Rapid Perception of Public Opinion in Emergency Events through Social Media

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Abstract: Due to its near-real-time crowdsourcing nature, social media demonstrates a great potential of rapidly reflecting public opinion during emergency events. However, systematic approaches are still desired to perceive public opinion in a rapid and reliable manner through social media. This research proposes two quantitative metrics—the fraction of event-related tweets (FET) and the net positive sentiment (NPS)—to examine the intensity and direction dimensions of public opinion. While FET is modeled through normalizing population size differences, NPS is modeled through a Bayesian-based method to incorporate uncertainty from social media information. To illustrate the feasibility and applicability of the proposed FET and NPS, we studied public opinion on society reopening amid COVID-19 for the entire United States and four individual states (i.e., California, New York, Texas, and Florida). The reflected trends of public opinion have been supported by the reopening policy timeline, the number of COVID-19 cases, and the economy characteristics. This research is expected to assist policy makers in obtaining a prompt understanding of public opinion from the intensity and direction dimensions, thereby facilitating timely and responsive policy making in emergency events. **DOI: 10.1061/(ASCE)NH.1527-6996.0000547.** © *2021 American Society of Civil Engineers.*

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Introduction

Public opinion plays a critical role in public administration because it is often a proximate cause of public policies (Page and Shapiro 1983). This criticality is particularly stressed in emergency events wherein government agencies need to manifest responsiveness to the public (Bullock et al. 2017). For example, in response to public opinion, FEMA has devoted many efforts (e.g., the expansion of its telephone and online application capability) to enhance disaster relief distribution efficiency (FEMA 2009). In this research, public opinion is defined as the aggregation of equally treated individual opinions. We will propose two quantitative metrics to measure the intensity and direction dimensions of public opinion. Here, the intensity dimension describes how strongly the public holds opinions, and the direction dimension describes where the public stands on issues, such as support and opposition.

Recently, social media—a near-real-time communication channel—has been widely used to communicate and share information in emergency events (e.g., hurricanes and pandemics) (Li et al. 2019; Martín et al. 2017; Yu et al. 2019). According to a study conducted by the American Red Cross, nearly half of respondents communicate emergency information on social media channels (American Red Cross 2011), which demonstrates the representativeness of social media for an entire population. Such a near-real-time and representative nature makes it promising to promptly understand public opinion in emergency events through social media (Ragini et al. 2018; Sasahara et al. 2013; Windels et al. 2018). However, to reliably indicate the intensity and direction dimensions of public opinion using social media, researchers need to address two main challenges: (1) normalization of social media usage is required since the amount of social media user highly depends on the population size (Fan et al. 2020), and (2) incorporation of the sampling uncertainty is necessary because social media users only represent a sample of the entire population (Chen et al. 2019; Ghahramani 2015).

This research aims to reliably measure the intensity and direction dimensions of public opinion through two quantitative metrics: the fraction of event-related tweets (FET) and the net positive sentiment (NPS). FET reveals public opinion intensity among various regions, and a large value of FET indicates a high level of intensity and vice versa. NPS examines public opinion direction under sampling uncertainty, and a large value of NPS indicates a high level of support and vice versa. To illustrate the feasibility of the proposed metrics, we studied public opinion on society reopening amid COVID-19 for the entire United States and four individual states (i.e., California, New York, Texas, and Florida). Research outcomes found that the public paid high attention to society reopening policy announcements, which suggests that a frequent update of reopening policies might increase public opinion intensity. Also, the public possessed a positive sentiment on society reopening,

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but the significant increase of COVID-19 cases and the society reopening pause hampered the positive sentiment. Such findings reveals that the public supports the society reopening policy if there is a successful control of COVID-19 spread. Methodologically, this research, for the first time to our knowledge, proposes two systematic social media–based metrics for promptly perceiving public opinion in emergency events. Theoretically, the research findings contribute to understanding the interplay between public opinion and government policies in emergency events.

The paper is organized as follows. First, we comprehensively review the definition and measurement of public opinion as well as social media–enabled disaster management. Second, we introduce the proposed methodology that comprises data collection, sentiment prediction, and public opinion analysis. Then, we demonstrate the feasibility of our approach via examining public opinion amid COVID-19. After that, we discuss the advantages of the proposed metrics and policy implications on society reopening. Finally, research contributions, limitations, and future work are concluded.

Literature Review

Public Opinion Definition

Although public opinion plays an indispensable role in democracy, it eludes a unified definition. Researchers have summarized four common definitions that are distinct but overlap to some extent (Glynn et al. 2015). The first definition is that public opinion is an aggregation of individual opinions, which is the most common definition in contemporary American politics (Berinsky 2017; Druckman and Jacobs 2006). In this definition, through random selections, individual opinions are equally treated and efficiently aggregated to make general claims about the entire population. The second definition is that public opinion is a reflection of the majority beliefs. In this definition, public opinion is an equivalent of social norms, wherein the majority values and beliefs are the true basis of public opinion (Noelle-Neumann 1974). This definition is not to judge the majority as being right or wrong—it is often used to reveal that people tend to conform to the majority opinion. The third definition claims that public opinion is represented by group interests—public opinion reveals how individual opinions are cultivated and communicated by interest groups (e.g., political parties and activity groups) (Gray et al. 2004). This definition assumes that interest groups are constantly engaged in defining social problems and providing solutions. The fourth definition is that public opinion reflects media and elite influence. Adherents of this definition argue that the common citizen could not possibly stay informed on all public issues and therefore could hardly produce meaningful opinions (Woodward 1948). Such argument suggests that public opinion consists of people's simplistic reactions to what they learn from opinion leaders. In practice, the definition of public opinion depends on the circumstance in which the public mood is being discussed. In this study, we conduct the research built on the first definition because (1) it equally aggregates individual opinions for deriving public opinion, and (2) it provides an easy way for conducting quantitative causal analysis between public opinion and policies.

Public opinion is generally investigated from four dimensions: direction, intensity, stability, and the information content (Asker and Dinas 2019; Claassen 2020; Reeskens et al. 2021; Segovia and Defever 2010). The direction dimension shows where the public stands on issues, such as support, oppose, or are uncertain about. The intensity dimension indicates how strongly the public feels about issues. The stability dimension refers to the consistency of public opinion over time. The information content reveals the particular content of public opinion and is critical for the public to form reasonable opinions on public issues. In this research, we explore public opinion from the direction and intensity dimensions for the following reasons: (1) these two dimensions provide significant decision insights on policy making, in which the public opinion direction determines if a policy should be continued and the intensity provides insights on the strength of policy implementation, and (2) the measurement of these two dimensions is straightforward and has been well established in existing literature (Asker and Dinas 2019; Claassen 2020). The direction of public opinion is often indicated from the sentiment perspective, such as indicating support via positive sentiment (Asker and Dinas 2019). The intensity of public opinion is often obtained by counting the number of individual opinions, such as the number of individuals supporting an issue (Sasahara et al. 2013).

Public Opinion Measurement

To measure public opinion, political leaders often rely on four types of methods: survey or polling methods (Glynn et al. 2015), public hearings or meetings (Adams 2004; McComas and Scherer 1998), focus group interviews (Merton 1987; Morgan 1996), and analyses of mass media content (Anstead and O'Loughlin 2015; Baum and Potter 2019; McGregor 2019). Survey or polling methods use sample information to measure the characteristics of an entire population. Commonly used survey and polling methods include in-person, telephone, mail-administered, and internet-based surveys. However, conducting a survey or polling is time consuming (Saris and Gallhofer 2014) and often requires a large number of professionals (e.g., agents in phone-based surveys). Another approach organizes public meetings or hearings for sharing information and discussing proposals (Adams 2004). Although public meetings are intended to bring together a full range of participants, they often reach a small segment of the community, making them less capable of indicating public opinion for the entire community (Gundry and Heberlein 1984). Meanwhile, public meetings have multiple time-consuming processes, such as the pre-meeting notice (e.g., three working days before the meeting) and post-meeting follow-ups. Focus group interview is a popular method for examining public opinion in a detailed manner (Morgan 1996). Unlike survey or polling methods that typically invite individuals to answer a series of closed-ended questions, focus group interviews involve open-ended discussions and interviews. Still, it is challenging and sometimes impossible to use a focus group interview for quantifying the relationship between public opinion and related policies. In recent years, media content analyses have been widely used to measure public opinion, especially when solving emergency management challenges (Anstead and O'Loughlin 2015; Baum and Potter 2019; McGregor 2019). Media content analysis is a nonreactive way to measure public opinion—it is not constrained by survey questions and does not engage a conversation with human participants. Consequently, it avoids interfering problems that researchers face when interviewing individuals or designing survey questionnaires. In addition, due to the advances in information technologies, media contents (i.e., social media posts) are collected in a near-real-time manner, which makes it promising to obtain rapid insights of public opinion in emergency events. Considering such advantages, social media content analysis is used in this research to derive the direction and intensity dimensions of public opinion.

Previously, researchers have quantified public opinion intensity using various social media–based measures ranging from built-in platform features (e.g., the number of comments, retweets, and likes) (Sasahara et al. 2013) to newly designed measures (e.g., the ratio of total likes to total posts) (Agostino and Arnaboldi 2016). However, these measures do not eliminate the variations of the amount of social media activities caused by population size, making them less capable of comparing public opinion intensity among various regions. In addition to the intensity dimension, researchers have extensively examined public opinion direction by analyzing social media sentiment (Ragini et al. 2018; Wang and Taylor 2018). Sentiment analysis comprises 1)) prediction of sentiment polarity (i.e., positive, neutral, and negative) of each social media post, and (2) aggregation of predicted sentiment polarities for a certain group of people (Chen et al. 2019; Yu and Kak 2012). Social media users only compile a sample set of the entire population, making social media–derived information sometimes have large uncertainty due to a small number of related social media posts. However, previous studies simply model social media–derived sentiment as a deterministic value (Ragini et al. 2018; Wang and Taylor 2018), which requires further exploration to enhance the modeling reliability. Therefore, to reliably reflect public opinion using social media, we highly desire systematic approaches that are capable of normalizing population size differences and modeling social media information uncertainty.

Social Media Studies in Disaster Management

Social media has been broadly used to study various emergency-related topics (e.g., damage assessment and evacuation behavior) (Chen et al. 2020; Wang and Ye 2018). Based on their research focuses, previous social media–based disaster management studies could be grouped into two categories: human behavior focused (Fan et al. 2020; Yuan et al. 2021) and decision support focused (Chen et al. 2020; Chen and Ji 2021; Kryvasheyeu et al. 2016). Human behavior–focused studies mainly investigate human behavior differences among social groups in disasters, which is beneficial for enhancing social equity in disaster management (Fan et al. 2020; Yuan et al. 2021). For example, human mobility patterns have been investigated by tracing the geolocation of Twitter users during hurricanes (Ahmouda et al. 2019). Decision support–focused studies provide timely and reliable insights to enhance situational awareness, thereby assisting practitioners in making informed relief decisions (Chen et al. 2020; Fan and Mostafavi 2019). For instance, researchers have proposed two social media–based measures to indicate the location and severity of disaster impacts on highways, which benefits the allocation of highway restoration resources (Chen et al. 2020). Recently, researchers have successfully utilized social media activities to investigate public opinion on COVID-19 (Han et al. 2020; Qazi et al. 2020). However, these studies are less capable of reliably modeling public opinion's intensity and direction dimensions because they have not (1) removed the variations of the amount of social media activities caused by population size, and (2) modeled the sampling uncertainty of social media information. To overcome these shortages, this research will create a systematic solution, for the first time, to achieve a reliable and rapid perception of public opinion using social media.

Methodology

This research proposes a systematic methodology to achieve reliable mining of public opinion using social media. The methodology comprises data collection, sentiment prediction, and public opinion analysis. In the data collection module, social media posts related to society reopening are collected. The sentiment prediction module predicts the sentiment polarities (e.g., positive, neutral, and negative) of the collected social media posts. Finally, in the public opinion analysis module, FET and NPS are derived to measure the intensity and direction dimensions of public opinion, respectively.

To illustrate the feasibility and applicability, we studied public opinion on society reopening amid COVID-19 for the entire United States and four individual states (California, New York, Texas, and Florida). Due to the breakout of highly transmissible coronavirus (COVID-19), much of the United States began to lock down from mid-March 2020. Despite successfully controlling the spread of COVID-19, lockdown restrictions had debilitating impacts on many aspects of society (Schleicher 2020; Young 2020). In this context, most states gradually lifted lockdown restrictions and reopened society from late April 2020 (Wu et al. 2020). To design sustainable society reopening plans, governments need to assess public opinion promptly for making informed and responsive reopening decisions. Such a practical need inspires us to illustrate the feasibility of the proposed methodology by studying public opinion on society reopening in the United States.

Data Collection

In this research, Twitter was used to extract social media data due to its popularity for communicating and sharing emergency information as well as its easy access for collecting large-scale data sets (Kryvasheyeu et al. 2016). Tweepy, an open-source Python package for implementing the Twitter streaming application programming interface (API), was used to collect geotagged tweets. Three filters (i.e., time span, location, and keyword) were employed to ensure that the collected tweets were posted in the United States and related to society reopening. The studied period was from March 13, 2020, to August 15, 2020. The location was within the contiguous United States, covering 48 adjoining states and the District of Columbia. The keywords were "reopen" and "reopening." Only original tweets were kept because they provide the raw information of public opinion on society reopening. Additionally, the tweets posted by extremely active users (posting frequency > 20) tweets per day were removed because these users are often agencies or bots. We collected 42,411 society reopening–related tweets posted by 15,668 Twitter users.

The largest numbers of reopening-related tweets occurred in California, New York, Florida, Texas. Table 1 presents the numbers of tweets and the corresponding percentages for the four states. The percentage is the number of tweets in a state to the total number of the collected tweets in the US. The major reason for the significant reopening-related Twitter activities in the four states is their large population sizes. Therefore, to reliably compare public opinion intensity among states, the variations of the amount of Twitter activities caused by population size differences should be eliminated.

Sentiment Prediction

Lexicon-based sentiment analyses have been widely used due to their easy implementation and human-interpretable prediction processes (Kundi et al. 2014). In this research, Valence Aware Dictionary and sEntiment Reasoner (VADER) was implemented to

Table 1. Distribution of collected tweets in four states (California, New York, Texas, and Florida)

State	Number of tweets	Percentage of US-wide tweets
California	6,019	14.2
New York	3,763	8.9
Texas	3,584	8.5
Florida	3,789	8.9

Table 2. Sentiment prediction performance of VADER

Metric	Positive	Neutral	Negative
Precision	90.3%	87.0%	71.5%
Recall	68.9%	88.3%	88.8%
F1-score	78.2%	87.6%	79.2%
Accuracy		83.2%	

predict the sentiment because it is specifically attuned to social media (Hutto and Gilbert 2014). VADER returns the sentiment of a text with a normalized score that ranges from −1 (most negative) to 1 (most positive). Because sentiment information is usually represented with categorical sentiment polarities (i.e., positive, neutral, and negative), the predicted continuous sentiment score is transformed into a sentiment polarity with a hard threshold. To ensure that each polarity possesses the same sentiment score range, the range is uniformly split to negative [−1, −0.333), neutral [−0.333, 0.333], and positive (0.333, 1] polarities. In addition, we made a necessary modification to VADER's inherent sentiment lexicon: the words "positive" and "negative" are set with zero sentiment score because they are broadly used to illustrate the COVID-19 test results that should have neutral sentiment.

To validate the reliability of VADER, 500 tweets were randomly selected and manually labeled by two coders that were native English speakers. To examine intercoder reliability, we calculated the percent agreement that is the proportion of the coding decisions that reached an agreement out of all coding decisions (Feng 2014). The percent agreement was as high as 92.3%, which proves the coding reliability. In addition, the coding decisions that did not reach an agreement were further discussed by the two coders to make final decisions. Finally, out of the 500 tweets, 158 were positive, 247 were neutral, and 95 were negative. The sentiment polarities predicted by VADER were compared with the manually labeled tweets to illustrate the sentiment prediction performances. The prediction performances of VADER are listed in Table 2. Overall, VADER has good performances in all these measures, and the accuracy is 83.2%. The recall is less promising for positive sentiment polarity, and the precision is less promising for negative sentiment polarity. A potential cause is the mismatch between the general sentiment lexicon used in VADER and the applied domain of society reopening amid COVID-19.

Public Opinion Analysis

Public Opinion Intensity

Previous studies have confirmed that social media data concentrate in populous areas (Fan et al. 2020; Malik et al. 2015), and the number of geotagged tweets is approximately linearly correlated with population size (Arthur and Williams 2019). Given these facts, FET is derived as the ratio of society reopening–related tweets to the population size, as shown in Eq. (1)

$$\mathrm{FET} = N/\mathrm{pop} \tag{1}$$

where N and pop = number of society reopening–related tweets and population size, respectively. The FET is not used to indicate the absolute level of public opinion intensity but for comparison among geographic regions.

Public Opinion Direction

In this research, public opinion direction is indicated by aggregating the predicted sentiment polarities of social media posts. Generally, the predicted sentiment polarities are usually aggregated as sentiment probabilities (Chen et al. 2019; Yu and Kak 2012). For formulation convenience, positive, neutral, and negative sentiment probabilities are denoted as θ_1, θ_2, and θ_3, respectively. Their formulations are shown in Eq. (2)

$$\theta_i = n_i/N \tag{2}$$

where n = number of society reopening–related tweets with a specific sentiment polarity i. In contrast to the FET formulation wherein the denominator is the population size, the denominator in sentiment probabilities is the number of society reopening–related tweets posted by only a small portion of the entire population. Therefore, it is necessary to incorporate the sampling uncertainty when solely using social media sentiment probabilities for deriving the sentiment information on the entire population.

In this research, sentiment probabilities are reliably modeled using a Bayesian-based method that integrates prior knowledge and new sentiment observations from social media. Newly observed sentiment information from social media is modeled as a likelihood function. Because sentiment polarity is a categorical variable (positive, neutral, and negative), the likelihood function is modeled with a multinomial distribution, as shown in Eq. (3)

$$L(\mathbf{n}|\boldsymbol{\theta}) = L(n_1, n_2, n_3|\theta_1, \theta_2, \theta_3) = \frac{\Gamma(\sum_i n_i + 1)}{\prod_i \Gamma(n_i + 1)} \prod_i \theta_i^{n_i} \tag{3}$$

where Γ is a gamma function. The prior knowledge on sentiment is modeled with a Dirichlet distribution because it is a conjugate prior to the likelihood function, which significantly eases the computational complexity, as shown in Eq. (4)

$$p(\boldsymbol{\theta}) = p(\theta_1, \theta_2, \theta_3) = \frac{1}{B(\alpha_1, \alpha_2, \alpha_3)} \prod_{i=1}^{3} \theta_i^{\alpha_i - 1} \tag{4}$$

where B is a multivariate beta function; and α_1, α_2, and α_3 = three shape parameters from prior knowledge. In this research, prior knowledge of sentiment probabilities on a certain day is calculated by averaging the number of sentiment observations in the preceding days. To remove the variations of the amount of social media activities on weekdays and weekends, the preceding 7 days were selected to derive the shape parameters in the prior knowledge on day j, as shown in Eq. (5)

$$\alpha_i = \sum_{j-7}^{j-1} n_{i,j}/7 \tag{5}$$

In this way, prior sentiment knowledge is updated in a daily manner to adapt to dynamic society reopening progress. The posterior distribution of sentiment probabilities is a closed analytical form due to the conjugate property, as shown in Eq. (6)

$$p(\boldsymbol{\theta}|\mathbf{n}) = \frac{L(\mathbf{n}|\boldsymbol{\theta})p(\boldsymbol{\theta})}{p(\mathbf{n})} = \mathrm{Dir}(\alpha_1 + n_1, \alpha_2 + n_2, \alpha_3 + n_3) \tag{6}$$

With the modeled sentiment probabilities, NPS is finally formulated as Eq. (7)

$$\mathrm{NPS} = \theta_1 - \theta_3 \tag{7}$$

Results

Nation-Scale Analysis of Society Reopening

Fig. 1 depicts the temporal variations of public opinion intensity on a nation scale. Each intensity spike indicates a reopening subevent (e.g., announcement of society reopening policies). For example, the first spike (indicated by the dashed circle) is caused by the tweet posted by President Donald Trump that "reopening the US by Easter is a beautiful timeline." At the early stage of society reopening (i.e., from late April 2020 to mid-July 2020), the intensity had many peaks, which is consistent with the fact that many society reopening subevents occurred in that stage (NGA 2020). The three states that have the highest intensity levels are Nevada ($\mathrm{FET} = 3.35 \times 10^{-4}$), New York ($\mathrm{FET} = 1.81 \times 10^{-4}$), and Florida ($\mathrm{FET} = 1.66 \times 10^{-4}$). The public in Nevada paid great attention to society reopening because the tourism industry—the largest employer in Nevada—had been severely affected by lockdown restrictions (Christiansen 2020). In addition, New York and Florida had high intensity levels. The potential reason for the high intensity level in Florida is that society reopening greatly benefits the tourism-sensitive economy. In New York, the high intensity level might have two reasons: (1) New York did not experience a significant increase of COVID-19 cases in June 2020 and continued to reopen society, which continuously triggers reopening-related discussions; and (2) Governor Andrew Cuomo provided frequent COVID-19 press briefings, which might increase public opinion intensity on society reopening. In the state-scale analysis, public opinion in California, Texas, Florida, and New York will be further investigated. Nevada was not studied in the state-scale analysis due to its small number of reopening-related tweets.

Temporal trends of NPS are presented in Fig. 2. The shaded area depicts the uncertainty of NPS: the larger width indicates greater uncertainty. The uncertainty is large in mid-March 2020 because there are few society reopening–related social media posts. From early May 2020 to early July 2020, the uncertainty gets smaller as states began to reopen society and triggered broad discussions. In addition, NPS is always larger than zero, which signifies that the public supports society reopening. To further understand the temporal dynamics of NPS, the number of COVID-19 cases is also included in Fig. 2. Here, the number of COVID-19 cases is processed with a 7-day moving average to remove the testing capacity variations between weekends and weekdays. NPS is inversely correlated with the number of COVID-19 cases—the Pearson correlation coefficient is −0.22 at a 0.01 significance level. Such a phenomenon suggests that the public opposes society reopening if there is an increase of COVID-19 cases while it supports reopening if there is a decrease of COVID-19 cases. Then, we divided the studied time into four periods according to the temporal trends of NPS and the number of daily confirmed COVID-19 cases, as shown in Table 3. These four periods will be used in the state-scale analysis for analyzing public opinion on the different aspects of society reopening.

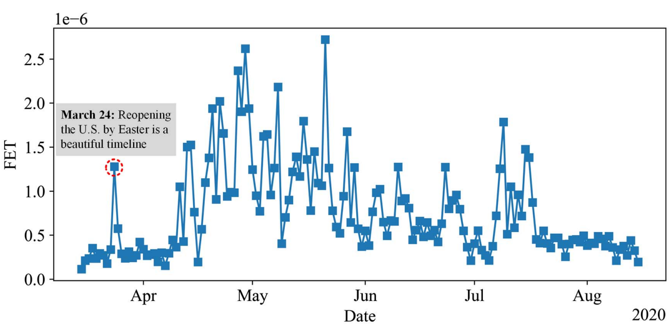

Fig. 1. Temporal trend of public opinion intensity on a nation scale.

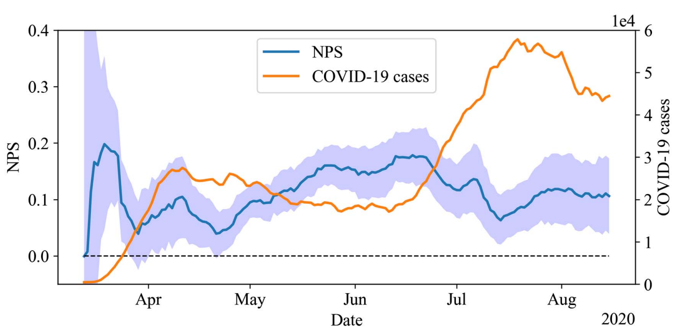

Fig. 2. Temporal trend of public opinion direction on a nation scale.

State-Scale Analysis of Society Reopening

This state-scale analysis aims to explore the interplay among public opinion, reopening policies, economic characteristics, and the number of COVID-19 cases. California, New York, Texas, and Florida were selected in this analysis to ensure enough society reopening–related tweets. The contextual information of the selected states is listed in Table 4. To restrict the spread of COVID-19, the four states issued lockdown orders to restrict movements for nonessential business (e.g., retail stores, food and drink, and personal care). Based on the North American Industry Classification System (Executive Office of the President 2017), nonessential businesses mainly fall into two industries: retail trade (RT) and arts, entertainment, recreation, accommodation, and food services (AERAF). We calculated the gross domestic product (GDP) percentage of the two industries for each state to understand the potential lockdown impacts on their economies. Florida has the highest percentage of RT and AERAF, which is consistent with the fact that the economy in Florida is tourism sensitive. In addition, researchers have pointed out that Republican-controlled states moved more expeditiously to ease lockdown measures than Democratic-controlled states (Kinnard 2020). Therefore, based on the 2020 presidential election results, partial lean is also presented in Table 4, wherein California and New York are Democratic leaning, while Texas and Florida are Republican leaning. The population percentage with internet access is also presented. California has a bit higher population percentage than the other states. In this research, we assume that there are no

Table 3. Reopening periods in the studied time span

Period	Date	Trend of NPS	Trend of COVID-19
1	March 13, 2020 to April 12, 2020	Decreasing	Increasing
2	April 13, 2020 to June 18, 2020	Increasing	Decreasing
3	June 19, 2020 to July 20, 2020	Decreasing	Increasing
4	July 21, 2020 to August 15, 2020	Increasing	Decreasing

Table 4. Contextual information of the four states

State	COVID-19 impacts	GDP percentage of RT and AERAF (%)	Population percentage with internet access (%)	Partisan lean
California	Lockdown	11.6	85.6	Democratic
New York	Lockdown	10.4	81.5	Democratic
Texas	Lockdown	16.5	81.9	Republican
Florida	Lockdown	7.1	81.0	Republican

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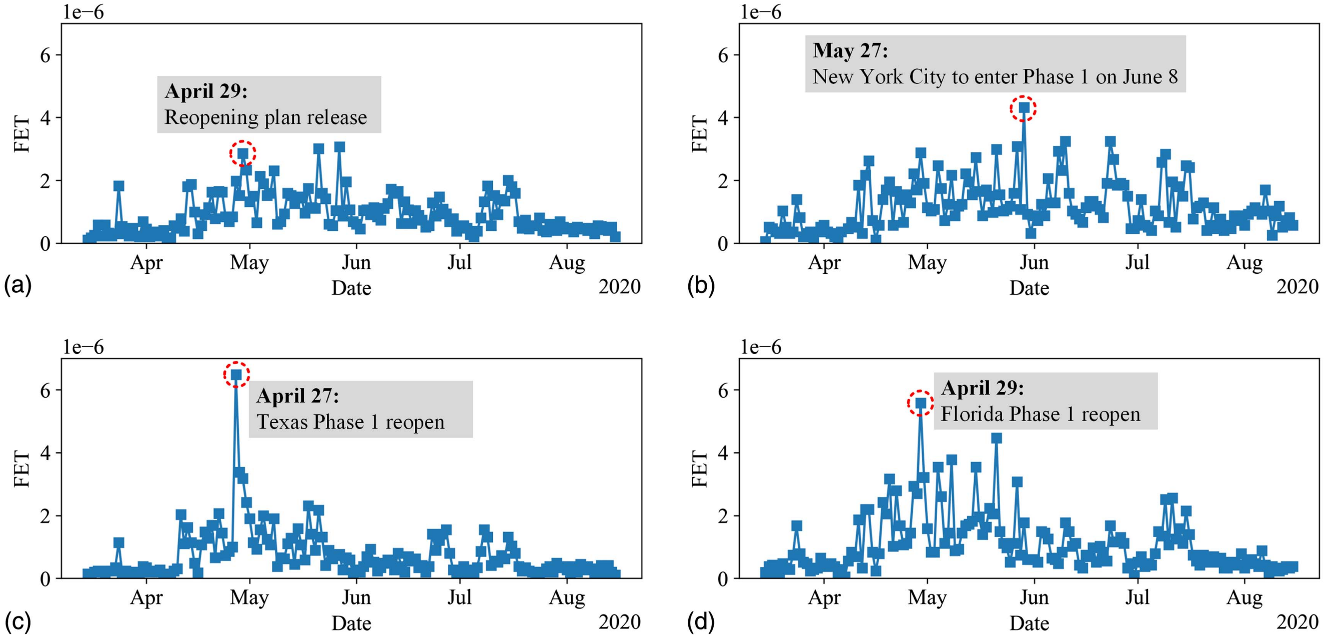

Fig. 3. Temporal trend of public opinion intensity in the four states: (a) California; (b) New York; (c) Texas; and (d) Florida.

significant differences in Twitter usage among the four states, and this assumption has been inherently made in existing studies (Hu et al. 2021; Wong et al. 2016).

To achieve a sustainable and safe reopening, the four states created their phased reopening plans (NGA 2020). However, the four states have different gating criteria for society reopening phases and varying local flexibilities for their counties. For example, counties may relax stricter local orders during Phase 2 in California, while in New York regions must meet gating criteria before reopening is allowed by the state. Texas has no specific statewide gating criteria for phased reopening, but New York has a set of specific criteria, such as counties much have a 14-day decline in hospitalization rates before they can reopen (NGA 2020). In summary, New York has the strictest and most cautious reopening plans, which is partially proved by the fact that New York City was the last city to reopen in the four states, and New York did not experience a significant increase of COVID-19 cases in June 2020.

Temporal trends of public opinion intensity in the four states are presented in Fig. 3. The first society reopening announcement for each state is marked with a dashed circle. In California, the two spikes in late May 2020 were induced by reopening small businesses (e.g., restaurants, retail stores, gyms, and hair salons) (Ellyatt et al. 2020; Jaclyn 2020). In New York, Texas, and Florida, the intensity levels on other reopening subevents are lower than that on the first society reopening announcement. The intensity levels on the first society reopening announcement in Texas and Florida are higher than those in California and New York. The potential reason for such intensity level differences is that reopening plans in Florida and Texas were announced to the whole state rather than counties or regions like in California and New York (NGA 2020). For instance, on May 4, 2020, Governor Ron DeSantis allowed restaurants, retail stores, libraries, and museums to open up to 25% of their building occupancy for the majority of Florida without allowances to Broward, Miami-Dade, and Palm Beach Counties (NGA 2020). In contrast, the society reopening announcement on May 17, 2020, in New York was only applied to New York City (NGA 2020). This is reasonable because Republican-controlled states were more expeditious to reopen society (Kinnard 2020).

Fig. 4 depicts the temporal trends of NPS and the daily number of COVID-19 cases. In California, Texas, and Florida, NPS increased from early April 2020; meanwhile, the numbers of COVID-19 cases remained at stable levels: a slight increase (California) or a slight decrease (Texas and Florida). This indicates that the public supports society reopening if COVID-19 spread is controlled. Starting from late June 2020, COVID-19 cases in California, Texas, and Florida began to increase significantly, and the three states pressed a reopening pause. Meanwhile, NPS decreased and remained at low levels. Such a phenomenon indicates that the significant increase of COVID-19 cases and the pause of society reopening make the public opposed to society reopening. The significant increase of COVID-19 cases in New York occurred in early April 2020. After the peak, NPS began to increase, and the daily number of COVID-19 cases decreased to a low level. In early June, there was a significant increase of NPS caused by the announcement of society reopening in New York City. Additionally, for the four states, there was large uncertainty in mid-March 2020 due to the small number of reopening-related tweets, proving the need of considering uncertainty when using social media to represent the entire community.

State-Scale Analysis of Business and Education Reopening

The previous nation-scale and state-scale analyses take all society reopening aspects as a whole. Therefore, they are incapable of discerning public opinion among different society reopening aspects. In this analysis, we investigate public opinion on the most discussed business and education reopening. To extract the social media data related to the business and education reopening, two keyword sets were identified by manually exploring the top words (the most frequent 100 words) in social media. The keywords were separately identified for each state to ensure that the most used keywords in each state were included. Such separate identification is necessary because the four states have different reopening policies and economic characteristics. For example, the keywords "beach" and "park" were frequently used in Florida but less mentioned in the other states. The identified keywords for each aspect in the four

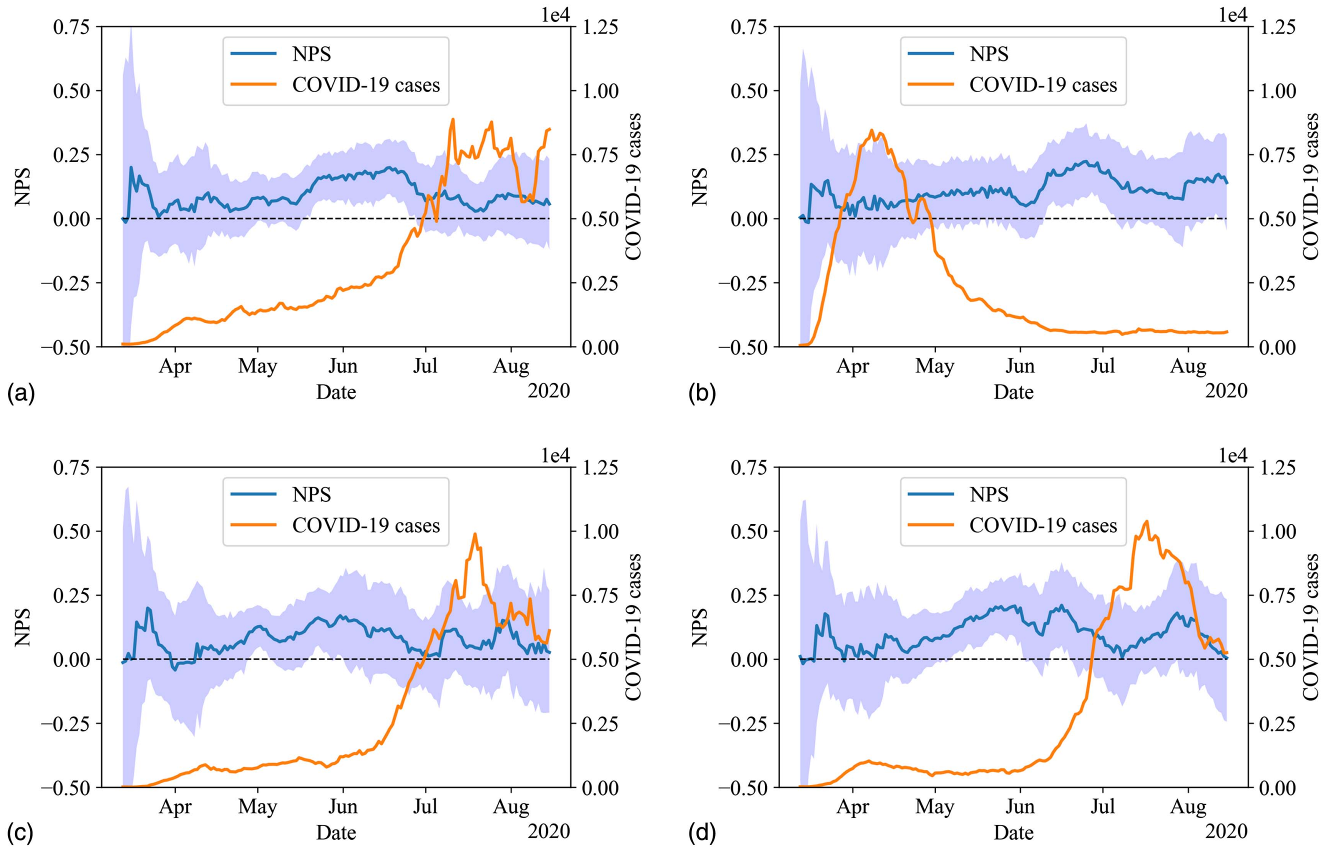

Fig. 4. Temporal trend of public opinion direction in the four states: (a) California; (b) New York; (c) Texas; and (d) Florida.

states were combined as the final keyword set for data extraction. The final keywords are listed in Table 5.

Public opinion on business and education reopening was investigated over the four periods defined in Table 3 instead of on each studied date. The major reason for this change is the small number of daily tweets related to a certain aspect of society reopening in a state. To provide the contextual information of the business and education reopening, the timelines of the major business and education reopening decisions are listed in Figs. 5 and 6. The major reopening decisions were applied to the majority of a state, the whole state, or a megacity (e.g., New York City). In Period 1, all the studied states issued stay-at-home orders to close schools and nonessential businesses. In Period 2, they began to reopen business and announced that schools would reopen in the fall semester, 2020. New York City was the last city to reopen. In Period 3, California, Texas, and Florida pressed a pause on the business reopening due to the significant increase of COVID-19 cases, while New York continued to reopen because it had controlled the spread of COVID-19 during this period. Also, states began to reopen schools in Period 3 with the release of guidelines or frameworks. In Period 4, there were not many major reopening decisions issued.

Table 5. Keywords for business and education reopening

Aspect	Keywords
Business	Restaurant, bar, retail, barbershop, hair, haircut, nail, salon, gym, store, curbside, carryout, delivery, food, drink, dining, economy, hotel, nightclub, construction, accommodation, casino, beach, Disney, park, theme
Education	Preschool, k12, k-12, education, school, student, university, college

Public opinion intensity on business and education reopening is presented with a group box plot in Fig. 7. Daily intensity levels in a period were used to calculate the box's characteristics to provide an overview. The intensity level of business is much higher than that of education. For the business reopening, Florida had a higher intensity level in Period 2, which is reasonable because reopening business greatly boosts the tourism economy in Florida. In the last two periods, New York had much higher intensity levels than the other three states. A potential reason is that New York continued to reopen business in the last two periods, but the other states pressed pause on business reopening due to the significant increase of COVID-19 cases at that period. For the education reopening, intensity levels were quite low in the first two periods. Even in Period 2, state governments announced that schools would reopen in the fall semester but got less attention from the public. Period 3 has the peak intensity levels on education reopening. This is because the four states released school reopening guidelines, which triggered many topics that include the preparation of school reopening, the discussion of reopening policies, and personal feelings of school reopening. In Period 4, New York had the highest intensity level on the education reopening, and a potential reason is that schools in New York continued to fully reopen in-person instruction, while the other three states switched to partially in person.

NPS of the business and education reopening is presented with group box plots, as shown in Fig. 8. The box length indicates the uncertainty: the larger the length, the greater the uncertainty of the NPS. NPS on education had a larger uncertainty in the first two periods. To reliably compare public opinion direction on education reopening, NPS differences between two states were calculated

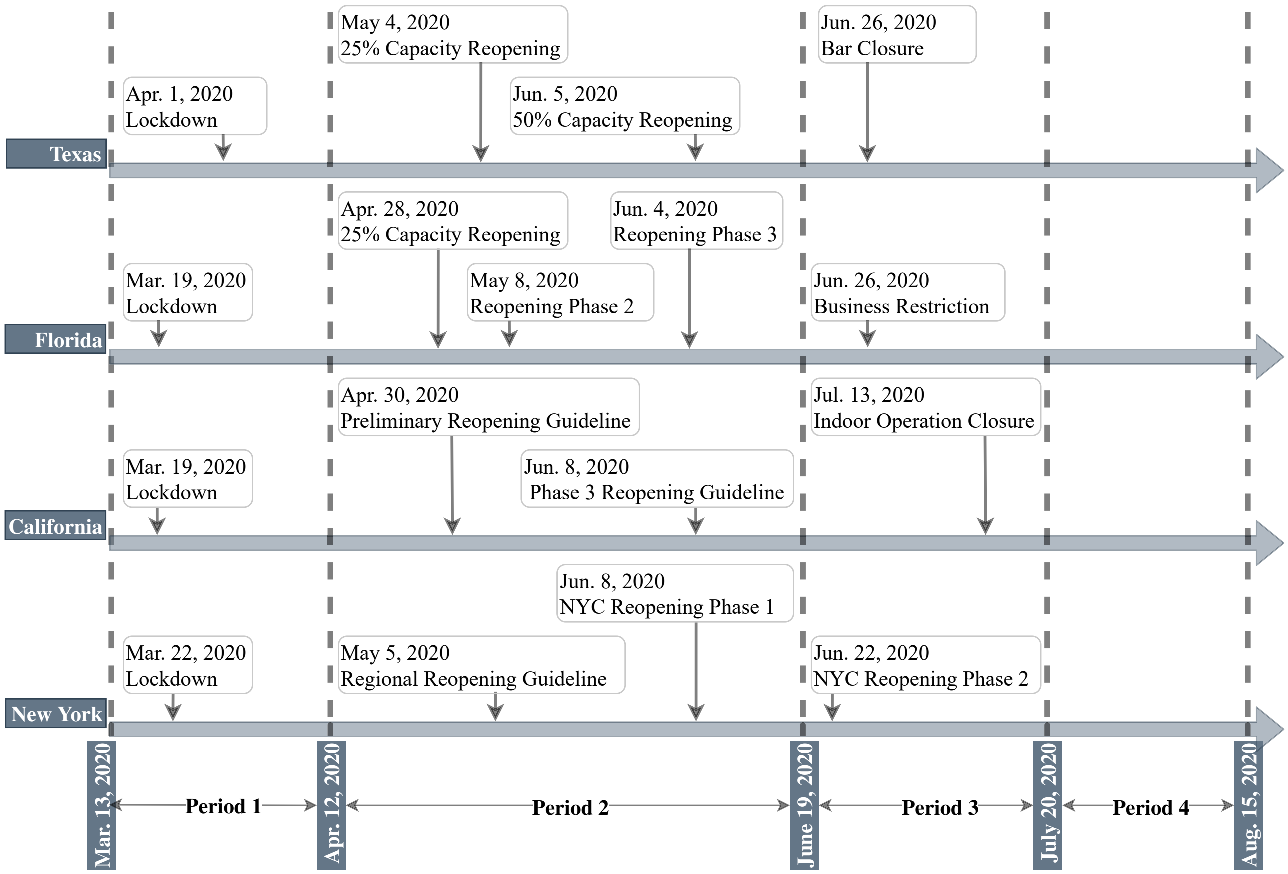

Fig. 5. Timeline of major business reopening subevents in the four states.

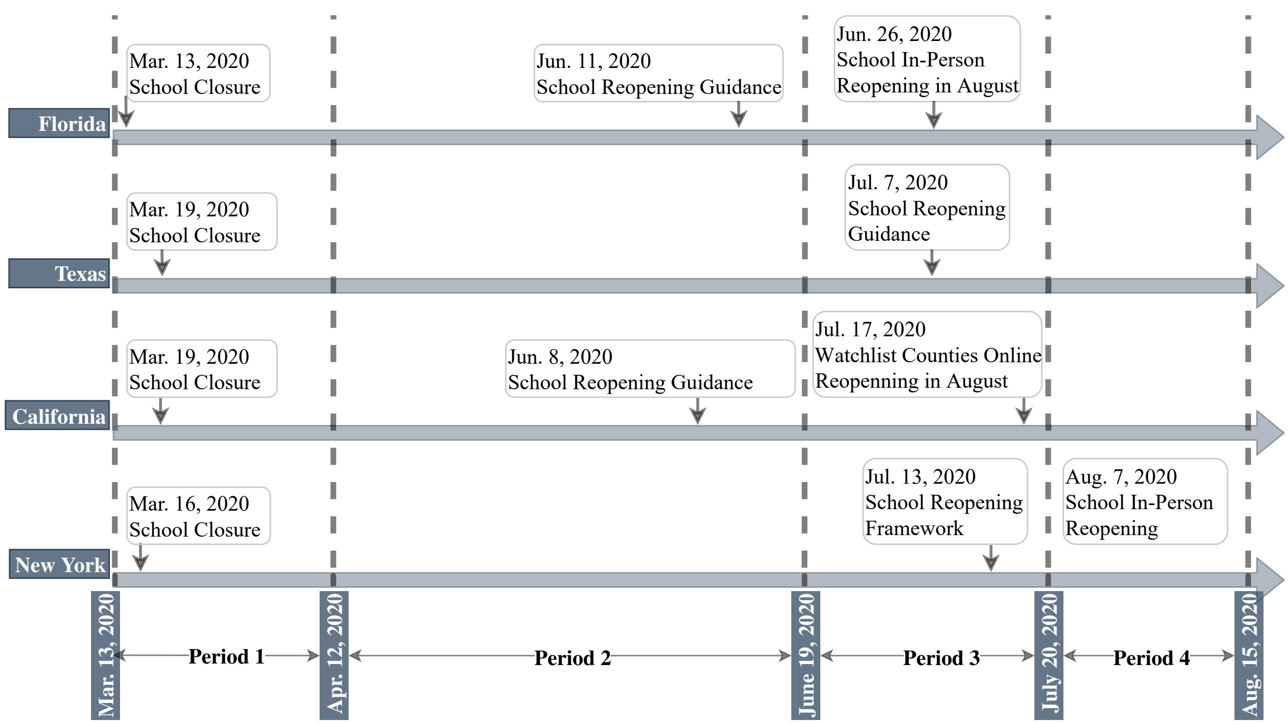

Fig. 6. Timeline of major education reopening subevents in the four states.

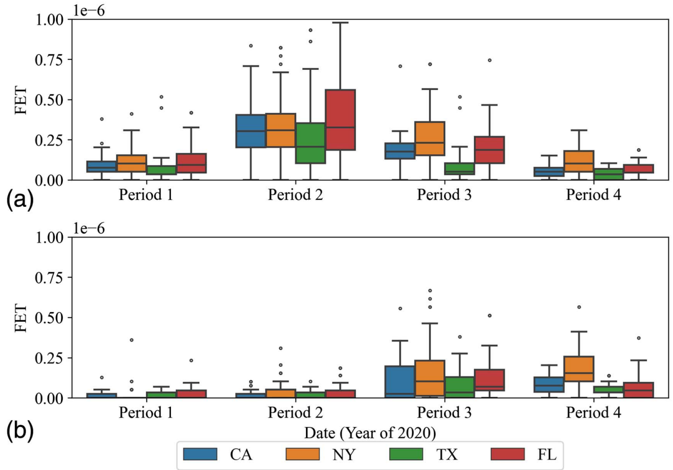

Fig. 7. Temporal trend of public opinion intensity on (a) business; and (b) education.

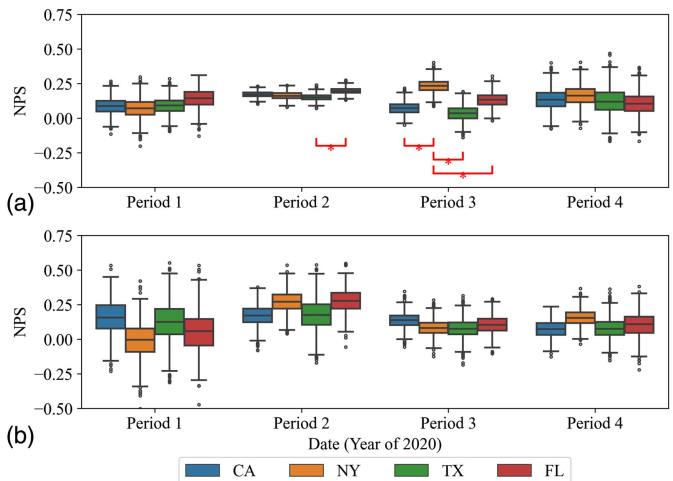

Fig. 8. Temporal trend of public opinion direction on (a) business; and (b) education.

based on a simple area overlap method: a difference level is indicated by the overlapped area (OA) between two normalized NPS histograms (area sum to 1). A small OA represents a high difference level and vice versa. We defined four difference levels (DLs) based on the overlapped area using Eq. (8)

$$\mathrm{DL} = \begin{cases} \text{Level 3}(***) & \mathrm{OA} \leq 0.003 \\ \text{Level 2}(**) & 0.003 < \mathrm{OA} \leq 0.05 \\ \text{Level 1}(*) & 0.05 < \mathrm{OA} \leq 0.32 \\ \text{Not significant} & 0.32 < \mathrm{OA} \end{cases} \tag{8}$$

This definition is consistent with the percentage of values that lie within standard deviations of the mean in a normal distribution. For the business reopening, significant NPS differences mainly occurred in Period 2 and Period 3. In Period 2, the public in Florida possessed the strongest support toward business reopening, which is consistent with the fact that business reopening greatly benefits the tourism-sensitive economy in Florida. In Period 3, New York possessed the strongest support on business reopening, and the difference between New York and any other state is significant. This is because New York continued to reopen, while other states paused reopening due to the significant increase of COVID-19 cases in late June 2020. Regarding the education aspect, there are not many differences among these states.

Discussion

This research proposed FET and NPS for investigating the intensity and direction dimensions of public opinion, respectively. FET reveals public opinion intensity, wherein the variations of the amount of Twitter activities caused by population size are removed. Compared to existing intensity measures (e.g., the number of likes), FET is capable of reliably comparing intensity levels among different regions. NPS indicates the public opinion direction, wherein a Bayesian-based method is used to model the sampling uncertainty of social media sentiment probabilities. The modeling of the sampling uncertainty is especially needed in the scenario with a small number of tweets. For example, NPS had a large uncertainty in mid-March 2020 due to the small number of reopening-related tweets. This uncertainty assists decision makers in understanding the risk of perceived public opinion direction.

Theoretically, the findings of public opinion on society reopening amid COVID-19 contribute to understanding human behavior dynamics in emergency events. There are high levels of public opinion intensity at society reopening subevents (e.g., announcement of reopening policies). Public opinion intensity highly relies on society reopening policies and economic characteristics. For example, Florida and Nevada have high intensity levels because lockdown restrictions have significantly impacted their tourism-sensitive economies. In general, the public supports society reopening, but the reopening pause and the significant increase in COVID-19 cases lead to a decrease in support. Such findings suggest that decision makers could obtain support through continued reopening and successful COVID-19 spread control.

The proposed metrics are easy to implement because the employed social media data are publicly available and ready to collect. The proposed metrics are expected to enhance the reliability of public opinion obtained from traditional approaches, i.e., surveys and public meetings. Compared to surveys, the proposed approaches are capable of providing new insights because social media posts are not restricted by survey questions. In contrast to public meetings, the proposed approaches enable a broad engagement of the public in a short time, which is desired for analyzing public opinion comprehensively. In practice, the proposed approaches are expected to be applied to (1) promptly monitor public opinion in dynamic emergency events, which is critical for policy makers to revise current policies or to create new policies for adapting to dynamic emergency conditions; and (2) provide a preliminary overview of public opinion to guide the conduct of traditional approaches (e.g., selection of public meeting topics and the design of survey questions).

Conclusion

The research proposes FET and NPS to perceive public opinion intensity and direction through social media. To prove the feasibility and applicability, we studied public opinion on society reopening amid COVID-19 for the United States as a whole and four individual states (California, New York, Texas, and Florida). The perceived public opinion has been supported by the society reopening policies, the temporal trends of COVID-19 cases, and the state economy characteristics. The research findings in the case study are expected to assist decision makers in making responsive reopening decisions amid COVID-19.

This research has theoretical and methodological advancements in mining public opinion using social media. From the theoretical perspective, this research provides a set of reopening-related findings that contribute to understanding human dynamics in emergency events. From the methodological perspective, we developed two systematic metrics, FET and NPS, for investigating the intensity and direction dimensions of public opinion in a reliable and rapid manner. In FET, the variations of the amount of Twitter activities caused by population size are eliminated, which is essential to compare public opinion intensity among geographic regions. In NPS, the uncertainty of sentiment information is modeled with a Bayesian-based method that integrates prior knowledge and new sentiment observations from social media, which is beneficial for assisting practitioners in understanding the risk of perceived NPS. Although the proposed metrics are presented in the COVID-19 context, they could be easily generalized to other emergency and nonemergency events because the collected social media posts are the only difference.

The presented research suffers four major limitations. First, the proposed FET and NPS only provide limited insights into public opinion direction and intensity. In reality, public opinion is inherently complex and ambiguous, which makes it extremely complicated to indicate public opinion comprehensively. Take the direction dimension of public opinion as an example: it could often be more complicated than simple support and opposition. For instance, while public opinion on abortion is usually characterized as either supporting or opposing legal abortion rights, many people believe that abortion should be legal in some circumstances but not in others (Glynn et al. 2015). In addition, public opinion is characterized by the measured intensity and direction dimensions as well as other important dimensions, such as stability and information content (Glynn et al. 2015). Second, the proposed metrics present the direction and intensity dimensions in an aggregated manner, making them less capable of revealing the details of public opinion. For example, compared to open-ended survey questions and interest group interviews, the proposed metrics only reveal the overall trends of public opinion, but fail to present public opinion content differences among social groups. Third, social media users are not an ideal sample for representing the entire population because researchers have pointed out behavior differences among social groups (Fan et al. 2020). For example, elderly groups (e.g., aged over 65 years) are less active on social media than young groups (e.g., aged between 18 and 29 years), which makes the elderly groups underrepresented while young groups are overrepresented on social media. Such under- and overrepresentation might lead to a biased mining of public opinion using social media. Fourth, the sparseness of reopening-related tweets constrains the usage of the proposed metrics in more detailed granularities, such as county level and community level. Meanwhile, the sparseness also leads to a high uncertainty level of measured public opinion, which increases the associated risks for policy making.

In the future, we aim to conduct the following efforts to enhance the reliability and applicability of the proposed metrics for investigating public opinion. The first effort is to employ data enrichment methods [profile-based (Kryvasheyeu et al. 2016) and content-based (Mao et al. 2019)] to increase available social media data size. The second effort is to integrate other social media data sources (e.g., Facebook, Instagram, and YouTube) with Twitter to produce a more reliable analysis of public opinion. The third effort is to integrate the proposed metrics with conventional methods (e.g., surveys and focus group interviews), thereby indicating both overall trends and details of public opinion. Through such an integration, we expect to achieve rapid and comprehensive analysis of public opinion in the future. Fourth, a COVID-19 sentiment lexicon will be customized to improve the sentiment prediction performance. Finally, the other dimensions (e.g., stability and informational content) of public opinion will be modeled to achieve a comprehensive analysis.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request: population data and all codes. Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions: only tweet IDs can be provided according to the Twitter Developer Agreement.

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