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RESEARCH ARTICLE

Influence of emotions on coping behaviors in crisis: a computational analysis of the COVID-19 outbreak

Hao Xu[1] · Smitha Muthya Sudheendra[2] · Jisu Huh[3] · Aadesh Salecha[4] · Jaideep Srivastava[2]

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Abstract

Widespread public crises often give rise to the proliferation of sensationalized rumors and conspiracy theories, which can evoke a variety of public emotions. Despite the growing importance of research on the relationship between emotions and coping behaviors in crisis, a dearth of natural observation-based investigation has been limiting theory development. To address this gap, this study conducted computational research to study the U.S. public's discrete emotions and coping behaviors during the COVID-19 outbreak crisis, analyzing Twitter data, Google Trends data, and Google Community Mobility data. The results revealed that anger and fear were relatively more prominent emotions experienced by the public than other discrete emotions. Regarding the impacts of emotions on coping behaviors, it was found that the prevalence of low-certainty and retreat emotions was related to increased information-seeking and information-transmitting behaviors. Also, the prevalence of both high-certainty and low-certainty emotions during the COVID-19 outbreak was positively related to the public's compliance with public health recommendations.

Keywords Public health crisis · Crisis communication · Discrete emotions · Coping behaviors · Data mining

Introduction

Public health crises, especially infectious disease outbreaks, can not only pose severe threats to the health of the population but also endanger social well-being [1], as evident in the Ebola and Zika and the most recent COVID-19 pandemic. Related threat perceptions encompass not only individuals' concerns about their susceptibility to contracting the disease but also widespread societal concerns about how governmental, non-governmental, and international organizations take measures to deal with the crises and communicate with the public [2]. Public health crises also often

Extended author information available on the last page of the article

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give rise to the proliferation of sensationalized rumors and conspiracy theories [3, 4]. These factors together can evoke a variety of public emotions, which would have a significant impact on how the public behaviorally cope with the crises.

In crises, emotions function as "one of the anchors of the publics' interpretation of the unfolding and evolving events" [5, p. 268]. According to psychological research on stresses of harm or loss, there is a common tendency for people in crises to act on their emotions and take emotion-corresponding actions to cope with stressful events [6]. In major public health crises caused by infectious diseases, for example, emotions and emotion-based information, fueled by the infectious nature of the diseases, have the potential to quickly spread across a broad population [7], and could influence people's various coping behaviors [8]. Given the critical importance of people's communicative behaviors sharing information and disease-prevention behaviors in saving lives during public health crises, it is imperative to build a solid understanding of how the general public emotionally react to a public health crisis and how their emotions influence their coping behaviors.

Research on the role of emotions has flourished in the fields of risk communication (e.g., the anger activism model [9]), crisis communication (e.g., the integrated crisis mapping model [5]), and health communication (e.g., the extended parallel process model [10]), but the extant research literature has several limitations. First, while most studies have considered emotions as individuals' responses to be managed in the public health crisis context, which mainly focuses on high variability in intensity and type of emotions (e.g., [11, 12]), research on emotions as a collective public reaction that prevails across a large population in a public health crisis, along with large-scale behavioral changes at the national or global level, is only starting to emerge (e.g., [13, 14]).

Second, most of the extant research has studied crises or risk events as a single incident, each of which can induce one discrete emotion. However, public health crises like pandemics unfold over extended periods, potentially evoking complex, layered emotional landscapes. As argued by Coombs et al. [15], prolonged crises can trigger diverse emotions, which constantly "affect how people interpret the crisis and react to the organization's efforts to manage the crisis" (p. 176). Additionally, emotions in these prolonged situations are likely to change and fluctuate over time. Studies like Lu and Huang [16] highlight the interplay between people's cognitive information processing and emotions during crisis, suggesting that coping behaviors may evolve alongside shifting emotional states. This dynamism, particularly relevant in long-term, multi-stage public health crises [17], demands research that captures the fluidity of changing emotions and their influence on behaviors.

In addition, while prior crisis communication studies have used experimental or survey methods to examine people's emotions and behavioral intentions using self-report measurements and hypothetical scenarios (e.g., [18, 19]), real-world evidence has been lacking on the relationship between public emotions and behaviors. This limitation is echoed in the work of Van Bavel et al. [20], who emphasize the need for empirical studies with real-life data that capture dynamic emotional responses in public health crises. These gaps in the research literature call for further research with different methodological approaches that can directly and unobtrusively examine the emotion-behavior relationship in a real-world public health crisis context.

Answering this call, this research utilizes a combination of robust computational methods to examine the public's evolving discrete emotional reactions to the COVID-19 outbreak crisis in the U.S. and the impacts of such emotions on their communicative coping behaviors, including information-seeking and transmitting, and protective behaviors. During the COVID-19 pandemic, a lot of human interactions and communications have shifted to online and social media, which has generated an enormous amount of naturally occurring social media data and an unprecedented opportunity to examine the emotion-behavior relationships in a real-life setting. By adopting a computational research approach to cross-analyze social media data, Google Trends data, and Google Community Mobility data, and obtain proxy measures of public emotions as well as communicative and protective behaviors, this study aims to enhance our knowledge of the public's changing collective emotions in prolonged public crisis situations and consequences of such emotions, and to advance the application of computational methods in research on emotions in crisis.

Literature review and hypotheses

Discrete emotions in public health crises

Research has identified a wide range of discrete emotions relevant to risk, crisis, and disaster situations (e.g., [6, 21]). To systematically examine people's emotional reactions to crises, the cognitive appraisal approach has been frequently used by risk and crisis communication researchers (e.g., [11, 22]). The cognitive appraisal approach defines emotions as "organized cognitive-motivational-relational configurations whose status changes with changes in the person-environment relationship as this is perceived and evaluated" [6, p. 38]. In other words, emotion is a mental state emerging from the appraisal of one's environment. In previous studies on people's reactions to public health crises in particular, Jin et al. [8] built upon Smith and Ellsworth's [23] categorization of discrete emotions and suggested three cognitive appraisal dimensions that can capture the unique nature of public health crises: predictability, controllability, and responsibility. This study, thus, relies on these three appraisal dimensions to understand people's emotions in public health crises.

Predictability refers to "the extent that an individual can predict what is happening in a risk or crisis situation" [8, p. 248]. In public health crises, perceived predictability is often influenced by the novelty of the disease and the sufficiency of information [24]. People can form either positive or negative appraisal of uncertainty, and how people appraise an uncertain event is associated with different corresponding emotions [25]. If one holds negative appraisal, negative emotions, such as anxiety and fear, are likely to occur. If one holds positive appraisal, positive emotions are likely to occur. In addition, if one believes the occurrence of the event is irrelevant to them, they would likely show neutral emotions, such as indifference [25, 26]. In a worldwide public health crisis like the COVID-19 pandemic which affects everyone, it can be expected that most people would likely appraise the outbreak situation as relevant and negative and thus widely experience negative emotions.

Controllability reflects people's perception that there is human agency to cope with the situation [8]. In public health crises, the controllability perception is often influenced by the possibility and availability of treatments or prevention. Novel diseases with high severity, coupled with inadequate information disclosure and management, usually lead to a high level of perceived uncontrollability [27]. At the outbreak stage of the COVID-19 pandemic, there was no effective vaccine to prevent the spread of the disease and no effective treatment. Even diagnosis was insufficient for a long time, making it difficult to determine conclusively that an individual carries the virus. According to Jin's [28] findings, in crisis situations with low controllability, individuals are likely to have negative emotions, such as fear, anger, and sadness. Especially when low controllability is combined with low predictability, fear would likely be most prevalently experienced [28].

Responsibility refers to "the extent to which oneself, or someone or something else, is responsible for bringing about the event that arouses emotion, and the legitimacy or fairness of the outcome" [23, p. 819]. Responsibility in public health crises contains two facets, including cause-related responsibility and solution-related responsibility [8]. On the one hand, in the crisis communication literature, the concept of responsibility centers on individuals or organizations responsible for the cause of a crisis event. In the case of the COVID-19 outbreak, the origin of the virus and possible early patients were prevalent topics that attracted much media attention. Existing research has shown that higher responsibility for causing a crisis is strongly related to negative emotions, such as anger, disgust, and contempt [29].

On the other hand, in the public health literature, the concept of responsibility focuses more on who is responsible for the solution of a disease, as most health-related issues require increased responsibility from the government and public healthcare institutions [30, 31]. Individuals may feel grateful or appreciative and have decreased negative emotions when the government and healthcare professionals take responsibility for addressing the crises [32]. However, if a public health crisis is not handled well, authoritative organizations may invariably become the object of blame for not preventing it from happening, which, in turn, can lead to prevalent anger among the public [33].

In general, predictability, controllability, and responsibility appraisals would work together to determine people's discrete emotions in public health crises. During public health crises, people are likely to experience a range of different negative emotions like anger, fear, and sadness. Moreover, the relative prevalence of each discrete emotion may change as the crisis evolves and would likely be determined by how the specific events in the crisis period are appraised. Importantly, emotions are not just individual feelings, but can be a collective property [34, 35]. In the research literature, collective emotion and cognition within a crisis has been defined as a "strong" emergent state, which rises from cognitions and emotions at the individual level and endures for a certain period of time [36]. Specifically, Dionne et al. [37] suggested a *convergence* process, which describes a bottom-up transition whereas an information-processing function shifts from the individual level to the group level. In this process, appraisals of events are shared in a group of people, and shared appraisals give rise to the specific emotions that are felt by the group [38]. Hence, it can be expected that similar to individuals' appraisals, groups and collectives appraise whether a crisis event is predictable (i.e., predictability perceptions) or is controllable by humans (i.e., controllability perceptions), and assess who should bear responsibility (i.e., responsibility perceptions). These appraisals by the collective can also lead to collective emotions in crisis.

Thus, focusing on collective emotions, this study explores the following research question:

RQ1 What were the primary negative emotions experienced by the public when the COVID-19 pandemic broke out and how did the emotions change as the crisis situation evolved?

Impacts of emotions on coping behaviors

During crises, the public would engage in a variety of behaviors, as they try to reduce the perceived risk and their likelihood of being affected by the crises. After initial exposure to information about a public health crisis, people often engage in additional information-seeking and sharing behaviors, so as to understand or help others understand the situation and cope with the threats [18, 39]. Also, when faced with a public health crisis, individuals make decisions on whether or not to comply with the protective actions recommended by the government and public health organizations [4, 40].

Emotions can have profound impacts on people's decision-making and communicative behaviors [41]. Given its widespread impact, COVID-19 is a significant event that can elicit shared emotions across a large population. While cognitive appraisal is traditionally viewed as an individual-level appraisal, groups and/or collectives appraise events as well [37, 42]. Researchers further suggested that emotions can not only be collectively felt but also influence collective behaviors [35]. Although current research on crisis emotions mostly draws on individual-level theories to predict individuals' crisis coping behaviors (e.g., [5, 11, 22]), Lichtenstein [36] suggested that collective emotion can exert downward causal effects on human behaviors at the collective level, following the same trajectory as seen in individuals. Hence, we borrow insights from existing literature on individual crisis emotions and coping behaviors to inform the development of hypotheses on emotions and behavioral reactions at the collective level in the COVID-19 outbreak.

The Appraisal Tendency Framework (ATF), as proposed by Lerner and Keltner [43], offers a comprehensive approach to understanding how discrete emotions influence individuals' behavioral coping mechanisms. This framework is particularly relevant to the current study as it provides a nuanced understanding of how different discrete emotions, such as fear, anger, or sadness, each with their appraisal tendencies, can lead to varied coping behaviors. According to the ATF, first, discrete emotions arise from how different situations are appraised by individuals, which is driven by different "appraisal themes" underlying specific events [6]. Second, the emotions evoked in the initial events would be carried over to subsequent events and determine the cognitive patterns of how emotions would influence sequential cognitive and conative coping [43].

Compared to the other related theories based on the valence-based approach, focusing on whether an individual is experiencing a positive versus negative mood or emotion and its impacts, the ATF offers a more nuanced explanation of the relationship between specific discrete emotions and behavioral reactions [44, 45]. As the ATF suggests, discrete emotions of the same valence (e.g., fear, anger, etc.) can have different effects on subsequent judgments and behaviors [46]. Moreover, the ATF also captures the dynamic nature of emotions, recognizing that emotions do not exist in isolation and in a static manner but are influenced by people's ongoing assessment of a situation [44]. Empirical studies utilizing ATF have demonstrated its applicability in crisis contexts similar to this research (e.g., [11, 22]). For instance, in a survey, Feng and Tong [47] showed how specific emotions, like fear and anxiety, influence people's preventive behaviors during COVID-19. Applying the ATF, the following subsections discuss the mechanism underlying the potential impact of different discrete emotions on the public's information and compliance behaviors during crises and review relevant research literature, leading to hypotheses.

Impact on information-seeking behavior

As mentioned above, different discrete emotions are related to different levels of perceived certainty. In crisis, uncertainty can arise among the public, especially when individuals face existential threats [6] or think authoritative information disclosure to be inadequate or even mistaken to help them cope with the crisis [27]. Certainty arises when individuals have somewhat reliable knowledge about the involved organization accountable for the harm, or that the situation could, to a large extent, be predictable as it evolves [23]. Smith and Ellsworth [23] identified two contrasting sets of emotions that can be grouped by high versus low perceived certainty, characterized by the different levels of perceived clarity and confidence people have in their appraisal of a specific situation. Accordingly, anger is considered a high-certainty emotion, which can be induced when individuals feel certain about the situation, whereas fear and sadness are considered low-certainty emotions induced by uncertainty about the situation [23].

In the public health crisis context, information-seeking is considered the primary communicative action that people take to address uncertainty [4]. According to the ATF and the uncertainty management theory, if uncertainty is appraised as relevant and negative, leading to negative discrete emotions like fear or anxiety, individuals are likely to try to reduce the uncertainty subsequently [26, 43]. As a result, in a long-lasting public health crisis, people with low-certainty emotions (e.g., fear and sadness) would be more motivated to understand the ongoing situation and thus actively seek relevant information in order to gain a sense of certainty [26]. On the contrary, high-certainty emotions (e.g., anger) are related to individuals' high confidence about ongoing situations [48], and thus they are likely to lead to a lower level of information-seeking. Connecting people's information-seeking behaviors to their appraisal tendency and resulting discrete emotions they feel in crisis, therefore, this study predicts:

H1 Prevalence of low-certainty discrete emotions (e.g., fear or sadness) during the COVID-19 outbreak will be positively related to COVID-related information-seeking, whereas prevalence of high-certainty discrete emotions (e.g., anger) will be negatively related to information-seeking.

Impacts on information-transmitting behavior

Transmission of crisis-related information, including both generating new information and sharing existing information, is also a common communicative behavior in crisis [18]. This type of behaviors would also be impacted by discrete emotions, and appraisals of controllability and responsibility are particularly relevant to the relationship between discrete emotions and information-transmitting behavior. Controllability and responsibility appraisals reflect the degree to which individuals blame others for causing or mishandling the crisis [49].

In line with Roseman [50], Harmeling et al. [51] identified two sets of negative emotions that contrast with each other in their coping tendencies: agonistic emotions (e.g., anger), which are approach-oriented, and retreat emotions (e.g., sadness and fear), which are avoidance-oriented. Perceptions of high levels of human control and others' responsibility are related to agonistic emotions, which generally refers to a cluster of emotions that arise from situations of conflict, competition, and challenge amidst a critical event [6, 50, 52]. In crisis situations, such emotions can often be manifested as anger toward the wrongdoing individual or organization [53]. In other words, agonistic emotions are more likely to be aroused when people perceive the involved organization as having control over the crisis or attribute blame to the organization for mishandling the crisis situation. In contrast, perceptions of high situational control and self-responsibility are more related to retreat emotions, such as sadness or fear [23]. These emotions are characterized by a perceived need to withdraw from a threatening or overwhelming situation [51].

In light of the ATF, while more retreat emotions (e.g., sadness or fear) would make people passively terminate their relationship with the wrongdoing agent or disengage from the event, agonistic emotions (e.g., anger) have been found associated more with approach tendencies [54]. Prior research found that, compared to anxious and fearful people, angry individuals were more likely to initiate competitive interactions [55], feel overconfident in their own opinions [56], and engage in verbal and physical aggression [57].

People with agonistic emotions tend to be more motivated to take proactive and aggressive behaviors because they believe that they can influence the situation [43]. In crisis situations, anger is found to be related to increased intention to communicate negatively about the organization in crises [58]. Jin et al. [11] also found that a higher level of anger could lead to more disaster information-sharing behavior. Thus, in the context of the COVID-19 crisis, we predict the following:

H2 Prevalence of agonistic discrete emotions (e.g., anger) during the COVID-19 outbreak will be positively related to COVID-related information-transmitting, whereas prevalence of retreat discrete emotions (e.g., fear or sadness) will be negatively related to information-transmitting.

Impacts on protective behaviors

The protective behaviors individuals engage or fail to engage in response to a crisis are perhaps the most important behaviors to understand in crisis, especially public health crisis situations, because taking recommended protective actions, such as sheltering in place or wearing appropriate personal protective equipment, can save lives. Research across various health risk topics has found that compliance to recommended protective actions is most likely to occur when people perceive a high level of threat and efficacy to protect themselves from it (e.g., [59, 60]).

The crisis communication literature suggests that people's behavioral responses are a function of emotions [5]. In line with the ATF and uncertainty management theory, if the uncertain situation is appraised as negative, people are likely to take appropriate actions to reduce the uncertainty subsequently. Heightened levels of anxiety and fear in the initial events would likely be particularly influential because people's protective actions are strongly driven by the motivation to reduce high uncertainty associated with severe risks [61]. This is supported by Jin et al. [11], which found that in a hypothetical terrorist attack, when individuals felt more fear and anxiety, they were more likely to take protective actions.

In the crisis context, protective actions recommended by authoritative sources can be considered a way to reduce uncertainty. Thus, we predict:

H3 Prevalence of low-certainty discrete emotions (e.g., fear or sadness) during the COVID-19 outbreak will be positively related to compliance with the government order, whereas prevalence of high-certainty discrete emotions (e.g., anger) will be negatively related to compliance.

Methods

A computational research method was used to examine the public's real-life discrete emotions and behaviors during the COVID-19 outbreak, using data from multiple sources. Specifically, focusing on the early outbreak stage of the COVID-19 pandemic, this study cross-analyzed: (1) tweet data to capture the public's discrete emotions triggered by the disease outbreak; (2) Google Trends data to capture the extent of public's information-seeking; (3) Twitter posting volume data to capture the extent of public's information-transmitting; and (4) Google's Community Mobility data to assess the public's social distancing compliance behaviors as a type of crisis protection behavior. The cross-analysis of these data was conducted at the aggregate level for each of the 50 states in the U.S. and the District of Columbia rather than the individual person level, due to a lack of appropriate individual-level data representing information-seeking, information-transmitting, and social distancing compliance.

The World Health Organization (WHO) declared the COVID-19 outbreak a Public Health Emergency of International Concern in January 2020, and a pandemic was declared in March 2020. In the U.S., the first case was reported on January 20, 2020, the first known deaths occurred in February, the federal government declared a national emergency in March, and by mid-April, cases had been confirmed in all 50 states. To examine the public's discrete emotions arising and connected behaviors manifesting at the crisis outbreak stage, this study focused on the first eight weeks of the COVID-19 outbreak period (March 1 to April 25, 2020).

Data sources

Twitter data

Twitter data were originally collected by Qazi et al. [62] using the AIDR tool via Twitter API.[1] For the selected eight-week period, their Twitter dataset included over 51 million COVID-19-related English tweets, retweets, and replies that can be annotated with geolocation at the U.S. state level based on the profile location information of associated accounts. Due to the Twitter API limitation and our computing power constraint, we randomly selected 1.75%[2] of the original Twitter data for this paper. After filtering out replies, deleted tweets/retweets, and tweets/retweets from removed accounts, our dataset contained 153,364 source tweets and 482,665 retweets posted in the U.S. Since Qazi et al.'s [62] dataset contained only each tweet's or retweet's unique ID, user ID, timestamp, and user location, we took extra steps to scrape the text content of the tweets/retweets in our sample using Twitter API.

Aggregated behavioral data from Google

The aggregated behavioral data obtained from Google included two sets. The first set of data—Google Trends data—was obtained from Google's official website.[3] Google Trends data provides aggregated, normalized indexes that show the relative popularity of specific search queries in Google Search across various regions and languages. We retrieved the weekly indexes of English searches of the three COVID-19-related terms ("coronavirus", "COVID", and "COVID-19") at the U.S. state level.

The second dataset was Google's *Community Mobility Reports*.[4] Throughout the COVID-19 pandemic period, Google has aggregated anonymized data provided by various smartphone apps, such as Google Maps, and produced regularly updated data reflecting peoples' movements trends. This dataset measured visitor numbers over time by geography, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential

[1] The complete list of keywords and hashtags used for Twitter data collection is available at: https://crisisnlp.qcri.org/covid19.

[2] It represented the maximum extent of data the researchers could process and analyze given the constraints in computational power and resource availability.

[3] Google Trends data in the U.S. is available at: https://trends.google.com/trends/?geo=US.

[4] Google's *COVID-19 Community Mobility Reports* are available at: https://www.google.com/covid19/mobility/.

areas. Google compared the numbers to those in baseline days before the COVID-19 outbreak (January 3 to February 6, 2020) and formed a series of indexes indicating relative changes in community mobility. We retrieved the weekly mobility indexes at the U.S. state level.

Variable computations

Independent variable

Public's discrete emotions We used modified Bidirectional Encoder Representations from Transformers (BERT) to develop the emotion-coding tool. The BERT is a transformer-based machine-learning model for natural language processing (NLP). It is built on a multi-layer encoder-decoder architecture that utilizes the attention mechanism, which can be used as a text classifier to learn and predict text meanings based on contextual relations between words in a text. For the purpose of our study, we adopted a combined training dataset developed by Garbas [63], which consists of 2617 sentences each annotated with one discrete emotion label and augmented it with a self-developed list of emotion-related keywords and emojis. This list contained keywords related to each of the different discrete emotions, which were gathered from relatedwords.org. We excluded jargon and field-specific terminologies from the list. The emojis used to express certain discrete emotions were annotated by three human annotators. The labeling with two or more annotators agreed was accepted. This augmentation created a new training dataset with more balanced classes and accounted for emojis in tweets. Using our augmented training dataset, we fine-tuned the pre-trained BERT model [64] with the *ktrain* Python library and developed our emotion-coding model.

This emotion-coding model can analyze text content and classify each tweet into one of the four discrete emotion categories: anger, sadness, fear, and other emotions or no emotion. This model achieved high accuracy (F1 score: 82.99%) on the emotion-coding task.[5] After the emotion-coding procedure was completed, relative prevalence of each discrete emotion for any given week at the state level was calculated as the percentage of the number of tweets classified into each discrete emotion category out of the total number of tweets posted weekly in each state (ranging from 0 to 100%). This state-level, weekly prevalence of each discrete emotion category serves as the independent variable in the hypothesis testing.

Dependent variables

Information-seeking behavior Internet search is one of the primary behaviors that the general public engage in to seek relevant information in crisis [65], and as of March 2020 Google Search accounted for approximately 90% of all U.S. web searches [66]. Thus, we used the state-level Google Trends indexes of the COVID-19-related terms

[5] The authors evaluated the accuracy of this self-developed model and compared it with other existing emotion-coding models.

during the selected eight-week period as a proxy measure of the level of COVID-related information-seeking. The indexes were calculated by geography and time range and normalized on a scale from 0 to 100 based on the relative proportion of COVID-related searches to all searches on all topics within each state for any given week. We averaged the indexes of the three COVID-19-related terms to form the scores representing the relative intensity of COVID-related information-seeking.

Information-transmitting behavior Twitter is one of the most popular social media platforms in the world and plays an important role in people's daily information exchange. Thus, Twitter data has been frequently used to observe various social phenomena and human behaviors [67, 68]. In crisis situations in particular, posting tweets and retweeting others' posts about the crisis are considered common information-transmitting behaviors [18]. To develop a proxy measure for information-transmitting behaviors, we calculated the weekly sums of the tweeting volume and retweeting volume by state and normalized them to represent relative changes over time within each state.

Protective behavior In response to the COVID-19 pandemic, the federal, state, and local governments in the U.S. implemented a range of stringent measures, including the stay-at-home order, restaurant and store closures, and restrictions on public transportation. These measures were implemented to slow the spread of the virus by enforcing physical distance between people. As suggested by Ophir et al. [69], the level of the general public's compliance with government orders can be inferred based on community-level people's movements. To capture the public's compliance to protective actions in each state by week, we used two sets of Google Community Mobility indexes: (1) the index of movements in the residential areas, and (2) the index of movements in the public areas, calculated as the average of the movement indexes of retail and recreation, groceries and pharmacies, transit stations, and workplaces.

Results

In order to address this study's research question and test hypotheses, the data was set up with "state × week" as the unit of analysis, by aggregating the computed data at the state level (50 states and the District of Columbia) and split the time series data into eight weeks (from Week 1: March 1–7, 2020, to Week 8: April 18–25, 2020). This procedure generated 408 units, each of which was comprised of a set of computed variables representing the state-level public's discrete emotions, information-seeking, information-transmitting, and protective behaviors. The descriptive statistics of these computed variables are reported in Table 1.

RQ1: Emotions during the COVID-19 outbreak

RQ1 examined the primary negative discrete emotions (classified into anger, fear, and sadness) experienced by the U.S. public and the fluctuations of the four categories of discrete emotions during the early breakout stage of the COVID-19

Table 1 Descriptive statistics of key variables

	Min	Max	Mean	SD	Variance	Skewness (SE)	Kurtosis (SE)
High-certainty/agonistic emotion	0.00	0.15	0.04	0.02	0.00	1.05 (0.12)	3.07 (0.24)
Low-certainty/retreat emotion	0.00	0.20	0.05	0.03	0.00	1.16 (0.12)	4.83 (0.24)
Information-seeking	4.90	72.88	38.12	15.22	231.79	−0.39 (0.12)	−0.54 (0.24)
Information-transmitting	−2.43	2.38	0.00	1.00	1.00	−0.54 (0.12)	−0.55 (0.24)
Movement in residential areas	−2.36	25.63	11.13	8.12	65.97	−0.34 (0.12)	−1.29 (0.24)
Movement in public areas	−59.83	10.21	−20.46	19.44	377.95	0.19 (0.12)	−1.35 (0.24)

Table 2 Changes in percentages of discrete emotions

Time	Anger		Fear		Sadness		Positive emotion		N
	n	%	n	%	n	%	n	%	
Week 1: 3/1–3/7, 2020	326	2.68	291	2.40	113	0.93	163	1.34	12,150
Week 2: 3/8–3/14, 2020	376	2.68	443	3.16	173	1.23	343	2.44	14,037
Week 3: 3/15–3/21, 2020	431	3.46	302	2.42	152	1.22	379	3.04	12,457
Week 4: 3/22–3/28, 2020	562	2.90	658	3.40	356	1.84	598	3.09	19,366
Week 5: 3/29–4/4, 2020	516	2.25	784	3.42	455	1.99	792	3.46	22,917
Week 6: 4/5–4/11, 2020	997	3.97	1071	4.27	620	2.47	782	3.12	25,097
Week 7: 4/12–4/18, 2020	1112	4.60	790	3.27	509	2.10	779	3.22	24,186
Week 8: 4/19–4/25, 2020	884	3.82	717	3.10	440	1.90	671	2.90	23,154
Total	5204	3.39	5056	3.30	2818	1.84	4507	2.94	153,364

Among the discrete emotions detected, anger is a high-certainty and agonistic emotion, while sadness and fear are low-certainty and retreat emotions

pandemic, as expressed in the tweets posted by individuals across the U.S. The percentages of different discrete emotions detected in the tweet dataset over the eight-week period are shown in Table 2 and Fig. 1.

As presented in Table 2, while anger was the most prevalently experienced emotion (3.39%) over the 8-week time period of the early outbreak, the percentage of anger was still very small and closely followed by that of fear (3.30%). Among the four types of discrete emotions, sadness was the least prevalent emotion (1.84%) during the early weeks of the COVID-19 breakout. Figure 1 illustrates the changes in each discrete emotion's percentages over the eight-week time period. Anger fluctuated considerably during the breakout: It reached a relatively high point in Week 3 and then decreased to its lowest point in Week 5; however, the relative prevalence of anger jumped to new heights in Weeks 6 and 7. Fear increased from Week 1 to Week 6 with some fluctuations and became the most prevalent emotion in Week 6. Sadness increased gradually from Week 1 to Week 6, before slightly decreasing

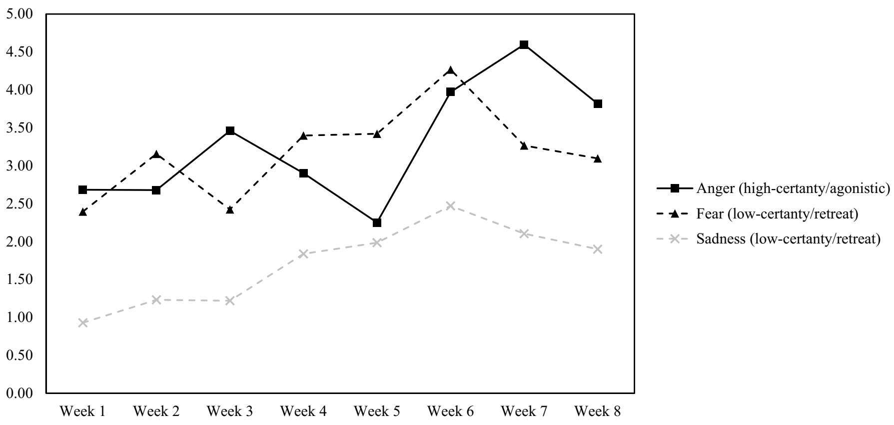

Fig. 1 Changes in prevalence of discrete emotions over time. *Note*: Among the discrete emotions detected, anger is considered a high-certainty and agonistic emotion, while sadness and fear are considered low-certainty and retreat emotions

in Week 7 and Week 8, and it remained the least prevalent emotion over the eight weeks.

In general, the emotion data patterns indicate that: (1) as the COVID-19 pandemic developed and multiple crisis events occurred along the way, people were experiencing a combination of negative emotions with varying degrees; and (2) in some weeks the high-certainty and agonistic emotion (anger) was relatively more prevalent whereas in some other weeks the low-certainty and retreat emotions (fear and sadness) were more prevalent.

Hypothesis testing results

H1: Impact of emotions on information-seeking behavior

H1 predicted that the prevalence of low-certainty emotions (e.g., fear or sadness) during the COVID-19 outbreak would be positively related to COVID-related information-seeking; whereas prevalence of high-certainty emotions (e.g., anger) would be negatively related to information-seeking. To test this hypothesis, the percentages of fear and sadness were added up to form the prevalence of low-certainty emotion and the percentage of anger was used as it is to indicate the prevalence of high-certainty emotion. Then, a linear mixed modeling analysis was conducted with the aggregated data at the state level and week level. For the fixed effect, the prevalence of high- and low-certainty emotions was included as the two continuous independent variables, and the standardized information-seeking behavior score was entered as the dependent variable. The state variable was included as a random effect.

Results indicated that the prevalence of low-certainty emotion ($B = 79.41$, $SE = 32.76$, $t = 2.42$, $p = 0.016$) was a significant positive predictor of the level of information-seeking, while the prevalence of high-certainty emotion ($B = -36.83$, $SE = 39.82$, $t = -0.93$, $p = 0.356$) was not significantly related to the dependent

Table 3 Estimates of fixed effects for emotions predicting information-seeking behaviors

Variables	B	SE	*df*	*t*	*p*
Predictor variables					
High-certainty emotion (i.e., anger)	− 36.83	39.82	355	− 0.93	0.356
Low-certainty emotion (i.e., fear and sadness)	79.41	32.76	355	2.42	0.016

The categorical “State” variable was included as a factor in the mixed models. None of its dummy-coded terms was a significant parameter

The percentages of fear and sadness were added up to form the extent of low-certainty emotion, and the percentage of anger was used to indicate the extent of high-certainty emotion

variable (see Table 3). In other words, the more prevalent low-certainty emotions experienced during the COVID-19 outbreak, the more information-seeking behaviors the public engaged in. The significant impact of the prevalence of low-certainty emotion supported H1.

H2: Impact of emotions on information-transmitting behavior

H2 predicted that the prevalence of agonistic emotion (e.g., anger) during the COVID-19 outbreak would be positively related to COVID-related information-transmitting; whereas the prevalence of retreat emotions (e.g., fear or sadness) would be negatively related to information-transmitting. To test H2, the percentage of anger was used to represent the prevalence of agonistic emotion detected, and the percentages of sadness and fear were added up to represent the prevalence of retreat emotion detected. A similar linear mixed modeling analysis approach as the one testing H1 was conducted with the standardized information-transmitting score as the dependent variable in the fixed effect. The state variable was added as a random effect. Results showed that the prevalence of retreat emotion ($B = 17.15$, $SE = 2.06$, $t = 8.32$, $p < 0.001$) was a significant positive predictor of the level of information-transmitting, while the prevalence of agonistic emotion was not significantly related to the dependent variable ($B = 1.73$, $SE = 2.50$, $t = 0.69$, $p = 0.490$) (see Table 4). In other words, the more prevalent retreat emotion the public experienced during the COVID-19 outbreak, the more information-transmitting behavior they engaged in. The result was opposite to the directions predicted by H2.

H3: Impact of emotions on protective behavior

H3 predicted that the prevalence of low-certainty emotions (e.g., fear or sadness) during the COVID-19 outbreak would be positively related to compliance with the social distancing order; whereas the prevalence of high-certainty emotion (e.g.,

Table 4 Estimates of fixed effects for emotions predicting information-transmitting behaviors

Variables	B	SE	*df*	*t*	*p*
Predictor variables					
Agonistic emotion (i.e., anger)	1.73	2.50	355	0.69	0.490
Retreat emotion (i.e., fear and sadness)	17.15	2.06	355	8.32	< 0.001

The categorical "State" variable was included as a factor in the mixed models. None of its dummy-coded terms was a significant parameter

The percentages of fear and sadness were added up to form the extent of retreat emotion, and the percentage of anger was used to indicate the extent of agonistic emotion

Table 5 Estimates of fixed effects for emotions predicting movements in residential areas

Variables	B	SE	*df*	*t*	*p*
Predictor variables					
High-certainty emotion (i.e., anger)	52.28	19.60	355	2.67	0.008
Low-certainty emotion (i.e., fear and sadness)	121.67	16.12	355	7.55	< 0.001

The categorical "State" variable was included as a factor in the mixed models. None of its dummy-coded terms was a significant parameter

The percentages of fear and sadness were added up to form the extent of low-certainty emotion, and the percentage of anger was used to indicate the extent of high-certainty emotion

anger) would be negatively related to compliance. To test this hypothesis, two linear mixed modeling analyses were performed, with the standardized score of movements in residential places and the standardized score of movements in public places as the dependent variable in each of the models, and the same set of independent variables as before as the fixed effect. The state variable was also included as a random effect.

Results indicated that for people's movements in residential areas, the prevalence of both high-certainty emotion ($B = 0.52.28$, $SE = 19.60$, $t = 2.67$, $p = 0.008$) and low-certainty emotion ($B = 121.67$, $SE = 16.12$, $t = 7.55$, $p < 0.001$) were significant positive predictors (see Table 5). For people's movements in public areas, on the other hand, prevalence of both high-certainty emotion ($B = -121.35$, $SE = 45.89$, $t = -2.64$, $p = 0.009$) and low-certainty emotion ($B = -295.56$, $SE = 37.75$, $t = -7.83$, $p < 0.001$) were significant negative predictors (see Table 6). The results

Table 6 Estimates of fixed effects for emotions predicting movements in public areas

Variables	B	SE	*df*	*T*	*p*
Predictor variables					
High-certainty emotion (i.e., anger)	− 121.35	45.89	355	− 2.64	0.009
Low-certainty emotion (i.e., fear and sadness)	− 295.56	37.75	355	− 7.83	< 0.001

The categorical "State" variable was included as a factor in the mixed models. District of Columbia was a significant parameter in the model ($B = -35.25$, $SE = 15.56$, $t = -2.27$, $p = 0.026$)

The percentages of fear and sadness were added up to form the extent of low-certainty emotion, and the percentage of anger was used to indicate the extent of high-certainty emotion

suggest that the prevalence of both high-certainty and low-certainty emotions during the COVID-19 outbreak was related to the level of the public's social distancing behavior compliance, which does not provide clear support for H3. However, the relatively larger coefficients of the lower-certainty emotion variable also indicate that the prevalence of low-certainty emotion might be a more prominent positive predictor of the public's protective behavior, which is in line with our general prediction.

Discussion

This study used a computational research approach, combining multiple established computational methods, to examine the impact of discrete emotions arising in public crisis situations on the public's coping behaviors in the recent COVID-19 crisis context. This robust combination of computational methods contributes to the current literature by providing new insight and methodological advancement to understanding collective public emotions and large-scale behavioral changes in a prolonged public health crisis with multiple stages. From computational analysis of tweet data, we discovered different types of negative discrete emotions, such as anger, fear, and sadness, among the U.S. public in reaction to the COVID-19 outbreak.

Overall, in the eight weeks that we studied, the prevalence of discrete emotions ranged between 0.93% to 4.60%. As compared to the total tweets relevant to the COVID-19 outbreak, those containing emotional expressions were relatively low. It is possible that people may refrain from expressing strong emotions on public platforms for various reasons. Crises with a clear external cause, such as an organizational misconduct, might provoke a more straightforward emotional response (e.g., anger) compared to more complex crises like the COVID-19 outbreak, where blame and understanding might be more diffused, affecting how emotions are publicly expressed [70, 71]. Also, during such a crisis, there might be a societal or community-level regulation of collective emotions, where expressions of extreme emotions are dampened to maintain social order or hope. Research has found that in a crisis, positive emotions like hope may spread at the collective level through emotional contagion [72], encouraging the public to express similar emotions and possibly underrepresenting expressions of fear or sadness. On public platforms, people may also engage in self-regulation of their emotional expressions, choosing to share only measured responses publicly.

In light of the cognitive appraisal perspective, each of the emotional reactions can be connected to particular appraisal themes underlying the crisis events that occurred in the studied period and reflect the unique nature of the prolonged COVID-19 crisis. Anger, which was relatively more prevalent emotion than the other negative emotions in many weeks during the early COVID-19 outbreak, is a type of emotion characterized by high certainty and strong human control in appraisal of the crisis situation [23], meaning that anger tends to be evoked when people are convinced that their loss can be attributed to someone's wrongdoing. This study found that people's feeling of anger reached a relatively high point in Week 3 and peaked in Week 6. Both time periods appear to coincide with rising public blaming for the government and public health authorities' inadequate response to the emerging crisis. In Week 3, as the COVID-19 cases began spreading throughout the U.S., huge gaps existed in the government's measures of controlling the crisis, as well as in public understanding of the government recommendations such as the stay-at-home orders. By Week 6, COVID-19 cases had been confirmed in all 50 states, and the number of deaths in the U.S. reached 20,000, making it the highest in the world. Higher levels of anger compared to other types of negative emotions during these time periods seem to be consistent with findings from Yang's [33] study on Ebola outbreak, which indicated that people attributed the responsibility of dealing with the crisis to the government and health organizations, blaming the lack of effective responses from them during the early stage of the disease outbreak. In times of an acute infectious disease outbreak, the government's level of responsibility, as well as the degree of public scrutiny, often far exceeds that in regular public health issues [27]. In such circumstances, anger can be easily evoked and become a dominant public emotion.

Fear, another prevalent emotion identified in this study, is characterized by the core appraisal theme of extreme uncertainty and high situational control [6]. In public health crises like the COVID-19 outbreak, the appraisal theme of fear seems to be centered on the uncertainty of escaping the imminent danger of being infected and a pessimistic estimate of how devastating the crisis might be [12, 33]. Research on organizational crisis also suggested that, when the public realize that the responsible organization is devoting limited or inadequate resources to the crisis when it should be more involved, fear can emerge because the public feel a high level of helplessness [5]. In the COVID-19 outbreak, high uncertainty stemmed from gaps in scientific knowledge about the virus, disease symptoms, and transmission routes. Such scientific uncertainty further led to organizational-level uncertainty among governmental and non-governmental organizations about how to deal with the pandemic. Thus, not surprisingly, fear became one of the prominent emotions felt by the public.

When it comes to the impacts of people's negative discrete emotions on their coping behaviors during the COVID-19 outbreak, we found some interesting and meaningful impacts of emotions, which can be explained by the ATF. As expected, the extent of low-certainty emotion was found to be positively related to information-seeking behaviors. From the cognitive appraisal perspective, both fear and sadness are characterized by strong unpleasant feelings, high perceived situational control, and high perceived uncertainty [23]. In disease outbreaks, fear and sadness are evoked when public health information is unavailable or inconsistent, and details of the situation are ambiguous and unpredictable [73], and when people experience or witness loss [6]. In those cases, while individuals suffer from deep uncertainty, they would look for help to restore the loss or search for information to regain certainty. This study's finding is consistent with this theoretical prediction and findings from prior studies on crisis emotions (e.g., [8, 32]).

This study also found that the prevalence of retreat emotion was positively related to people's information-transmitting behaviors, which is opposite to our hypothesis, while the prevalence of agnostic emotion was not significantly related. This result is inconsistent with the ATF prediction but in line with Jin's [28] study, which found that when people appraise a crisis as unpredictable and uncontrollable, they tend to experience more fear, and in turn, resort to emotional coping, including emotional support and venting. In crisis situations, emotional venting on social media is an essential channel for self-expression, compassion seeking, and stress reduction. Thus, what our data pattern shows seems to be increased self-expression behaviors among people who experienced stronger retreat emotions in the COVID-19 crisis.

Besides the communicative behaviors, this study further found that the prevalence of high- and low-certainty emotions were both positively related to people's protective behavior during the COVID-19 outbreak. Nonetheless, the effect mechanisms underlying each of these discrete emotions may be different. For anger, as it is associated with a strong action tendency to blame for the inefficiency of institutional crisis management (e.g., ineffective government responses in the early stage of COVID-19) and rectify the wrongdoing, it would lead to personal preventive behaviors. For fear, since it invokes a strong intention to avoid potential risks, the emotion could facilitate avoidance-oriented precautionary actions, such as staying at home and away from public places. For sadness, it not only converges with fear on their contribution to avoidance behavioral tendencies, but would also foster empathetic feeling about others' suffering, which could lead to behaviors that could benefit communities [74].

Theoretical and practical implications

Despite the growing importance of the topic, research on the impacts of the public's collective discrete emotions on large-scale coping behaviors in complicated and evolving crisis situations has been limited (e.g., [13, 14]), and the natural observation-based investigation is particularly lacking [20]. Looking at the widespread impact and complexity of the COVID-19 pandemic and the accumulation of massive social media data during the prolonged crisis situation, which provides an unprecedented context to examine this topic in a natural setting, we designed a computational research approach combining multiple established methods to address this research gap. Using the machine-learning emotion detection algorithm and behavioral data, this study demonstrates the feasibility of computational analysis of social media data to examine the public's discrete emotions and their impact on coping behaviors in complicated and evolving crisis situations. By investigating emotional fluctuations and behavioral responses over time, the combination of robust computational methods used in our study allows for a nuanced understanding of the dynamic interplay between changing discrete emotions and coping strategies in an evolving crisis. This methodological approach complements the traditional social science research approaches that are prevalent in the crisis communication research field, which primarily rely on experimental or survey methods with self-report measurement bias and ecological validity issues. Our research approach also overcomes the limitations of smaller-scale, controlled studies and enables the analysis of large-scale, longitudinal data from diverse populations.

Furthermore, the study's findings offer unique and meaningful insights regarding how different types of discrete emotions arising in the public health crisis situation would impact the public's coping behaviors. Specifically, using the ATF as the main theoretical framework, this study provides valuable empirical evidence on discrete emotions as predictors of how the public behaviorally cope with crisis and risk situations. Moreover, research on complicated and evolving crises is lacking in the current literature. The study addresses this gap by examining a long-lasting disease outbreak crisis and gives rise to the possibilities of extending current knowledge to more complex and challenging crisis contexts.

Interestingly, this study's results obtained in the naturalistic real-life setting are not fully consistent with findings from the relevant previous survey and experimental studies. One possible reason is that individual-level emotional appraisal theories were used to inform our hypotheses on collective emotions and coping behaviors, while individual reactions may not be completely translated to the aggregated level. Group dynamics, social norms, and contextual factors often play important roles in shaping collective cognition and behaviors, which individual-level theories may not fully capture. Further theory-building efforts on collective emotions in crisis and coping behaviors across a large population are warranted. Meanwhile, since strategic communication in disease outbreak crisis situations is a growing multidisciplinary research field that intersects crisis communication, risk communication, and health communication, with some inconsistent findings, additional efforts are needed to bridge the different theoretical and methodological approaches across different disciplines. The inconsistent findings also call for further research on this topic.

This study also offers important practical implications suggesting that it is crucial for the government and public health organizations to pay close attention to the fluctuating emotions arising during complex public health crisis situations in order to develop effective strategies to facilitate the public's appropriate coping behaviors while dealing with the public health issues. The findings can help practitioners better understand how to segment the affected population in public health crises based on their different discrete emotions as well as geolocations [75] and tailor their crisis communication to address the prevalent emotions in each segment.

During infectious disease outbreaks, besides the infectious nature of such diseases, emotion-based conversations about the crisis can quickly spread to a wide population [7]. In addition to the challenge of providing the public with timely information, correcting vast amounts of misinformation is also critical [3]. Noticeably, this study found that people with fear and sadness tended to have both increased information-seeking and information-transmitting behaviors. This suggests that such emotions as fear and sadness might augment misinformation transmission, as fearful and sad individuals would have a greater chance of accessing misinformation and spreading them rapidly, particularly when the sensationalized content appeals to their emotions [8, 76]. Understanding the emotions that drive information seeking and transmitting can help public health practitioners better combat misinformation.

More importantly, cross-analyzing social media data with temporal and geographical data has shown great potential in facilitating effective crisis management [77]. This study suggests that practitioners can gauge publics' emotions and effectiveness of crisis responses using appropriate online social media and behavioral data. The emotion detection algorithm developed and used in this study could serve as a potentially useful tool for crisis communication practitioners to assess the public's real-time emotion fluctuations, which can help improve the effectiveness of crisis management.

Limitations and future research

This study has some limitations. First, our emotion detection algorithm is limited to classifying only a limited number and type of emotions. In addition to anger, fear, and sadness, many other types of discrete emotions, such as anxiety, despair, and sympathy, can be induced by disease outbreaks and other types of public crises. Future research should develop more expansive and sophisticated machine-learning algorithms to investigate other types of emotions and further test the relationships between discrete emotions and crisis-coping behaviors.

Second, while this study relied on Twitter data to infer public emotions, other communication channels have also played important roles in the COVID-19 outbreak. Similarly, public's compliance to protective actions includes not only following the stay-at-home orders but also obtaining and using appropriate personal protective equipment, handwashing, and getting vaccinated. Further research is warranted to explore other digital traces as proxy measures for emotions and crisis-coping actions.

Additionally, this study focused on the first eight weeks of the COVID-19 outbreak and thus the research findings are limited within this time frame. Future research is encouraged to expand the timeline and further examine how people's discrete emotions and various coping behaviors change over time as the crisis keeps developing and starts to abate.

It is also of importance for future research to compare and cross-validate this study's findings using controlled experimental methods. Such cross-validation research using different types of social science and computational research methods can help further improve the accuracy of the computational analysis of psychological variables and contribute to advancing theory. Moreover, it should be noted that this study relies on individual-level theories on emotional appraisals, while the unit of analysis in the computational research was at the aggregated level. As evident in this study, collective emotions and coping behaviors may not always be the same as individuals. Further investigation of collective emotions in crisis is needed.

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Data availability The GeoCoV19 data by Qazi et al. [62] are available from the Crisis Computing team at Qatar Computing Research Institute (QCRI) at https://crisisnlp.qcri.org/covid19. The processed datasets are available from the authors upon reasonable request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Authors and Affiliations

Hao Xu[1] · Smitha Muthya Sudheendra[2] · Jisu Huh[3] · Aadesh Salecha[4] · Jaideep Srivastava[2]

✉ Hao Xu
hao.xu@unimelb.edu.au
https://scholar.google.com/citations?user=3YN1r_MAAAAJ&hl=en

Smitha Muthya Sudheendra
muthy009@umn.edu
https://scholar.google.com/citations?user=CU_MLR0AAAAJ&hl=en&oi=ao

Jisu Huh
jhuh@umn.edu
https://scholar.google.com/citations?user=SaAcACcAAAAJ&hl=en

Aadesh Salecha
asalecha@stanford.edu
https://scholar.google.com/citations?user=Cnwzl3oAAAAJ&hl=en&oi=ao

Jaideep Srivastava
srivasta@umn.edu
https://scholar.google.com/citations?user=Y4J5SOwAAAAJ&hl=en

1 School of Culture and Communication, The University of Melbourne, Melbourne, VIC, Australia

2 Department of Computer Science and Engineering, University of Minnesota, Minneapolis, MN, USA

3 Hubbard School of Journalism and Mass Communication, University of Minnesota, Minneapolis, MN, USA

4 Department of Computer Science, Stanford University, Stanford, CA, USA