Great Divisions: The Evolution of Polarization During the Man-made Emergency of January 6, 2021.

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Abstract

Polarization, which refers to the formation of opposing groups based on peoples' beliefs and opinions, is a phenomenon that has existed for eons. However, in the recent past, social media has caused a quantum change in the dynamics of polarization since beliefs may change almost instantaneously on social media because of unfolding events. We investigate social media communication that has resulted in polarized opinions among individuals prior to, during, and after a crisis event; the January 6th US Capitol riots. Analyses of the dominant narratives on Twitter surrounding the incident reveal a high level of polarization throughout the unfolding of the event, with increased polarization possibly attributable to the onset of the crisis. We also observe the evolution of the phenomenon: as the event unfolds, polarization changes. We suggest that understanding the evolution of polarization is important for timely crisis resolution by crisis managers. We utilize three measures, spread, distinctness and regionalization, to examine polarization during a crisis. Based on these measures our findings indicate that social media discussions exhibit an increase in the negative sentiment during the crisis as compared to pre-crisis, but there is a rebound in terms of positive sentiments emerging in the post crisis period. Also, the results signal reduced diversity in discussion topics during the crisis as compared to pre and post-crisis.

Keywords: Polarization, Sentiment Analysis, Capitol Riot, Crisis, BERTopic.

1. Introduction

In recent past, polarization has increased among American citizens. Polarization is often used in social science (especially political science) to characterize concentrations of divergent opinions which is referred to as "ideological polarization" (Dalton, 1987). Another alternative definition is of "affective polarization" which refers to strength or warmth of likes and dislikes between each opposing side (Iyengar et al., 2019). Affective polarization results in tendency of partisans to like or dislike those from the opposition party.

Researchers note how over the years citizens have become more polarized in their opinions (Bail et al., 2018) with many engaging in echo chambers that not only promote polarized discussions, but also make misinformation rampant and contribute to its virality (Acemoglu et al., 2021). The January 6th U.S Capitol crisis (referred to as Riot in this paper) serves as natural experiment to determine magnitude of such divide.

Previous research has focused on studying issue-based politics, such as abortion rights or gun control, that polarize citizen's opinions on either side (Zhang et al., 2022). Some researchers have investigated the effects of echo chambers and how they are effectively slow-moving crises that have been exacerbated by the continuous tussle of opinions between the right and the left (Ye et al., 2021). Yet other researchers have attempted to specifically analyze election campaigns and its results, such as studies on US Presidential elections of 2016 and 2020 (Allcott & Gentzkow, 2017; Baker et al., 2020). Some of the literature has also focused on studying whether it is possible to invert the opinions of people that are at the opposite ends of the political spectrum (Asimovic et al., 2021). Much of the past research using social media data has investigated user interactions from a social network perspective and used social network analysis to study the formation of echo chambers (Ye et al., 2021). Yet, there is little research on how social media political viewpoints evolve organically over time, including on open-ended platforms like Twitter (which ranks first in delivering news to the public (Pew Research Center, 2021)). Nor is there any research on the topics that drive social media polarization that evolve over time.

In the first section of this paper, we investigate temporal disparities in social media conversations of the January 6 Capitol Riot. We study polarization over the course of eight days using a time-divided Twitter

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dataset. We then study the differences in topics across time in user conversations on the platform. Exploring the intensity of discussions through the number of tweets and the sentiment expressed in the tweet text allows an analysis of polarization during crisis events. This exploration of intensity is more akin to the concept of affective polarization (Iyengar et al., 2019) rather than that of ideological polarization. For the first aspect (time), we collect timestamped social media data from three different time periods and investigate: 1) the pre-incident data that contains social media conversations leading up to the January 6th attack, 2) the during-incident data that consists of real time discussions over the period of two days from January 6th till January 7th and 3) the after-incident data that is made up of the people's reaction to the U.S Capitol Riot and its aftermath discussed until January 10th. These reactions showcased a wide range of people's sentiments and emotions which is typical of public responses to crisis events that are shared on social media platforms (Brynielsson et al., 2014). Therefore, for the latter aspect (sentiment) we use empirical methods to determine the intensity of polarization by a) analyzing its different measures - spread, distinctness, and regionalization (Bramson et al., 2017; Dixit & Weibull, 2007); and b), using artificial intelligence-based topic modeling that output central topics of discussion based on data from across all the three time periods (Blei, 2012; Singh et al., 2018).

To summarize, this paper studies polarization in the context of a crisis situation and examines emotional response in social media communication. This study focuses on the nature of polarization and its evolution in a fast-moving crisis i.e., the January 6th riot. The incident provides a real-life event in which we can clearly identify two opposing groups of thoughts regarding the event. We distinguish between views that opposing groups hold in terms of who they blame for the crisis. Also, we establish the nature of the discussion in relation to the crisis by studying social media conversations that debate why the crisis occurred and how to solve it. In this paper, we focus on the Twitter social media platform. With these objectives in mind, we pursue the following research questions:

RQ 1 - How does social media discourse evolve during crisis stages and change between pre-crisis, during and post-crisis stages?

RQ 2 – How does the nature of polarization in social media discussion, i.e., topics, change over time in pre-crisis, during-crisis, and post-crisis situations?

In the next section, we discuss polarization, crisis events, and social media user discussions. Next, we discuss research model, methods, data collection, analysis, and results. The conclusion includes discussion and research contributions.

2. Research Background

2.1 Crisis History

In this paper, we focus on a particular crisis that happened on January 6th, 2021, in Washington DC, the nation's capital. A group of thousands of supporters of the former president stormed the legislative capital of the United States to block the legislative process that would transfer power to President elect Joseph Biden. The events that transpired during the riot at U.S Capitol on January 6th were primarily a result of the culmination of several social media driven hashtags and campaigns that were being actively shared on many social networking sites (Hitkul et al., 2021) since the 2020 US Presidential elections were announced. Joe Biden was declared the winner of 2020 US presidential election, which was announced on January 6, 2021, on major US news networks. A pro-Trump mob clashed with police, burst into the U.S Capitol building, and forced members of Congress to evacuate. Many of the rioters originated from a protest planned a few days prior to the 6th, and intense conversations about storming into the United States Capitol persisted for another 3-4 days across various news channels and on television.

2.2. Polarization

From studying the role of echo chambers and homophily (Acemoglu et al., 2021) in the creation and propagation of polarization, to researching the impact of social media platforms in increasing or mitigating polarization (Allcott & Gentzkow, 2017), there have been several studies that have researched polarization, particularly political polarization (Finkel et al., 2020). Other research has shown that the COVID-19 pandemic has further exacerbated polarization in the community with opposing views and discussions being shared by people who view it as a political issue rather than a health issue (Bruine de Bruin et al., 2020). The discussions around the effectiveness of masks, lockdowns and vaccines have been a contentious issue especially along party lines. To this end, studies have not considered the temporality of polarized discussions on social media, especially over shorter timeframes. We aim to address this gap by empirically measuring how levels of polarization change in crisis stages.

Past research in polarization has been conducted from a variety of perspectives (Tucker et al., 2018). We adapt Dixit & Weibull (2007) to the social media setting of our study. In their work, there are two polarizable perspectives: the individual's and the probabilistic world view. In our work, the individual views are extracted using artificial intelligence-based topic modeling that output central topics of discussion based on the dataset from across all the three time periods (Blei, 2012; Singh et al., 2018). The aggregate world view is extracted by finding out the aggregate number of tweets within the individual views which then gives us the level of polarization seen in the community that we quantitatively measure using the metrics of spread, distinctness and regionalization (Bramson et al., 2017).

2.2. Crisis Events

Crisis events and crisis response rely heavily on information, experience and swift decision making (Romanowski et al., 2015) of all parties involved. Social media platforms have been used during crisis events as an emerging domain to gain key data regarding events that transpired or resulted in creation and progression of the crisis (Xie et al., 2017). To analyze crises, event studies focus on collecting several critical data points using crowdsourcing methods. These include filtering real-time images from the event to aid in response efforts (Jongman et al., 2015), as well as collecting user descriptions about events to provide focused alerts to affected people in a particular geographical location (Xu et al., 2020). Social media has provided invaluable information that has helped to make sense of crisis events and aided response & recover efforts.

2.3. Social Media Platforms

As social media become the significant source of information, online political polarization has seen considerable increase in research interest over the last decade. These include studies focusing on US Presidential election of 2020 (Baker et al., 2020) as well as platform specific studies that investigate how online social networking sites (Facebook, Twitter, Reddit) differ in the manner in which they contribute to the rise (Bail et al., 2018) or decline in polarization (Cinelli et al., 2021).

Previous studies explore polarization from multiple perspectives, such as platform or country differences, but there are few that focus on polarization through social media conversations (Zhang et al., 2022). Also, the current literature on polarization has treated it as a static concept that does not evolve over time. In this work, we study the evolution of polarization across a 10-day period and quantitatively analyze the spread and movement of polarized discussion on Twitter. We also research polarization and crisis response and show that temporal differences exist in the level of polarization seen in society, particularly during the crisis.

3. Research Model

In this work, we focus on studying users' conversations related to the crisis event on Twitter social media platform across three phases: pre-crisis, during-crisis, and post-crisis. This has enabled the uncovering of user discussions about nature, causes and consequences of the crisis, through AI-based topic modeling and qualitative topic analysis. In the research methods section, we describe the data collection, analysis, and modeling techniques in detail.

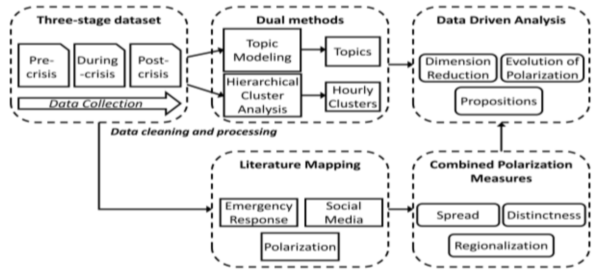

Figure 1. Data Driven Research Model.

Initially, we divide our selected crisis incident into three separate phases of pre-crisis, during-crisis, and post-crisis. This separation of data is driven by situation awareness theory which has clear demarcation of stages through which an event progresses as identified in recent studies that investigate public's emotional response on Twitter (Bachura, et al., 2022). A particularly prominent campaign was associated with the hashtag '#StopTheSteal' which was used for collecting our dataset. We also tracked similar hashtags across different time periods, for example '#election results' and '#CapitolRiot'. Using these hashtags, we follow a data-driven approach to analyze the differences in polarization across the January 6^{th} incident.

We segregate the collected dataset accordingly as per the three phases, each of which is analyzed in isolation. We then proceed to apply empirical methods to these three data sets. For this we focus on two methods using i) AI based topic modeling methods for detecting topics and ii) using hierarchical cluster analysis for determining clusters across datasets. We then map the existing literature on social media, crisis response and polarization to derive various measures that can determine the level and evolution of polarization in the social media space based on users' conversations that have been aggregated through clusters and topics identified in the previous step. After we extract the topics and empirical measures of polarization, we apply them to derive a data-driven analysis of the January 6 attack and examine several polarization measures and present results related to the evolution of polarization. Finally, we apply the identified empirical measures of polarization to these topics to determine the difference in individual views as compared to the world views. We repeat the analysis for each of the three datasets and present the data driven analysis of the Jan 6 Capitol Riot.

4. Methodology

4.1. Data

The data was collected over a period of one month (December 21, 2020 – January 20, 2021) for analyzing users discussions related to the US Presidential election results. January 6th provided us with a unique opportunity to study a man-made crisis incident as it unfolded in real time on social media. Therefore, in this paper we utilized data for only the first 10 days of January which effectively marks the pre-crisis, during-crisis, and post-crisis stages of this crisis incident. We categorized the data from January 3rd to 5th as the pre-crisis dataset (N = 336,574), from January 6th to 8th as the during-crisis dataset (N = 3,035, 452), and from January 8th to 10th as the post-crisis dataset (N = 897,060). In total, we analyzed 4,269,086 tweets which we collected using the Twitter streaming API and a developer account. The search strings were based on a set of Hashtags associated with the 2020 US Presidential elections which focused on directed campaigns aimed at disputing the election results such as #StopTheSteal and #BidenWillNeverBePresident which have been directly tied to the Capitol Riot (Hitkul et al., 2021).

The number of topics extracted in each phase were proportionate to total number of tweets in that phase. The topics were based on aggregate user conversations that discussed different perspectives of the election; from voter fraud to threats to democracy, to the potential role of social media platforms in inciting violence. Based on the topics of discussion in each phase they were assigned reduced dimensions that reflected the main topic of discussion. We restricted the analysis in this study to tweets in English. The number of tweets and reduced dimensions of topics as well as the hashtags used for data collection are presented in Table 1.

Phase	**No. of tweets**	**Dime nsion**	**Hashtag Examples**
Pre-crisis (Jan 3-5)	336,574	5	#USPresidential Election; #electionresult;
During (Jan 6-7)	3,035,452	3	#CapitolRiot; #StopTheSteal
Post (Jan 8-10)	897,060	8	#Trump Rioter; #BidenWillNev erBePresident
Total	4,269,086	16	#StopTheSteal; #Trump; #Biden

Table 1. Data Metrics.

4.2. Method 1: Topic Modeling

We used LDA Topic modeling (Blei, 2012) and the latest BERT transformer based BERTopic procedure (Grootendorst, 2022). BERTopic creates a class-based TF-IDF procedure to map each word to a topic using a pre-trained contextual word embedding representation called BERT. BERT (Devlin et al., 2018) is the current state-of-the-art pretrained contextual representations, which are based on a massive multilayer Transformer encoder architecture (BERT-Base has 110M parameters and BERT-Large has 330M parameters) and are trained using masked language modeling and next-sentence prediction tasks. Topic modeling techniques have increasingly been used to study polarization on social media platforms especially on Twitter (Walter et al., 2020). Twitter allows a limited number of characters, which makes it easier to efficiently summarize users' conversations. In essence, topic models provide sets of keywords that are closely related to individual tweets and can be used as proxy to establish the point of discussion within the said tweet. Despite the fact that BERTopic and LDA both provided many similar topics, LDA's topic has many overlapping keywords, confirming previous findings that BERTopic outperforms LDA in generating short topics from short text such as social media tweets (Egger & Yu, 2022). Across the three datasets, we systematically analyzed these keywords and classified the tweets into various topics that were related to election results, capitol riot and its aftereffects. We further segregated the topics into hourly clusters that provided a much more granular view of the topics of discussion during the January 6th attack.

4.3. Method 2: Hierarchical Clustering

For extracting topics, we used an n-gram keyword analysis composed of unigrams and bigrams (one-word and two-word based keywords) and trigrams (three-word phrases). We further augmented the n-gram topic modeling approach for text classification by using the hierarchical clustering technique (Bhatt et al., 2022; Singh et al., 2018) to derive the central hourly topics within social media conversations that relate to the discussions around the January 6th U.S Capitol Riot. Using the model, a general distribution can be obtained that showcases how social media users are split while discussing the election results, its impact on American democracy and the legitimacy of the election. The use of hierarchical clustering technique is appropriate to capture user discussions on Twitter as has been evidenced by previous studies on social media (Albanese & Feuerstein, 2021). For each of the three topic models across our datasets, hourly clusters were generated so that temporal patterns in user discussions about the attack could be observed.

4.4. Polarization Measures

Various studies have attempted to study polarization from different perspectives, such as measuring the boundary of a polarized group (Zhang et al., 2022), spread, dispersion, and regionalization (Bramson et al., 2017). In addition, some studies derived qualitative measures by using surveys of voters to determine how far apart two groups of voters are from each other. In this study, we have focused on determining quantitative measures of polarization so that they can be used to identify the evolution of polarization across a crisis event such as the January 6th attack. In this regard, we have adapted Dixit & Weibull (2007) to define polarization within two sets of views – individual view versus world view. We derived the individual view by analyzing the tweets of users and the topics to which they correspond. For example, the tweets classified in the 'Supporting Trump' topic mean that the users who posted such tweets support President Trump's claims about voters and consider themselves as Patriots protecting the sanctity of an election (or in the opposite topic of 'Against Trump' they would be considered as Rioters). This is at an individual tweet level. To derive the world view, we focus on the entire corpus of tweets associated with a particular topic within a topic model. For example, the absolute number of tweets within a particular topic group is N = 22,755 for 'Supporting Trump'.

We also use several measures of polarization (Bramson et al., 2017) to test for polarization across topics. While there are multiple measures available that could be used for our preliminary results, we have selected the three most relevant for our purpose. To measure the degree of acceptance or rejection of an opinion of individuals, we use the sentiment expressed in a sentence to understand the level of polarization by utilizing the metric of spread which measures how far apart the extreme opinions within a topic are. It is the absolute difference of opinions between a tweet with the most negative sentiment and a tweet with the most positive sentiment. We capture the spread across various topics over time. Such a measure points to the divergence in public opinions at each phase of the crisis across various sub-events (topics) within the broader event (crisis itself).

Topic Name	Dimension
Supporting Fraud narrative; Georgia Election Stolen; Stop Election Lies	Believe in Fraud/Stolen Elections
Fake News; Report facts; Media News; Propaganda; Journalism	Biased Media
Biden Won; Welcome Efforts; BidenHarris	Believe in Biden
Love for Country; Be a Patriot; Don't Lose Hope	Believe in Country
Stand with Trump; Trump Rally; People believe Trump	Believe in Trump

Table 2. Pre-Crisis Bert Topics.

The second measure, distinctness, is the degree to which group distributions can be separated. Each topic within the broader crisis event exhibits various levels of sentiments. The "Distinctness" property of measuring polarization helps us measure which topics stand out among the list of topics. To capture the distinctness of opinions within each topic, we captured the distinctness at timely intervals for each topic. For example, if there are N time intervals, we capture the overall sentiment of each of these N intervals to create N samples for topic Tk where k is in the range of [1, K] topics. Distinctness measures the average sentiment of each topic over the total number of time intervals, or it is the mean sentiment over a given time.

Finally, the third measure, regionalization, is the difference in views within same topic groups. For example, the different opinions shared under a similar topic. In the case of 'Supporting Trump' topic group, there are a couple of other topics that are similar to the category of supporting Trump such as "Stolen Election" and "Believe in Country". As we are operationalizing the polarization measure based on the sentiment expressed in the tweets, we need a measure to capture the topic polarization to answer if topics are related to polarization among the users. The comparative difference in group sentiment between two similar topics could help us answer to what extent users (or tweets) agree (or disagree) that 'Election Fraud' happened or agree that 'Ballots were Destroyed'. This measure, regionalization, enables a comparison between within group and out-group polarization, which we describe briefly in the following results section.

5. Results

Based on topics generated by BERTopic, we perform content analysis on similar topics using keywords and sample tweets. Table 2., 4., 6., show final topics during each phase of the event.

5.1. Pre-Crisis

Our results from pre-crisis topic models were mostly skewed to one group since social media conversations were dominated by claims such as the 'election was (is being) stolen' and there is a need to ‘stand with President Trump’ and get him back in power. Almost a quarter of the tweets (24.66 %) in this dataset supported the ‘fraud narrative’ that the 2020 election was rigged. The other major topic was that the ‘Georgia election is being stolen’ (21.60 %) and that ‘people still believe in President Trump’ (11.10 %). After dimension reduction we narrowed the topics based on what people believe in regarding the election results. Five major topics emerged as ‘believing President Trump’, ‘believing Biden’, ‘believing that fraud happened, or the elections are stolen’, ‘biased media’, and ‘believing that the country needs people who fight for injustice’ to protest. Clearly, two possible groups of individuals form polarized opinions about five key discussion topics. Taking the sentiments of the views they expressed on each of these topics over hourly time intervals, there is a strong positive sentiment in the "Believe in Country" category, while there is a strong negative sentiment in the "Stolen Elections" category as seen in the figure 2. One group of Twitter users created a strong negative sentiment in the claims that the elections were stolen and in their encouragement of other users to be patriotic and participate in the Capitol Riot. On the other hand, there is a strong negative sentiment within the "Biased Media" category, where many users favor "Supporting Biden."

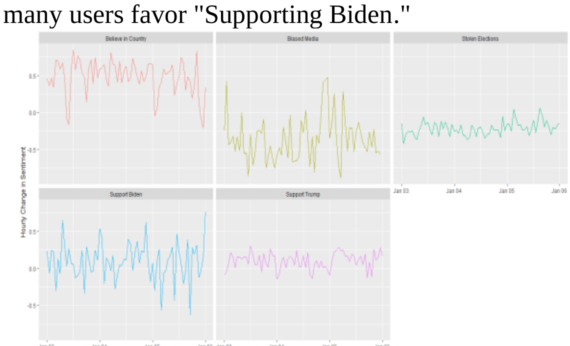

Figure 2. Pre-Crisis Topics Polarization.

To understand extent of polarization during pre-crisis stage, we captured the polarization measures as shown in table 3. For each topic, there is a polarity “spread” followed by a “distinctness” measure (in parenthesis).

Polarization measure	Spread (Distinctness)
Believe in Country	1.988 (0.5397)
Biased Media	1.916 (-0.3595)
Stolen Elections	1.952 (-0.2449)
Support Biden	1.939 (0.09846)
Support Trump	1.976 (0.09368)

Table 3. Polarization Measures – Pre-Crisis.

On a zero to two scale our findings indicate that polarization is spread out uniformly across the different topics of discussion (ranging from 1.91 to 1.98). This is true for either side of the polarized topic. For instance, in the topic “Biased Media” the difference in opinion between those who believe the media is biased versus those who do not believe it so is 1.91 indicating the presence of two opposing camps or groups. Similarly on the topic of “Stolen Elections”, the gap between people who believe the 2020 US Presidential election was rigged or fraudulent is 1.95 again indicating the existence of two salient groups.

In the case of the polarization measures of distinctness, Twitter users are more negatively polarized when it comes to "Biased Media" and "Stolen Elections", indicating a greater degree of negative sentiment associated with these topics of discussion and showcasing the existence of dissent amongst people. Such people believe either the election is stolen and the media is too biased to report it as such, or there is no election fraud and the media is unbiased. Our findings also indicate that although the topics "Support Biden" and "Support Trump" are polarized, yet the overall distinctness measure for both of them is close to zero or neutral (0.09). This indicates that people do not express extreme emotions in support of either candidate.

5.2. During-Crisis

A sharp contrast is observed from the pre-crisis to the during-crisis stage. First, election fraud claims have far less support than before, as none of the dominant topics in the during-crisis stage reference discussions about fraudulent or stolen elections. Second, several topics directly target President Trump, turning the discussion against him as evidenced by the lack of existence of the dominant topic “Support Trump” in the pre-crisis stage. The discussions in the during-crisis stage take an almost 180 degree turn with several users tweeting and calling out for him to be impeached (22.11%), debating his role in 'inciting violence' (5.31%), and calling him a 'dangerous President' (2.85%). Third, we observe the emergence of another polarizing debate: 'Terrorist Attack' versus 'Antifa Protests' (11.40%). This debate focuses on whether the Jan 6th US Capitol Riot can be called a terrorist attack or is it no different than the violent protests that occur during rallies held by the far-left group Antifa.

Prop 1: *Social media discussions in pre-crisis events show a mix of positive and negative emotions.*

We used content analysis to reduce dimensions of crisis-stage data. We then summarized the topics based on the crisis event using three high-level unigrams and bi-grams. The reduced dimensions in this phase explain the 'nature', 'causes'/'motives', and 'consequences' of the event as shown in the table 4.

Topic Name	Dimension
Reclaim Presidency; Trump vs Biden; White Supremacy;	Causes of Attack

Dangerous President; MAGA Crowd Fight; President Incites Violence; Role of Parler	
25th Amendment and Impeachment; Deploy National Guard; FBI Investigation; Republicans should resign; Officer Shot; Threat to Democracy	Consequences of Attack
Antifa Protests; Fascists Attack; Flags and Slogans; Terrorist Attack	Nature of attack

Table 4. During-Crisis Bert Topics.

The extent of polarization is shown in the figure 3., and the polarization measures are shown in the table 5.

Figure 3. During-Crisis Topics Polarization.

Polarization measure	Spread (Distinctness)
Cause of Attack	1.964 (-0.2074)
Consequences of Attack	1.955 (-0.05466)
Nature of Attack	1.975 (-0.2053)

Table 5. Polarization Measures – During-Crisis.

As in pre-crisis stage, the spread measure still remained nearly the same at over 1.9 across all three topics. However, the during-crisis stage revealed that all three topics show significant negative polarization, with the consequences of attack having the lowest average value (approximately -0.055) of the three. This low value can be attributed to the tendency of social media discourse to be focused on discussing current events rather than analyzing the underlying reasons for its occurrence or its long-term consequences (Boulianne, 2015).

Prop 2: *Social media discussions during crisis show predominantly negative emotions.*

5.3. Post-Crisis

In the post-crisis phase, negative sentiments were consistently higher in topics such as "Stolen Elections," "Storming Capitol," "People Shot to Death," and "Biased Media". Also, "People Shot to Death" and "Stolen Election" showcase higher levels of polarization, according to our polarity measures. Based on our data analyses, the topic that the election was stolen has consistently evoked negative emotions from the users across all the three stages. The topic "Believe in Country" continues to convey a positive message, but its spread of polarity is very high at 1.98, indicating that there are extreme ends of opinions within this topic. As people share both positive and negative opinions on this subject, it leads to lower distinctness as shown in Table 6 which indicates that the social media discourse within this topic remains neutral.

Prop 3: *Social media discussions in post crisis show majority of negative emotions and a few positive emotions.*

Prop 4*: Social media discussions exhibit an increase in the negative sentiment during the crisis but there is a rebound in terms of positive sentiments emerging in the post crisis period.*

Polarization measure	Spread (Distinctness)
Believe in Country	1.98 (0.2132)
People Shot to Death	1.972 (-0.518)
Storming of Capitol	1.944 (-0.3667)
Consequences of Attack	1.907 (-0.2967)
Response to Attack	1.957 (-0.1601)
Biased Media	1.958 (-0.1948)
Democracy at Stake	1.938 (0.1965)
Stolen Election	1.941 (-0.3558)

Table 6. Polarization Measures – Post Crisis.

This phase also indicated a return to the status quo observed in the pre-crisis stage as the social media discussions became more polarized with two clear groups of thought emerging from our analysis. Most users called out the Capitol attack as a ‘riot orchestrated by Trump supporters’ (30.72 %), however almost a similar percentage of users called for people to ‘stand up for their country’ and President Trump (25.59 %), thus reverting back to original debate between two groups, with one against President Trump versus the other supporting him. A dominant topic focused on how the Jan 6th US Capitol Riot was ‘watched live by the world’ but in its aftermath the support for President Trump remained unshaken as many users still posted tweets about the existence of ‘Election Fraud’ (17.02 %). Also, the polarizing debate observed in the during-crisis phase (Terrorist vs Antifa) carried over to this phase as well, with people still debating the difference between an ‘Antifa protests versus the Patriots protest’ (11.34 %). Surprisingly, ‘President Trump being banned’ from social media platforms was a neutral topic of discussion during this phase and in terms of emotions, did not have any distinct discussions related to his ban. We also observed the emergence of fissures in the two groups as within the broader topic of "Capitol attack," there emerged various sub-topics like "people who died" in the riot, "Democracy at Stake," and other sub-topics like

"Believe in Country" and "Stolen Elections." We divided these topics into eight distinct categories based on the keywords as shown in table 7., and their polarities are plotted in the Figure 4.

Prop 5: *The diversity in discussions as measured by the number of topics reaches its lowest value during the crisis with higher values pre and post crisis.*

Figure 4. Post-Crisis Topics Polarization.

Topic Name	Dimension
Patriots; save America; America great; USA survive; giant voice; America voted	Believe in Country
Election stolen; Fraudulent; voter fraud; Audit; Rigged;	Stolen Elections
Fake news; silenced voice; press room; Fox; CNN; propaganda	Biased Media
25th Amendment and Impeachment; treason; treasonous; arrest; jail	Consequences of Attack
Storming Capitol; Capitol Building; Coup Attempt;	Storming Capitol
Trump Supporters Riot; Election Fraud	People Shot to Death
Trump Banned; Stand up for Country	Response to Attack
Freedom of Speech; Democracy; Protected;	Democracy at Stake

Table 7. Post-Crisis Bert Topics

5.4. Regionalization Measure

The regionalization metric captures the degree of polarity between two similar user/event categories. It is the difference between the polarity values of two similar groups. Since this requires a pair wise comparison across two similar groups, we discuss this separately here. In our case, "Believe in Country" and "Stolen Elections" are common for both pre-crisis and post-crisis events because in both cases similar keywords show support for Trump winning the election and democratic elections. Regionalization is measured as difference in polarity between these categories. The pre-crisis and post-crisis mean sentiment values for "Believe in Country" are 0.5397 and 0.2132, respectively. Regarding the stolen elections, the respective values are -0.2449 and -0.3558. Thus, for each of these similar topics the sentiment value became increasingly negative. The regionalization values are 0.2948 and -0.1426 for pre-crisis and post-crisis, respectively, while considering two similar groups. We have taken the absolute polarity difference, as polarity itself has a sign associated with it. By comparing the two common topics, "Believe in Country" and "Stolen Elections," the regionalization measure provides evidence that negative sentiment becomes more dominant.

Prop 6: *There is an evolution of sentiments towards greater negativity in social media discussions from pre to post crises.*

6. Discussion

This research aimed to comprehend how polarization evolves during a crisis event on social media. Using the polarization measures from Bramson et al. (2017), we find there is polarization throughout the event, while spread and distinctness measures provide insight into degree of polarization, confirming that there is high spread in the post-crisis situation overall. During each phase, the spread of polarization is comparable, whereas the polarization of various discussions or topics varies. Consequently, identifying the topics while simultaneously recording the timeline of discussions plays an important role during a crisis, a fact that has been neglected in previous research. Moreover, using contextual embeddings for topic extraction via BERTopic provides robustness to our results.

From the perspective of individual topics, our findings indicate that there is high degree of polarization throughout the Capitol riot. While many social media users supported the stolen election narrative prior to the riot, they changed their position after the riot because the attack on the Capitol could call the nation's democracy into question. The Polarity measure of distinctiveness that we adopted is close to zero for "Support Biden/Democrats" and "Support Trump/GOP" topics, which provides sufficient evidence that neither the Democratic Party nor the Republican Party received full support from its supporters via opinions expressed on Twitter. We have operationalized polarization using sentiment expressed in tweets, as the written text provides evidence of whether a user supports or opposes a particular viewpoint. Due to the possibility of multiple parallel discussions on social media, it is crucial to group sentiments by topic rather than aggregating them for the entire crisis. Moreover, the discussions on social media are time-dependent; as a new event unfolds, the public's perspective may transition. Due to nature of the event, we were able to group discussions into pre, during, and post-capitol riot categories. Using common topics from pre-crisis and post-crisis, we use a regionalization measure (Bramson et al, 2018) that allows us to answer the research question regarding evolution of polarization over time. Despite the fact that, when considering only the "Stolen Election" narrative, it appears that negative sentiment decreased from pre-crisis to post-crisis, comparing this topic to another widely discussed topic reveals the opposite. To compare topics over time, we therefore considered the regionalization measure. Comparing common topics "Believe in Country" and "Stolen Elections," based on the regionalization measure, the negative sentiments have become more prevalent over time. The key results in this study include the following: 1) the topics that showed the largest levels of polarization changed between pre, during and post Jan 6th. 2) while pre Jan6th sentiments were more in favor of then President Trump, the dominant polarized topics discussed during and post Jan 6th were less sentimentally in favor of then President Trump, and 3) the sentiment in "Stolen Elections" were stronger post Jan 6th than pre–Jan 6th. If polarized topics are more contentious and indicate likelihood of a crisis such as January 6th US Capitol Riot, knowing which topics are more polarized can help us understand how polarization evolves during a crisis. Similarly knowing which discussions are more polarized in the aftermath of a crisis facilitates approaches towards resolving such crisis. Thus, this early exploration contributes towards building approaches toward monitoring, predicting, and resolving crisis spawned in social media communications.

7. Conclusion

As with any empirical study, there are limitations to our study. Using content analysis, the authors extracted topics from English tweets. If non-English tweets were translated, additional topics might be displayed. We extracted topics from daily tweets using BERTopic. If hourly topics were extracted, we would have more uncommon ones. However, this may result in a substantial amount of noise that must be manually filtered, requiring a substantial amount of effort. In addition, group-level polarization can be examined by analyzing all submitted messages prior to, during, and after an event, as well as messages about the event. As our data is not filtered by user, we cannot determine if a user posted multiple messages during the course of our research.

Our research has multiple theoretical and practical implications. Using polarity measures and tweet sentiment, we operationalized polarization. This allowed us to empirically validate shift in polarization over time, thereby making a theoretical contribution to polarization theory. Evaluation of polarization in man-made crises is essential for effective management and mitigation, as it helps crisis managers address polarizing topics. In the current study, we answer three distinct questions regarding presence of polarization through spread, aggregate level of polarization through dispersion, and relative polarization within a crisis event through regionalization. All three levels of polarization are essential for evaluating the current situation. Future work will study the dynamics (hourly changes) in polarization in each stage and topic to understand its evolution. In addition, the future work will a) develop a causal framework for using polarization to predict and mitigate a crisis, b) expand the number of polarization measures used and test their robustness, and c) compare their predictive power to other social media polarization measures (Tucker et al., 2018). Thus, in our future work we will focus on how measures of polarization can be used to study evolving crisis situations and events. Also, we will further research the application of AI based methods for automatic detection of polarized discussions on social media that can endanger community safety or hint at the onset of a crisis in the community.

8. References

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