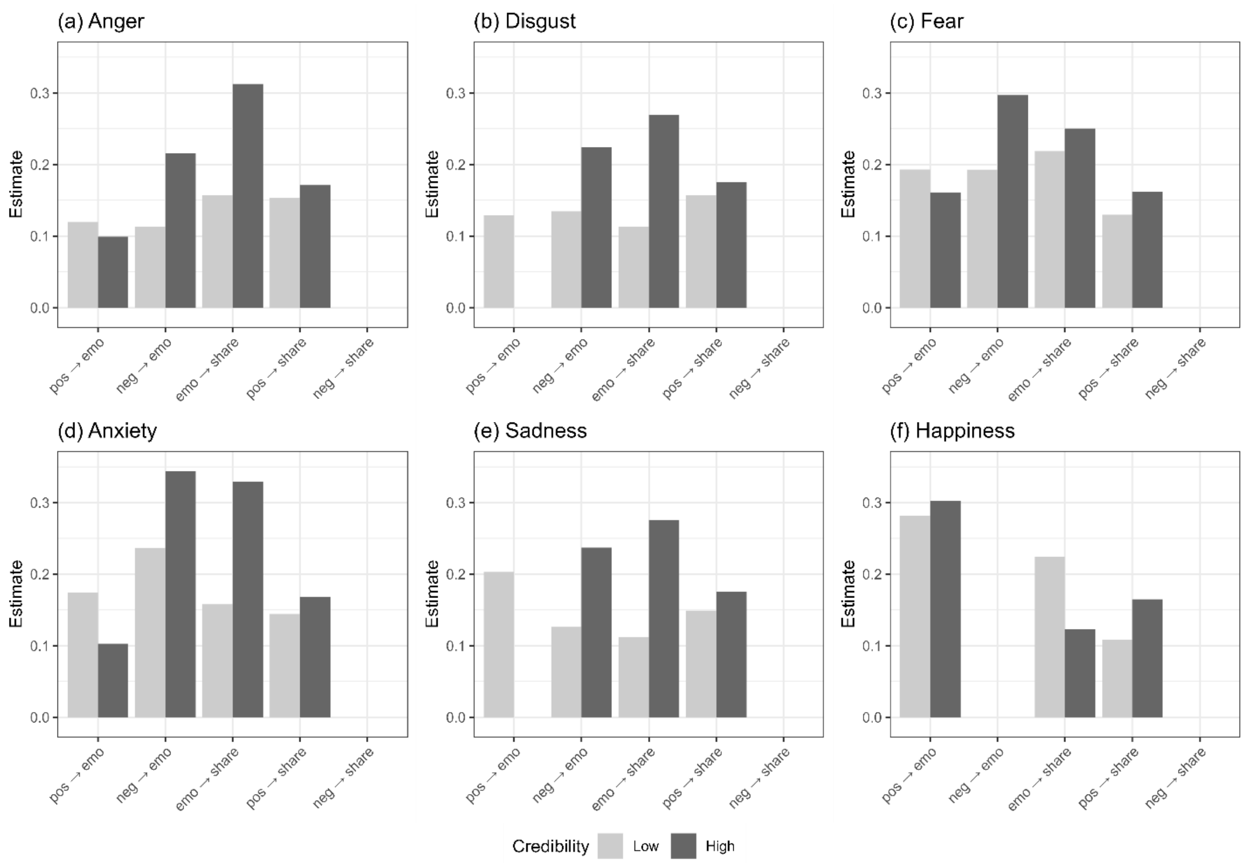

Figure 5.2 Structural model coefficients for low and high credibility fake news grouped by emotion. The word emo on the x-axis represents the respective emotion (a-f) as cause or effect. The coefficient value corresponds to the bars' height. Only significant results are displayed ($p < .05$). For details of the coefficients, see Table C1 in Appendix C

To assess the differences between experimental conditions of H2, a linear mixed-effects model was used to assess the effect of the low and high credibility conditions on content sharing. The model included the experimental conditions as fixed effects and participants (IDs) as random effects. The results indicated a significant effect of the high credibility condition compared with low credibility as baseline (B = 0.14, SE = 0.03, t (602) = 4.37, p < .001)), suggesting that participants in high credibility condition exhibited a higher mean content share than those in low credibility condition. The variance components for the random effects showed an intercept variance of 0.09 (SD = 0.30) for participants, and a residual variance of 0.11 (SD = 0.33).

To complement the analysis of H2, Table 5.1 shows the comparison of the structural models for each emotion between the original model and a constrained model in which the parameter estimates for the low and high credibility conditions are set to be equal. The results reveal that constrained models, which assume no difference between the two experimental conditions, perform worse than unconstrained models, which confirms that the credibility level of the stimuli influences content sharing.

Further analysis of the significant effects of moods and emotions on sharing behavior shows that the estimated relationships between emotions and sharing (emo → share) and positive emotions and sharing (pos → share) are stronger in the high credibility condition, except for happiness → share, which is higher in the low credibility condition. This finding suggests that higher credibility information is positively associated with emotions and content sharing, with emotions having a more substantial impact on sharing behavior, primarily supporting H2.

The analyses for H1 and H2 were replicated for robustness using linear mixed-effects models, producing largely consistent results. For details, see online Supplementary Material.

Table 5.1

Comparison of nested models using chi-squared difference by emotion

Model	χ^2	df	$\Delta\chi^2$	Δ df	p value
Anger	30.64	22			
Anger constrained	93.37	34	49.01	12	.000
Disgust	53.35	22			
Disgust constrained	215.24	34	99.81	12	.000
Fear	67.10	22			
Fear constrained	134.15	34	36.25	12	.000
Anxiety	70.33	22			
Anxiety constrained	133.29	34	40.33	12	.000
Sadness	91.28	22			
Sadness constrained	146.42	34	28.62	12	.004
Happiness	75.76	22			
Happiness constrained	162.66	34	36.71	12	.000

Note: The chi-square difference ($\Delta\chi^2$) is computed using the Satorra-Bentler scaled chi-square difference test, which is a function of the standard (not robust) χ^2 statistics in the table and a scaling correction factor to account for non-normality in the data.

5.4.2 RQ Impact of Mood and Emotions on Visibility

To analyze the research question about the relationship between mood and emotions with the chosen level of visibility to share content, a structural model was adjusted with the subset of participants that answered positively to share the videos. The models presented an acceptable fit to the data for anger (CFI = .99, RMSEA = .06, SRMR = .02), disgust (CFI = .98, RMSEA = .05, SRMR = .03), fear (CFI = .99, RMSEA = .06, SRMR = .02), anxiety (CFI = .96, RMSEA = .09, SRMR = .04), sadness (CFI = .88, RMSEA = .10, SRMR = .05), and happiness (CFI = .99, RMSEA = .07, SRMR = .02).

The results in Table 5.2 show that, in the low credibility condition, the level of visibility chosen for sharing information, categorized into four levels ranging from low-visibility 1-on-1 direct messages to highly visible, publicly accessible messages on social media feeds, is significantly influenced by positive mood. The relationship between positive mood and visibility (pos mood → visibility) is consistently positive, indicating that individuals experiencing higher levels of positive mood are more likely to share content in public venues rather than in private channels. Also, in the low credibility condition only one emotion significantly affects visibility: disgust. The relationship between disgust and visibility (disgust → visibility) is positive. For the high credibility condition, the only significant effect on visibility is the positive influence of happiness (happiness → visibility).

The findings that disgust increases the visibility of shared content align with previous results in this dissertation, emphasizing disgust's significant role in driving information sharing within information cascades. Additionally, it is noteworthy that positive mood and positive emotions influence visibility, possibly reflecting individuals' desire to present themselves positively to their audiences.

Table 5.2

Structural Model coefficients for the effect of mood and emotion on the level of visibility for content sharing.

	Low credibility		High credibility	
	β	p-value	β	p-value
Anger → Visibility	0.060	.301	0.032	.607
Pos Mood → Visibility	**0.144**	.029	0.025	.687
Neg Mood → Visibility	-0.063	.295	0.051	.464
Disgust → Visibility	**0.106**	.051	-0.011	.863
Pos Mood → Visibility	**0.151**	.017	0.018	.772
Neg Mood → Visibility	-0.072	.222	0.061	.396
Fear → Visibility	0.014	.821	0.023	.707
Pos Mood → Visibility	**0.143**	.041	0.019	.746
Neg Mood → Visibility	-0.052	.383	0.049	.495
Anxiety → Visibility	0.006	.935	0.015	.823
Pos Mood → Visibility	**0.145**	.040	0.022	.723
Neg Mood → Visibility	-0.051	.419	0.052	.484
Sadness → Visibility	-0.024	.714	0.080	.207
Pos Mood → Visibility	**0.149**	.028	0.033	.594
Neg Mood → Visibility	-0.040	.543	0.043	.523
Happiness → Visibility	0.026	.674	**0.152**	.025
Pos Mood → Visibility	**0.137**	.029	-0.057	.385
Neg Mood → Visibility	-0.051	.400	0.075	.260

Note: Statistically significant coefficients in bold

5.5 Discussion

5.5.1 Moods, Emotions, and Misinformation Sharing

Misinformation on social media is a widespread phenomenon that has been shown to be associated with the moods and emotions of platform users. Examining a mechanism that can explain how these two elements act simultaneously in the process that leads to misinformation sharing, the initial findings of this study of H1 suggest that mood and emotions play a joint role in the sharing process, but there exists a specific mechanism. The process consists of the two components of mood (positive and negative) affecting the emotion experienced by individuals with a positive and significant relationship. Subsequently, the experienced emotion also affects sharing behavior in the same manner. However, the results show that only the positive component is significant when considering how mood affects sharing behavior. This mechanism works for all negative emotions studied (anger, disgust, fear, anxiety, and sadness), independently of the content's credibility level. Essentially, considering mood as an overarching affective state, it influences the emotion caused by the stimuli directly with its positive and negative components; for the subsequent sharing behavior, the effect of mood is only significant for the positive component. This finding suggests that the negative component of mood presents an effect on sharing behavior mediated by negative emotions, where the indirect effect of the analysis drives the total effect. In comparison, the positive component of mood presents both direct and indirect effects. In the case of happiness, the only positive emotion in the group, the negative component of mood does not impact happiness; therefore, the mediated process only occurs with the positive mood component.

The mechanism previously described incorporates interesting details to the current research results examining the effect of mood and emotions in misinformation sharing. While some literature has found that the positive and negative components of mood are relevant for believing in misinformation (Martel et al., 2020), others have shown that emotions play a crucial role in believing and sharing misinformation (De Coninck et al., 2021; Greenstein & Franklin, 2020; Weeks, 2015). The outcomes of this work bring together previous results by showing the importance of moods and emotions simultaneously and establishing a mechanism for both to influence misinformation sharing. Furthermore, in line with the analysis of Martel et al. (2020), as all the significant estimates are positive in this study, the relevance of mood for the sharing behavior is based on its intensity, not its valence.

Another aspect of the mechanism is that mood and emotion effects on misinformation sharing are consistent for almost all negative emotions in both credibility conditions, except for disgust and sadness in the high credibility condition, where positive mood does not significantly influence them. An explanation of the differences observed between the group formed by anger, fear, and anxiety; and the group of disgust and sadness can be related to the type of negative emotions they represent. Using the core affect map (Russell & Barrett, 1999), the former group can be classified as high arousal, while the latter as low arousal; therefore, it can be argued that for high arousal emotions, both components of mood always influence them significantly, while low arousal emotions are influenced only by the negative dimension of mood in some scenarios.

Regarding the analysis of credibility for H2, the difference test shows that both conditions are significantly different, and the estimated values indicate that more credible misinformation in short videos has a more substantial positive impact on the relationship between negative emotions, moods, and content sharing. One possible explanation for this phenomenon can be associated with negativity bias, which suggests that ambiguous information is more likely to be perceived negatively (Rozin & Royzman, 2001). Therefore, when misinformation videos appear more plausible, the experience of negative emotions is likely to be intensified compared to when a video seems implausible or obviously fabricated. Additionally, considering that online content sharing behavior is influenced by both affective and cognitive factors (C. Kim & Yang, 2017), it is reasonable to conclude that the overall effect of negativity bias plays a significant role in increasing content sharing. Regarding positive emotions, the findings reveal a larger effect of happiness on content sharing in the low credibility condition. This result aligns with the understanding that easily debunked fake videos are unlikely to evoke strong negativity bias; instead, they might be perceived as ridiculous or amusing. Thus, such videos can increase individuals' happiness, significantly influencing their inclination to share content. Reflecting on these findings, it is evident that the increasing accessibility of technology for creating synthetic videos and images presents a growing concern about the potential societal impact of convincing deepfake videos on social media.

5.5.2 Visibility

The research question of this study sought to analyze the relationship between mood, emotions, and the level of visibility people choose to share short misinformation videos. The findings indicate that the conditions of the experiment are significantly different in terms of the effects of mood and emotions on visibility. For high credibility videos, only happiness increases the level of visibility significantly, while all other emotions and moods do not produce a relevant effect. On the other hand, for low credibility videos, positive mood and disgust significantly increase the visibility level. The appearance of disgust gives an interesting perspective on the role of low arousal emotions in communication. Even though most research has found that high arousal emotions play a more salient role in online information sharing, it can be argued that personal emotional experiences are a combination of various emotions that is more similar to a train of emotions instead of an easy-to-single-out emotion. In that scenario, it seems that low arousal emotions play a latent role that can trigger higher arousal emotions or behaviors and contribute to communicational interactions on social media. For example, previous results of this dissertation on Chapter 3 show that sadness can predict the appearance of anger and fear in the aftermath of earthquakes (Flores & Hilbert, 2023b) or that disgust triggers responses expressing more disgust in information cascades on Chapter 4 (Flores & Hilbert, 2023a), both of these behaviors involve public display of information.

Results about the positive and significant relationship between the level of visibility and the positive spectrum of mood can be explained by different reasons. Social information sharing in everyday life can involve potential risks, but these risks are often perceived as more significant when sharing occurs through social media platforms (Hasell & Nabi, 2023). Consequently, when disclosing information online, individuals generally consider their audience, trying to maintain authenticity while simultaneously engaging in selective self-presentation (Walther, 2007). Furthermore, the concept of context collapse, which refers to the fact that social media users have multiple audiences converging into a single environment (Marwick & boyd, 2011), also influences how people share information. Considering the circumstances of social media described, it makes sense that individuals are more prone to give higher visibility to content that makes them experience positive affective states; otherwise, they might portray a negative image to their audience.

5.5.3 Limitations

Different limitations should be considered when interpreting this study. First, the data collection method involved using a Qualtrics survey optimized for personal computers and laptops. While this optimization enabled participants to view the video stimuli on larger screens, given that a significant portion of social media engagement occurs through mobile applications (Silver et al., 2019), the study conditions might not fully capture the authentic user experience in real-life situations. This discrepancy between the study setting and typical social media consumption habits could potentially limit the validity of the findings. Future research should consider employing mobile-optimized surveys or developing dedicated mobile applications to more closely mimic real-world social media interactions and enhance the generalizability of the results.

Second, another limitation of the current study is its specific focus on misinformation within the context of the United States. The study's sample was drawn exclusively from the U.S. population, which may limit the generalizability of the findings to other cultural contexts. Misinformation, while a global phenomenon, can manifest differently across various cultures and countries due to differences in media landscapes, political systems, and societal norms. Therefore, extrapolating the results of this study to other contexts or cultures should be done with caution. Future research could benefit from conducting cross-cultural comparisons to investigate the potential variations in the spread and impact of emotions on misinformation across different societies.

5.6 Supplemental online material

An online repository with supplemental materials is available at https://osf.io/fsdjm/?view_only=1433578ac8ad4de9a2e87af99e126a75. The repository contains supplementary information, databases, and code for analysis.

Chapter 6: Conclusions

This dissertation develops three studies that collectively seek to contribute to understanding the complex interactions of online communication and information diffusion, with a particular focus on the role of emotions in these processes. Each study approaches the topic from a different perspective, using diverse theoretical frameworks and methodologies to understand human interactions on social media platforms. The studies build upon existing communication, psychology, and computational social science literature while introducing fresh methodological approaches to studying online emotional interactions.

The following sections of this conclusion chapter synthesize the key findings from the studies, discuss their methodological contribution, and propose directions for future research in this evolving field.

6.1 Research Findings

Chapter 3 examined the communication dynamics of emotional expressions on social media in the aftermath of large-scale upheavals. Using observational data from three earthquakes, the results suggest that while the duration of the stages varies between cases, the structural changes in the information shared on social media in the aftermath of catastrophic events align with the stages of Pennebaker's model (Pennebaker, 1993). A comparison between the Los Angeles and Mexico cases showed striking similarities, yet the Turkey case highlights the possibility of deviation in further replications. Regarding the analysis of emotions, sadness, and interest were the two most frequently expressed emotions in the aftermath of the earthquakes, both characterized in the core affect map (Russell & Barrett, 1999) by low arousal levels but contrasting valences—negative for sadness and positive for interest. Concerning the search for a predictive cycle of emotions, the results presented significant predictions mostly in the adaptation phase, where sadness and interest were the most repeated predictors. These findings illustrate the extension of a theoretical offline model to online communication using data from Twitter. Although three cases are not sufficient to prove a model in general, the replication shows consistency with some variability. Furthermore, the study sheds light on how emotions evolve and establish relationships in online interactions and how rapidly this process develops.

Chapter 4 studied passive and proactive online information sharing mechanisms, expanding the concepts of lean-back and lean-forward behavior used in online news consumption (Park & Kaye, 2018; Picone, 2007). Utilizing data extracted from Twitter across six cases divided into politics, earthquakes, and sporting events, the findings suggest that discrete emotions reveal differences between lean-back and lean-forward behaviors, with the arousal dimension being more relevant than valence in distinguishing between lean behaviors. There is also evidence that the categorical emotion intensity in lean-forward messages converges with that of lean-back messages, indicating the emergence of emotional synchronization and contagion. From the causal analysis of lean-forward messages, disgust displays a consistent interaction that triggers the creation of messages with more disgust across all cases. In parallel, anger also interacts with disgust, particularly in political discussions. The findings of Chapter 4 align with the notion that from a communicational perspective, emotional categories provide the necessary distinction to explain individuals' actions in more detail (Nabi, 2010). Regarding emotional cascades, studies typically separate cascades produced by replying (Chmiel et al., 2011; Dang-Xuan & Stieglitz, 2012; Goldenberg et al., 2020) and forwarding information (Alvarez et al., 2015; W. J. Brady et al., 2017). This study revises the coexistence of both lean behaviors in the same analysis, contributing to a more realistic assessment of the communication dynamics that produce emotional synchronization and contagion. Additionally, the preponderance of disgust in lean-forward messages again portrays the importance of low arousal emotions in online communication.

Chapter 5 examined a mechanism that simultaneously incorporates the effects of mood and emotions on misinformation sharing and visibility when individuals are exposed to short social media-like videos. Using a preregistered survey experiment with a single-factor design, the results suggest that mood and emotions play a joint role in the sharing process, with positive mood having both direct and indirect effects on sharing behavior. In contrast, negative mood influences sharing behavior mediated by negative emotions. Furthermore, more credible misinformation in short videos has a more substantial positive impact on the relationship between negative emotions, moods, and content sharing than less credible information. The level of visibility chosen for sharing information is influenced by positive mood and disgust in the low credibility condition, while only happiness significantly increases the level of visibility in the high credibility condition. The findings in Chapter 5 show that the relationship between affective states and misinformation sharing operates through an interrelated mechanism that clarifies previous results that have studied the influence of mood (Martel et al., 2020) and emotions (De Coninck et al., 2021; Greenstein & Franklin, 2020; Weeks, 2015) on misinformation without considering their combined effect. The preponderance of negative emotions in the sharing process with more credible information contributes to the evidence of negativity bias found previously in the misinformation literature (van Huijstee et al., 2022; Youngblood et al., 2023). Regarding the emotions-visibility relationship, this study also portrays the impact of low arousal emotions on the communication dynamics on social media, which has consistently appeared in the cases of Chapters 3 and 4.

Building upon the conceptual framework introduced in Chapter 1, Figure 6.1 illustrates the various aspects of the framework covered by each study in this dissertation. These studies investigate the relationship between emotions that drive information sharing and those emotions generated through the sharing process. Study 1 employs time series analysis and Granger-causality to establish the relationship between different emotions. Study 2 examines pre- and post-sharing emotions to identify differences in lean behaviors, while Study 3 utilizes a structural model to understand how emotions and moods influence misinformation sharing.

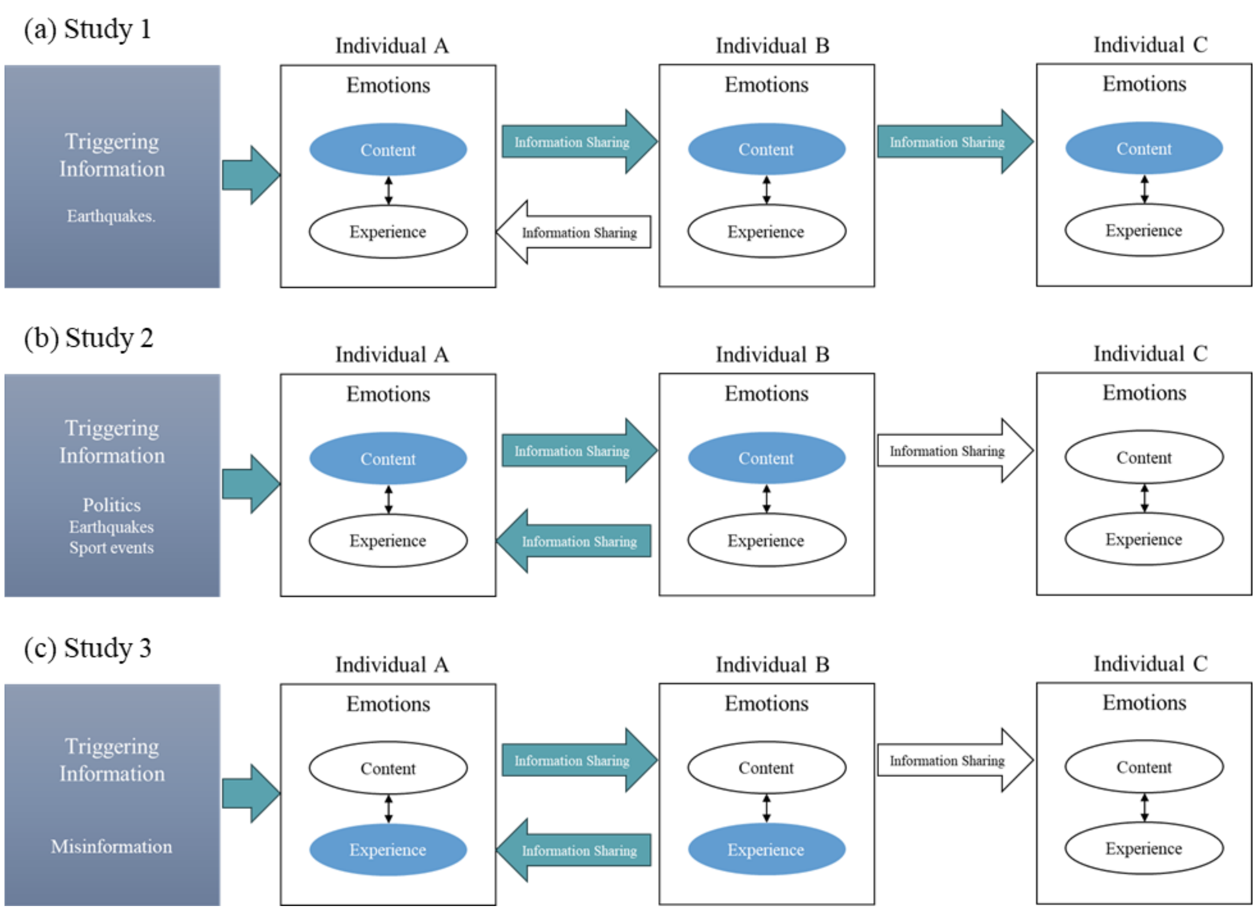

Figure 6.1 Conceptual framework applied to dissertation studies. Colored elements highlight aspects covered for each study.

From the complementary relationships of emotions as causes and effects across the studies in this dissertation, it is possible to uncover the important role of low arousal emotions, such as sadness, interest, and disgust, as drivers in information sharing. These emotions have shown that they can trigger the expression of higher-arousal emotions like anger. Existing literature has established a relationship between high arousal negative emotions and content virality (Berger, 2011; Berger & Milkman, 2012; Meng et al., 2018). However, the findings of this dissertation demonstrate how low arousal emotions complement the mechanisms of this process.

One explanation for these findings is that low arousal emotions can have a latent presence that motivates content sharing actions. Once online discussions intensify, high arousal emotions become more prominent as people feel the need to "shout to be heard." This process complements the descriptive findings of high-arousal emotions and virality by revealing a mechanism of information sharing that involves the role of low arousal emotions. These results fill the gap in understanding how emotions interact throughout the information sharing process and help explain the nuanced pathways through which different emotional states can contribute to spread information, particularly within the digital ecosystem.

6.2 Methodological Contribution

Chapter 2 provided a review of the causal analyses used in this dissertation. One of the objectives of using these specific analyses was to use a set of methodological tools that covered different levels of the concept of causation, advancing in incremental steps from the association with time-dependent variables in Chapter 3 to an experimental design with a mechanism in Chapter 5.

The first study showcases the potential of time series analysis and computational methods in extending traditional offline societal models to study online communication dynamics. The use of change point analysis and Granger-causality tests to unveil temporal patterns and associations highlights the importance of considering the temporal dimension in communication, as the interactions of interest in the discipline normally occur in continuous time. The time analysis topic has gained so much importance in communication that one of the flagship journals in the area, the Journal of Communication, made a special issue call named "Time in Communication Research and Theories" for March 2024 (*Journal of Communication*, n.d.). Even though Granger-causality cannot measure cause-effect processes, it does provide information about predictive structures, which is a necessary condition for the study of causality.

The second study portrays the value of observational data analysis mixed with causal inference techniques. Structural models, in the form of Structural Equation Models (SEM), have been used to study social science questions for a long time. The difference introduced by Structural Causal Models (SCM) is that SCM allows causal analysis with observational data as long as the model is founded on theoretical grounds and the proper set of assumptions is made explicit. SCM provides different criteria for making causal claims depending on the model analyzed. In the study of Chapter 4, the back-door criterion was used, but the front-door criterion or instrumental variables are available options for these types of analyses. The SCM approach underscores the potential of observational studies in making causal inferences and informing the design of interventions (Pearl & Mackenzie, 2018), which is important when, for ethical reasons, it is not possible to design experiments to measure causation.

In the case of the third study, the methodology employed exemplifies the relevance of developing mechanisms when designing experiments to establish causal relationships. It is common that, under the assumption of experiments removing confounder variables, the statistical analyses performed in research studies make comparisons between experimental conditions without considering other variables. However, I argue that these studies can be enriched by incorporating models in their analysis. In Chapter 5, the elaboration of a model proved that it is possible to combine different results of previous research into one to give a more integrative view of the phenomenon.

Finally, the data, code, and analyses of this dissertation are publicly available in online repositories to support the Open Science Framework (OSF). Sharing the materials through the OSF website allows other researchers to access, scrutinize, and build upon the work presented in this dissertation. By embracing the principles of Open Science, this dissertation demonstrates a commitment to transparency, reproducibility, and collaboration in social science research.

6.3 Future Directions

The findings and methodological approaches presented in this dissertation offer several avenues for future research in online communication and information diffusion. First, while the three case studies of earthquakes provide insights into the temporal dynamics of emotional expressions in the aftermath of large-scale upheavals, future research could expand the analysis to include a larger number of cases across different types of disasters and cultural contexts. A more extended dataset would allow for a more comprehensive understanding of the generalizability of Pennebaker's model in online environments and the potential influence of cultural factors on the expression and evolution of emotions in times of crisis.

Second, examining lean-back and lean-forward behaviors could be extended to other social media platforms and contexts. Future studies could investigate the emotional dynamics of lean behaviors in the context of health communication, marketing, or social movements, providing a more nuanced understanding of how emotions shape information diffusion across various domains. Additionally, researchers could explore the potential of combining the analysis of lean behaviors with network analysis techniques to uncover how the structural properties of social networks influence the spread of emotions and the emergence of emotional synchronization via lean-forward messages.

Third, the experimental study could serve as a foundation for future research on the interplay between mood, emotions, and the spread of any type of information, as misinformation is only a particular case. Using the model as a base to add modifications, scholars could incorporate additional factors, such as individual differences, media literacy, or political ideology, to develop a more comprehensive model of information sharing behavior. Additionally, future studies could explore the effectiveness of interventions designed to mitigate the spread of misinformation by targeting the emotional and cognitive processes identified in this dissertation.

Declaration of AI-assisted Technologies in the Writing Process

During the preparation of this work, the author used ChatGPT-4 and Claude.AI to clarify some paragraphs of this dissertation. After using this tool/service, the author reviewed and edited the content as needed. The author takes full responsibility for the content of the dissertation.

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Appendix A

Table A1.

Complete results of Granger causality tests for LA earthquake.

		Emergency		Inhibition A		Inhibition B		Adaptation	
Predictor	Causes	Chisq	p	Chisq	p	Chisq	p	Chisq	p
fear	anger	5.62	.229	0.00	.952	1.84	.175	0.30	.861
fear	disgust	5.63	.228	0.00	.960	4.62	**.032***	1.66	.436
fear	sadness	7.73	.102	0.01	.914	5.92	**.015***	2.82	.244
fear	joy	2.90	.574	0.43	.511	0.56	.456	2.41	.299
anger	fear	4.54	.338	0.30	.587	0.37	.544	0.84	.658
anger	disgust	3.82	.430	0.14	.708	1.77	.183	1.72	.424
anger	sadness	8.25	.083	0.02	.895	1.96	.162	1.39	.499
anger	joy	6.15	.188	0.47	.495	2.04	.153	0.04	.978
disgust	fear	9.91	**.042***	2.44	.118	0.01	.925	0.51	.774
disgust	anger	5.30	.258	0.37	.540	3.87	**.049***	1.16	.561
disgust	sadness	14.73	**.005***	0.30	.583	1.03	.310	4.66	.097
disgust	joy	7.20	.126	0.21	.650	1.80	.179	3.59	.166
sadness	fear	2.30	.680	0.61	.433	4.03	**.045***	5.10	.078
sadness	anger	2.11	.715	0.57	.451	0.00	.999	2.30	.317
sadness	disgust	4.03	.402	1.31	.253	1.28	.259	8.31	**.016***
sadness	joy	4.62	.328	0.62	.431	0.44	.505	4.51	.105
joy	fear	3.99	.407	0.52	.470	1.46	.226	23.07	**.000***
joy	anger	1.55	.818	3.84	**.050***	3.24	.072	17.20	**.000***
joy	disgust	7.06	.133	2.39	.122	1.96	.162	19.85	**.000***
joy	sadness	10.10	**.039***	1.77	.184	4.01	**.045***	25.73	**.000***

Note: * significant results ($p < .05$)

Table A2.

Complete results of Granger causality tests for Mexico earthquake.

		Emergency		Inhibition A		Inhibition B		Adaptation	
Predictor	Causes	Chisq	p	Chisq	p	Chisq	p	Chisq	p
fear	anger	1.64	.440	0.15	.696	0.54	.462	15.18	**.002***
fear	disgust	11.70	**.003***	0.28	.597	0.10	.746	4.49	.214
fear	sadness	5.01	.082	0.09	.761	0.53	.465	6.55	.088
fear	joy	5.95	**.051***	0.10	.753	2.00	.158	8.23	**.041***
anger	fear	0.46	.793	0.45	.503	2.41	.120	1.58	.664
anger	disgust	0.40	.818	0.02	.892	3.56	.059	0.18	.981
anger	sadness	0.02	.989	0.38	.539	1.20	.273	2.94	.402
anger	joy	1.55	.461	0.18	.668	0.02	.901	3.72	.294
disgust	fear	0.07	.967	0.01	.934	0.13	.718	5.52	.138
disgust	anger	0.56	.756	0.22	.640	0.22	.642	3.99	.263
disgust	sadness	0.28	.871	1.01	.314	0.19	.666	6.58	.086
disgust	joy	0.14	.931	0.68	.408	0.45	.501	3.56	.313
sadness	fear	0.44	.801	0.00	.954	2.93	.087	5.04	.169
sadness	anger	11.25	**.004***	0.17	.677	1.47	.226	15.84	**.001***
sadness	disgust	5.30	.071	0.67	.413	1.08	.299	11.28	**.010***
sadness	joy	0.07	.968	1.95	.163	1.28	.258	3.41	.332
joy	fear	2.28	.320	4.67	**.031***	0.08	.775	19.69	**.000***
joy	anger	5.12	.077	0.02	.884	0.47	.492	38.48	**.000***
joy	disgust	3.06	.217	0.06	.814	0.36	.548	28.66	**.000***
joy	sadness	6.17	**.046***	0.45	.501	0.27	.605	9.07	**.028***

Note: * significant results ($p < .05$)

Table A3.

Complete results of Granger causality tests for Turkey earthquake.

		Emergency		Inhibition A		Inhibition B		Adaptation	
Predictor	Causes	Chisq	p	Chisq	p	Chisq	p	Chisq	p
fear	anger	2.44	.295	1.81	.772	1.49	.222	8.26	.310
fear	disgust	0.95	.623	4.20	.380	2.31	.128	11.30	.126
fear	sadness	2.65	.266	4.30	.367	1.28	.258	9.85	.197
fear	joy	3.39	.183	14.34	**.006***	0.21	.650	6.64	.467
anger	fear	0.28	.867	1.11	.893	1.12	.289	5.50	.600
anger	disgust	0.65	.722	2.70	.609	0.87	.352	3.50	.835
anger	sadness	0.11	.947	2.04	.729	1.43	.231	5.83	.560
anger	joy	2.84	.241	3.62	.460	0.50	.478	5.11	.647
disgust	fear	2.13	.344	5.79	.215	0.17	.678	8.36	.302
disgust	anger	4.99	.082	2.80	.592	0.35	.556	22.74	**.002***
disgust	sadness	0.97	.616	6.37	.173	0.18	.673	17.96	**.012***
disgust	joy	2.11	.348	6.08	.193	0.70	.402	7.59	.370
sadness	fear	0.51	.776	5.82	.213	0.07	.787	19.23	**.008***
sadness	anger	3.12	.210	8.34	.080	1.21	.272	14.54	**.042***
sadness	disgust	1.15	.562	2.23	.693	0.18	.672	15.80	**.027***
sadness	joy	1.09	.581	3.35	.501	0.43	.511	9.80	.200
joy	fear	4.22	.121	1.47	.832	0.33	.565	6.56	.476
joy	anger	0.85	.653	1.15	.886	1.14	.285	8.96	.256
joy	disgust	0.84	.658	4.67	.322	1.25	.264	4.08	.770
joy	sadness	0.88	.645	3.26	.516	2.68	.102	5.51	.597

Note: * significant results ($p < .05$)

Table A4.

The number of lags for VAR models.

	Emergency	Inhibition		Adaptation
Case		A	B	
LA	3	1	1	4
Mexico	2	1	1	5
Turkey	1	1	1	7

Appendix B

Table B1.

Emotional intensity difference between lean-forward and lean-backward behaviors.

	Lean-forward (qt)		Lean back (rt)					Cohen's	
	M	SD	M	SD	95% CI	*t*	*p*	*d*	95% CI
JB - fear	0.08	0.05	0.06	0.06	[0.02, 0.02]	26.43	< .001	0.38	[0.35, 0.41]
JB - anger	0.11	0.08	0.07	0.07	[0.03, 0.04]	33.76	< .001	0.56	[0.52, 0.59]
JB - disgust	0.10	0.07	0.18	0.14	[-0.08, -0.07]	-49.14	< .001	-0.57	[-0.65, -0.54]
JB - sadness	0.24	0.11	0.22	0.14	[0.01, 0.02]	11.31	< .001	0.16	[0.13, 0.19]
JB - joy	0.27	0.11	0.30	0.21	[-0.03, -0.02]	-9.79	< .001	-0.13	[-0.16, -0.1]
JJ - fear	0.07	0.04	0.05	0.05	[0.01, 0.02]	14.15	< .001	0.37	[0.32, 0.43]
JJ - anger	0.11	0.08	0.07	0.08	[0.04, 0.05]	20.24	< .001	0.59	[0.53, 0.65]
JJ - disgust	0.18	0.12	0.31	0.20	[-0.14, -0.12]	-30.66	< .001	-0.73	[-0.79, -0.67]
JJ - sadness	0.20	0.10	0.18	0.13	[0.01, 0.02]	5.18	< .001	0.13	[0.07, 0.19]
JJ - joy	0.27	0.15	0.29	0.21	[-0.02, 0.00]	-2.91	.003	-0.07	[-0.13, -0.02]
LA - fear	0.17	0.13	0.18	0.15	[-0.02, 0.00]	-1.93	.054	-0.07	[-0.15, 0.01]
LA - anger	0.08	0.07	0.06	0.07	[0.01, 0.02]	6.26	< .001	0.25	[0.17, 0.32]
LA - disgust	0.05	0.04	0.09	0.08	[-0.04, -0.03]	-16.80	< .001	-0.50	[-0.58, -0.43]
LA - sadness	0.21	0.01	0.24	0.14	[-0.04, -0.02]	-6.47	< .001	-0.23	[-0.31, -0.15]
LA - joy	0.39	0.18	0.34	0.20	[0.03, 0.06]	6.09	< .001	0.23	[0.15, 0.3]
NZ - fear	0.21	0.13	0.21	0.14	[-0.03, 0.01]	-0.63	.523	-0.05	[-0.22, 0.12]
NZ - anger	0.05	0.05	0.03	0.03	[0.01, 0.03]	5.37	< .001	0.62	[0.45, 0.79]
NZ - disgust	0.03	0.04	0.05	0.05	[-0.03, -0.01]	-5.75	< .001	-0.42	[-0.59, -0.25]
NZ - sadness	0.25	0.13	0.26	0.14	[-0.04, 0.01]	-1.28	.203	-0.10	[-0.27, 0.07]
NZ - joy	0.33	0.18	0.32	0.17	[-0.02, 0.04]	0.71	.477	0.06	[-0.1, 0.23]
N20 - fear	0.06	0.05	0.06	0.05	[-0.00, 0.00]	-0.55	.579	-0.01	[-0.06, 0.03]
N20 - anger	0.07	0.07	0.06	0.06	[0.01, 0.02]	10.77	< .001	0.27	[0.22, 0.31]
N20 - disgust	0.09	0.07	0.12	0.08	[-0.03, -0.02]	-16.46	< .001	-0.36	[-0.41, -0.32]
N20 - sadness	0.21	0.13	0.25	0.14	[-0.05, -0.03]	-12.92	< .001	-0.30	[-0.34, -0.25]
N20 - joy	0.47	0.21	0.45	0.21	[0.01, 0.03]	3.92	< .001	0.09	[0.05, 0.14]
N21 - fear	0.07	0.07	0.07	0.08	[-0.01, -0.00]	-2.02	.043	-0.05	[-0.1, 0]
N21 - anger	0.07	0.07	0.06	0.06	[0.00, 0.01]	5.15	< .001	0.14	[0.09, 0.2]
N21 - disgust	0.10	0.07	0.13	0.09	[-0.04, -0.03]	-15.51	< .001	-0.38	[-0.43, -0.32]
N21 - sadness	0.19	0.13	0.23	0.14	[-0.04, -0.03]	-9.89	< .001	-0.25	[-0.3, -0.2]
N21 - joy	0.48	0.21	0.45	0.22	[0.03, 0.05]	6.66	< .001	0.18	[0.12, 0.23]

Table B2.

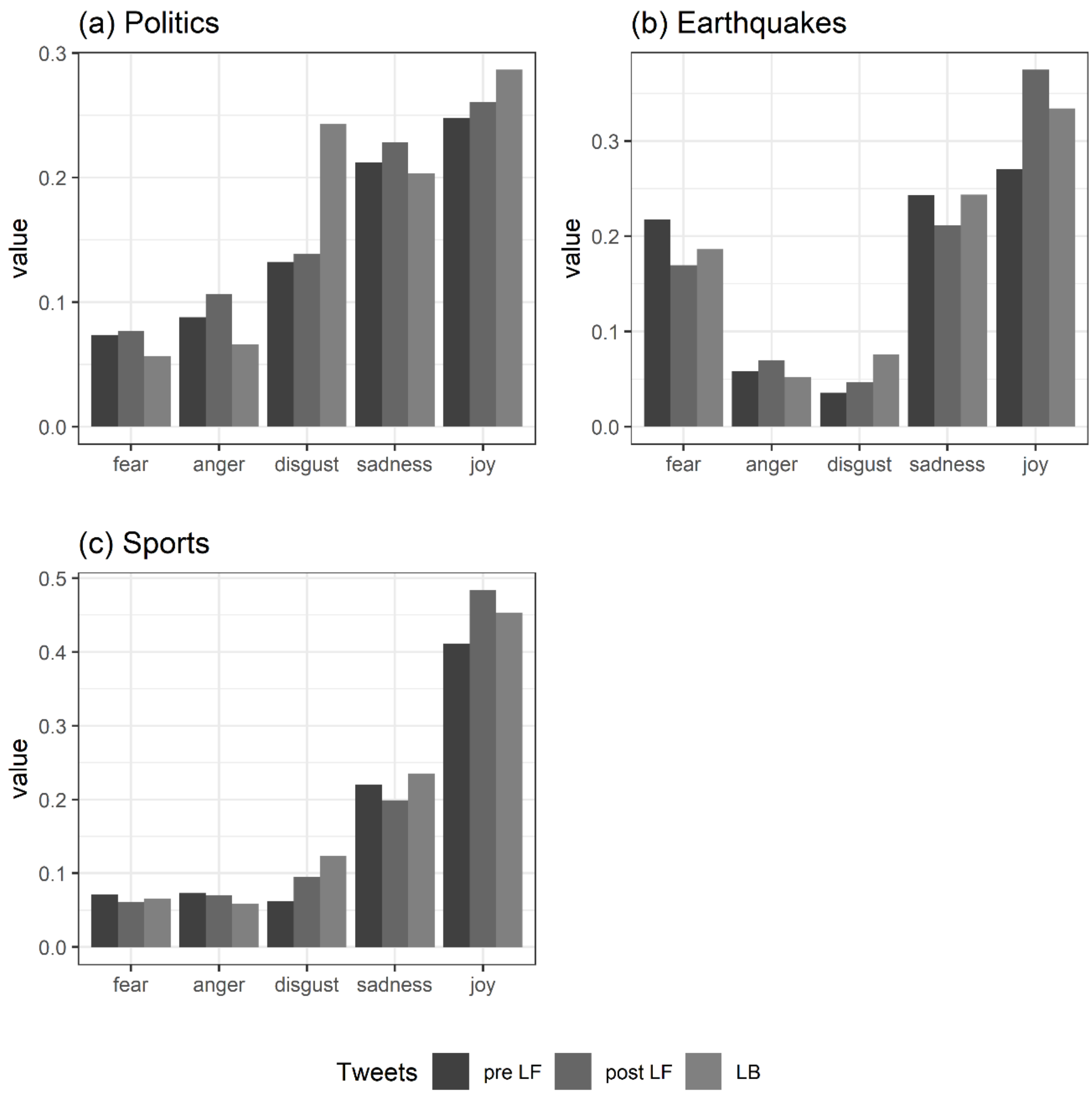
Standard estimates for SCM by topic: politics, earthquakes, and sports.

	β politics	p value pol	β eartquakes	p value ethq	β sports	p value spo
fear → M	0.11	.148	-0.08	.281	-0.09	.276
ang → M	0.21	**.002**	0.13	.097	0.07	.336
dis → M	-0.31	**.000**	-0.28	**.000**	-0.22	**.005**
sad → M	-0.01	.534	-0.11	.160	-0.18	.058
joy → M	-0.10	.219	0.02	.534	-0.08	.313
M → fear	0.14	.034	0.10	.166	0.04	.331
M → ang	0.15	.033	0.05	.314	0.11	.107
M → dis	-0.32	**.000**	-0.35	**.000**	-0.37	**.000**
M → sad	0.03	.468	0.00	.555	-0.05	.339
M → joy	-0.10	.129	-0.17	**.006**	-0.10	.155
fear → fear	0.02	.192	-0.01	.450	0.00	.553
fear → ang	0.02	.199	0.00	.510	-0.01	.350
fear → dis	-0.03	.153	0.03	.286	0.03	.280
fear → sad	0.00	.529	0.00	.641	0.00	.515
fear → joy	-0.01	.261	0.01	.310	0.01	.427
ang → fear	0.03	.052	0.01	.266	0.00	.512
ang → ang	0.03	.051	0.01	.363	0.01	.390
ang → dis	-0.07	**.004**	-0.04	.101	-0.03	.340
ang → sad	0.01	.481	0.00	.589	0.00	.548
ang → joy	-0.02	.151	-0.02	.128	-0.01	.436
dis → fear	-0.04	.041	-0.03	.175	-0.01	.351
dis → ang	-0.05	.039	-0.01	.323	-0.02	.132
dis → dis	0.10	**.000**	0.10	**.000**	0.08	**.007**
dis → sad	-0.01	.474	0.00	.559	0.01	.356
dis → joy	0.03	.139	0.05	.010	0.02	.181
sad → fear	0.00	.549	-0.01	.344	-0.01	.388
sad → ang	0.00	.552	-0.01	.441	-0.02	.179
sad → dis	0.00	.537	0.04	.165	0.07	.061
sad → sad	0.00	.685	0.00	.621	0.01	.385
sad → joy	0.00	.570	0.02	.194	0.02	.236
joy → fear	-0.01	.270	0.00	.614	0.00	.543
joy → ang	-0.01	.276	0.00	.659	-0.01	.394
joy → dis	0.03	.225	-0.01	.537	0.03	.316
joy → sad	0.00	.556	0.00	.717	0.00	.545
joy → joy	0.01	.320	0.00	.548	0.01	.413

Note. A → B denotes the effect of A on B. We are using a fully mediated model. Then, the effect (fear → fear) is computed as (fear → M) x (M → fear). M (dichotomic) represents lean-forward (lean-back) if equals 1 (0). In bold p values < .008 for a familywise significance level of .05.

Figure B1.

Average level of emotions for lean-back and lean-forward behaviors.



Note. For each topic under analysis from left to right, the bars represent the average level of emotion for the pre-lean-forward tweets (pre LF), post-lean-forward tweets

Appendix C

Table 5.1

Structural Model coefficients for low and high credibility fake news grouped by emotion.

	Low credibility		High credibility		χ^2 Diff
	β	p-value	β	p-value	
Pos Mood → Anger	**0.120**	.002	**0.099**	0.044	
Neg Mood → Anger	**0.113**	.001	**0.216**	0.000	
Anger → Share	**0.157**	.000	**0.313**	0.000	49.01*
Pos Mood → Share	**0.153**	.003	**0.171**	0.001	
Neg Mood → Share	0.059	.168	0.016	0.745	
Pos Mood → Disgust	**0.129**	.003	0.100	0.064	
Neg Mood → Disgust	**0.135**	.003	**0.224**	0.001	
Disgust → Share	**0.113**	.017	**0.269**	0.000	99.81*
Pos Mood → Share	**0.157**	.003	**0.175**	0.000	
Neg Mood → Share	0.062	.160	0.023	0.637	
Pos Mood → Fear	**0.193**	.000	**0.161**	0.001	
Neg Mood → Fear	**0.193**	.000	**0.297**	0.000	
Fear → Share	**0.219**	.000	**0.250**	0.000	36.26*
Pos Mood → Share	**0.130**	.011	**0.162**	0.001	
Neg Mood → Share	0.035	.413	0.009	0.864	
Pos Mood → Anxiety	**0.174**	.001	**0.103**	0.045	
Neg Mood → Anxiety	**0.237**	.000	**0.344**	0.000	
Anxiety → Share	**0.158**	.004	**0.329**	0.000	40.33*
Pos Mood → Share	**0.144**	.005	**0.168**	0.001	
Neg Mood → Share	0.039	.365	-0.030	0.548	
Pos Mood → Sadness	**0.203**	.000	0.097	0.089	
Neg Mood → Sadness	**0.126**	.007	**0.237**	0.000	
Sadness → Share	**0.112**	.025	**0.276**	0.000	28.62*
Pos Mood → Share	**0.149**	.004	**0.175**	0.000	
Neg Mood → Share	0.063	.139	0.017	0.720	
Pos Mood -> Happiness	**0.282**	.000	**0.303**	0.000	
Neg Mood -> Happiness	0.052	.182	-0.022	0.657	
Happiness -> Share	**0.224**	.000	**0.123**	0.012	36.71*
Pos Mood -> Share	**0.109**	.031	**0.165**	0.001	
Neg Mood -> Share	0.065	.135	0.086	0.074	

Note: * p < .05

Figure C1

Pairwise comparison videos selected as stimuli.

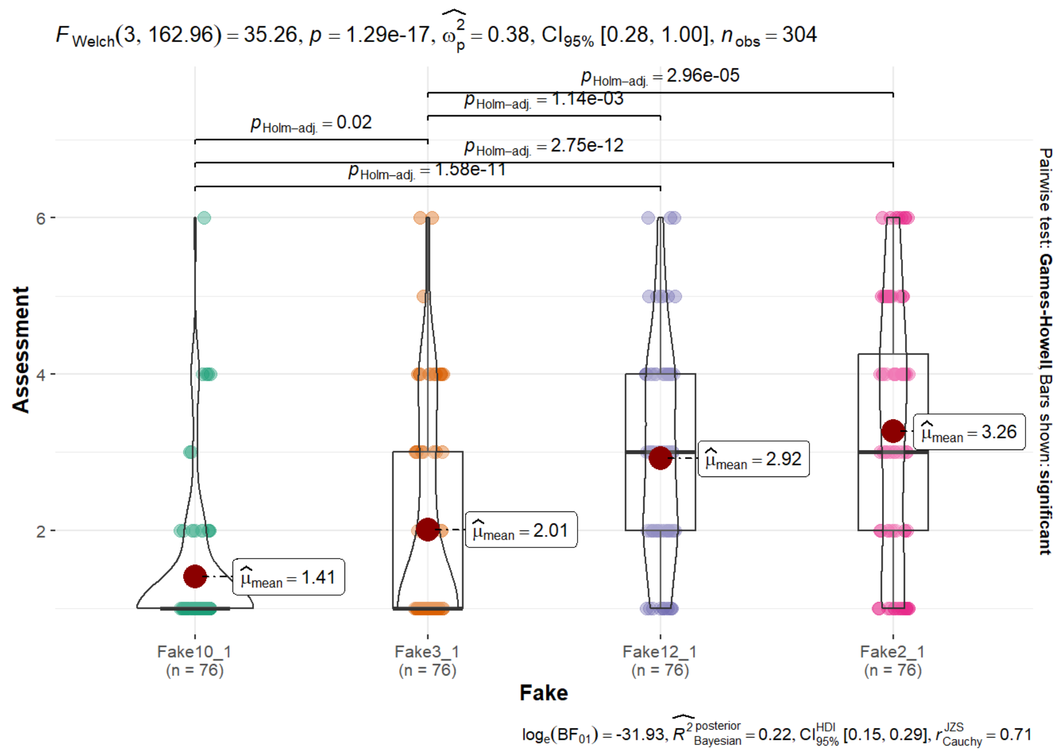
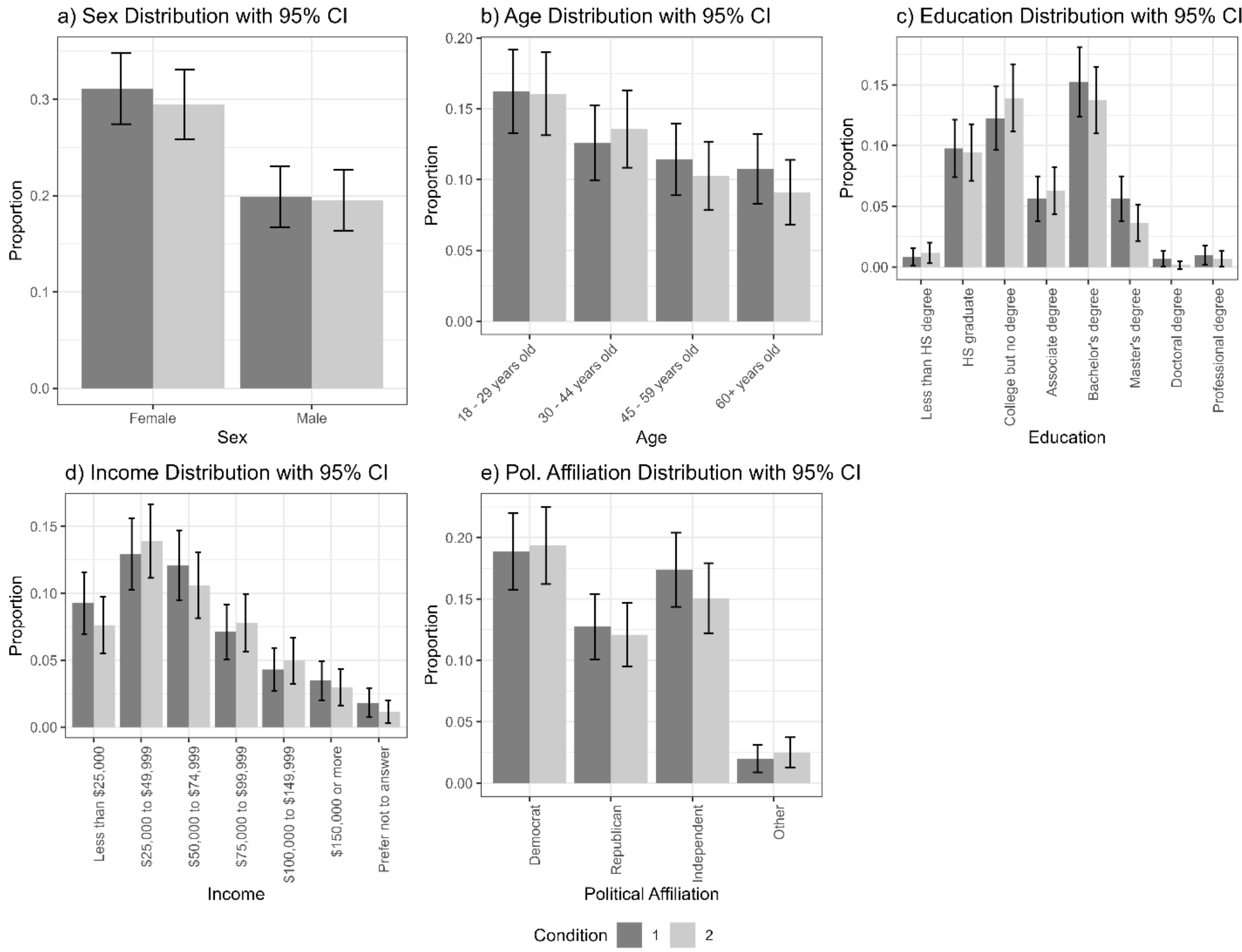


Figure C2

Distribution of Demographics Variables by Experimental Condition



Note. Condition 1 refers to low credibility videos, and condition 2 refers to high credibility videos