The Effectiveness of Social Media in Timely Disaster Communication: A Case Study of Train Derailment in East Palestine, Ohio, February 2023

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ABSTRACT

Social media plays an important role in information sharing and can be used as a platform to communicate and engage with the public. This study aims to examine the effectiveness of social media in terms of timeliness when it comes to capturing public attention towards disasters. In particular, we propose a framework to explore the role of social media in information dissemination during the recent train derailment disaster in Ohio on February 3rd, 2023. First, our temporal analysis of social media activities and search behavior on Google shows the importance of social media in initiating disaster-related discourse. Second, our geographic analysis using a 2D Lagrangian Dispersion model suggests a lack of awareness of the actual pollution levels in high-risk areas. Lastly, we demonstrate that GRU models can effectively capture long-term dependencies in time-series social media data and predict search volumes on Google, as evidenced in the nuclear leak incident in Minnesota in November 2022. Our study highlights the importance of timely response to disasters and the practical implications of social media in emergency management.

1 INTRODUCTION

Social media plays various roles in modern societies, ranging from primary functions such as informing and educating the public to special functions of communicating between the media and other social systems during emergent times [10]. However, in terms of providing information and value for society, several concerns about social media deserve our attention. First, timeliness is one of the core values that define useful information [15]. The more promptly information is delivered, the more complete stories can be told and earlier decisions can be made, especially for events that are time sensitive, like market dynamics, ongoing policy deliberations, the outcome of battles, and disasters. Second, social media is often utilized in a political or social context, rather than offering objective information [17]. This requires the audience to develop a critical point of view when utilizing social media in acquiring information or conduct research.

In the context of disaster management, the role of social media is two-faced. On one hand, the media has direct links and outreach to the public. Before a disaster, the media can sensitize people to the importance of being prepared. During a disaster, citizen reporters can provide local information and critical alerts. After a disaster, the media can summarize the event's missing information, casualty, damage, and losses [20]. On the other hand, the vast volume and wide variety of social media data can create an obstacle for disaster management, as the information is so overwhelming that it is difficult to transform such data into real actions in time to help combat the disaster [13].

The train derailment in East Palestine, Ohio on February 3rd was certainly one of those disastrous events that caused considerable attention from the media, the public, and government agencies. The releases of hazardous substances, such as Vinyl Chloride, that occurred after the derailment and subsequent fires have caused series health concerns for nearby citizens. With an increasing amount of information being released, the timeline, event caused, and preliminary impacting scope of the derailment have been slowly disclosed. However, as mentioned above, for such an emergent event, where timely information is crucial, we are interested in how social media has impacted people's awareness of the derailment. To answer such a question, we aim to study the role of social media plays in disasters, specifically in the case of the train derailment and the following hazardous material leaks in East Palestine, Ohio. To achieve this, we will (1) first, explore the time series pattern between various mainstream social media platforms and public attention towards the derailment, and compare the peaks of social media activities to public attention during the disaster; (2) second, create a spatial simulation for the Vinyl Chloride leak and conduct a spatial-temporal analysis between pollutant distribution and public awareness to study the timeliness of media reports; and (3) finally, train GRU models to predict search behavior on Google based on social media activities during the disaster. We seek to highlight the practical implications of social media in disasters and discuss potential improvements in emergency response in our study.

2 RELATED WORK

There has been a substantial amount of research that explores the role of social media in disaster management. One of the key roles identified in the literature is utilizing social media to monitor situations for extending emergency response with an emphasis on creating social cohesion [3]. A noteworthy case is the emergency response taken in response to the catastrophic flooding caused by Hurricane Katrina, a Category 4 storm, that landed near Buras, Louisiana on August 29th, 2005. To assess disaster impact and organize subsequent recovery, information about people's perceptions towards the hurricane was converged through various news media and polls. A following keyword analysis of converged data was utilized to identify recovery priorities among inbuilt (electricity, roads, infrastructures), human (race, class, poverty), and social (community, civic, church) capitals [10]. Social media was thus shown to play a critical role in building social cohesion and constructing narratives, which eventually drove social change.

Furthermore, social media is shown to be a source of psychological support in the early stages of disaster and can assist in fostering aspects of community resilience [18]. Such support is particularly crucial during anthropogenic disasters where there may be a lack of transparency and willingness to take accountability. One example is the communication initiated by local citizens during a massive chemical leak occurred in the Elk River in West Virginia in 2014, resulting in the contamination of the drinking water supply for around 300,000 residents of the Charleston area. Soon, local citizens raised awareness by taking initiative to share firsthand information about the leak via Twitter and Instagram. Those posts strongly helped advocate and reinforce the place identity for the local community and connected the local with the general public [11].

Previous studies have shown that social media is often capitalized for disaster reporting, recovery, and framing in a general context [8] [9] [21]. However, most studies have only focused on the use of social media for information sharing during a disaster but they have neglected the examination of the physical impact of the disaster, as well as the potential discrepancies or similarities between the information spread through social media and the actual spread of the disaster. In addition, given that the derailment in Ohio is a recent incident, content on social media, such as news, videos, and posts has mainly served as a reporting tool to share information after the event took place. As such, a majority of the recent studies and media are limited to reporting updates at a single point in time and do not necessarily explore patterns or trends of attention to the disaster from a time series perspective. That is, a comprehensive analysis of the changes in social media activities over time as the disaster proceeds. In this study, we aim to bring in this time series perspective and study the timeliness of social media in response to a disaster by examining the relationship between information spread and the actual spread of disaster and highlighting its impact on disaster management.

3 DATA SOURCE

We collected data from four main data sources, including Google Trends, Twitter, TikTok, and Google Earth Engine. Social media platforms and Google Trends offer unique advantages for studying information dissemination during a disaster. Content on social media platforms is often user-generated and multimedia, which can provide rich and dynamic ways of sharing and consuming information. In contrast, Google Trends offers the ability to view the popularity of search terms by geographic region, providing valuable insights into what information people are actively seeking. Google Earth Engine is a cloud-based planetary-scale geospatial analysis platform that offers satellite imagery and geospatial datasets, which was used to perform spatial-temporary simulation on the dissemination of PVC leaks across areas in our study.

For the purposes of comparison, online content and search results data were extracted using the keyword “derailment” which directly refers to the train derailment incident in Ohio, on February 6th. We also experimented with other related terms such as “train wreck”, “vinyl chloride”, and “East Palestine”, and found out that these terms demonstrated similar attention trends as the word "derailment". Thus, moving forward in our analysis and modeling, we focused on the keyword “derailment ” in all data sources to narrow down on content and avoid repetitive search results.

3.1 Google Trends

Due to the limitation that there is no official Google Trends API, and the existing open-source APIs are relatively unstable, we decided to manually extract Google Trends data for geographic analysis with the time range from the start of 02/03/2023 to the end of 02/11/2023 EST with hourly intervals by modifying Google Trends URL patterns. Since metro-level data is the most granular we can get from Google Trends, we decided to analyze it on the metro level. It is worth mentioning that such metro-level Google Trends data is relative, in that values have been already normalized with a min-max scaler across all areas. For instance, if metro areas A, B, and C have search values of 1, 0.5, and 0, it means that the value for area B is equal to the mean of areas A and C. As for Google Trends in temporal analysis, we have extracted the relative search volume data from 02/03/2023 to 02/28/2023 EST.

3.2 Social Media Data

In terms of social media platforms, we focused on disaster-related information on Twitter and TikTok, which represent two different types of social media platforms, one identified as the leading text-based social media and the other as the trending video-based social media.

3.2.1 Twitter. Due to its real-time nature and high volume of activity, Twitter can be a valuable tool for keeping up with the latest news and serves as a platform for dialogue among users. By using Twitter Developer API, we extracted tweets ranging from 02/03/2023 to 02/28/2023 EST that is related to the word "derailment" to analyze the trend of the keyword mentioned over the month.

3.2.2 TikTok. TikTok has gained popularity in recent years, especially among the younger generation. Its unique features allow users to easily create short videos, reducing the barrier to content creation. We used TikAPI, an API platform on top of TikTok, to collect TikTok data from 02/03/2023 to 02/28/2023 EST that pertains to the term "derailment." We aim to examine the pattern of the keyword’s usage throughout the month.

3.3 Google Earth Engine

To access wind data for dissemination simulation, we extracted wind data from the Land Data Assimilation System (LDAS) provided by Google Earth Engine. LDAS is an image collection that combines various sources of observations, including precipitation gauge data, satellite data, and radar precipitation measurements, to produce estimates of climatological properties at or near the Earth’s surface [12]. We utilized the `wind_u` and `wind_v` band to measure the velocity of the wind in two perpendicular directions, U and V, where U is the velocity toward the east and V is the velocity toward the north. Both wind components were measured in m/s at 10 meters above the surface. To get the wind velocity of a targeted point, we filtered down the image using the x and y coordinates of the point of interest. As for the timeline, we set the starting time of the simulation to be 10 pm, 02/03/2023 EST, which was roughly the time of the derailment according to various news until 9 am, 02/11/2023 EST.

4 METHODOLOGY

This study aims to explore the role of social media in disseminating information during a disaster and its potential for predicting search behavior on Google. To achieve this, we developed a framework that encompasses three components: (1) a temporal analysis of the content on social media platforms and Google Trends during the disaster period, (2) a spatial-temporal analysis of pollutant distribution in comparison to information dissemination on social media, and (3) a prediction of search behavior on Google by training a GRU model on historical data of information spread on social media platforms. We applied this methodology to investigate the train derailment incident in Ohio that occurred in February of 2023 and evaluated the effectiveness of the proposed model in predicting information dissemination during the Minnesota nuclear leak incident in November 2022.

4.1 Temporal Analysis of Online Content

To examine the relationship between changes in social media activity and search behavior on Google during a disaster, we conducted a temporal analysis of disaster-related content on social media platforms and relative search volumes on Google Trends. Our temporal analysis involved identifying patterns and extracting features from social media data, which we then used to predict search behavior on Google in a later section.

4.1.1 Temporal Analysis of Social Media - Twitter and TikTok.

To gain a more comprehensive understanding of the disaster-related content being discussed and shared on Twitter, we examined both textual and link data in tweets. Textual data gives us insight into the prevalence of public discourse around the disaster within the platform. On the other hand, as links included in tweets direct users to external sources of information, such as news articles and other websites, link data enables us to understand how users are promoting and sharing content produced by the press outside of the platform. The popularity of content is determined by the extracted features from social media data, including the number of related tweets, referenced urls, and website domain names, where the counts are scaled to a standardized range of 0 to 1 to account for variations in overall activity levels.

Given the potential intertwinement of disasters with political and social issues [5] [4], we further examined the extent to which tweets related to the derailment incident are politically motivated by comparing the dominance of political and non-political discourse. After conducting an initial analysis of the top 10 tweets related to the disaster, we categorized tweets that contained the most commonly used three politics-related words, “Trump”, “Biden”, and “politics”, as political tweets, and the remaining tweets as non-political. We then compared the overall trends of these two types of discourse by normalizing the counts of the number of tweets, reference URLs, and domain names concerning political and non-political content.

Regarding the TikTok data, we considered three primary attributes of a video to understand the popularity of TikTok content and its impact on information sharing. First, the video count is defined as the number of videos related to a specific keyword. Second, video play refers to the number of times a video is watched. Finally, the video author followers, which is used to describe the number of followers that a video creator has at the time of posting. To capture the overall content trend on TikTok, we developed three new attributes that were used in our analysis and prediction model: the total video count, the video attention, and the author attention. We aggregated the video count for each keyword-related video to get the total video count attribute and computed the total number of views received by each video as the video attention attribute. Lastly, we calculated the average number of followers per video creator to obtain the author’s attention attribute. These attributes were created by normalizing the counts between 0 and 1, thereby indicating the relative popularity of content on TikTok.

In summary, the following features were selected from Twitter and TikTok data to understand activity patterns on social media:

- Text-based Twitter features:
  - Tweet Counts
  - Political Tweet Counts
  - Non-Political Tweet Counts
- Link-based Twitter features:
  - URL Counts
  - Popular URL Counts
  - Popular Political Domain Counts
  - Popular Non-Political Domain Counts
- TikTok features:
  - Video Counts
  - Video Attention
  - Author Attention

4.1.2 Temporal Analysis of Google Trends.

Aside from measuring how people are discussing and sharing content related to the disaster on social media, we aimed to measure the level of attention that the public is paying to the disaster. As Google is widely used and provides a more comprehensive sample of search behavior across different demographics and geographic locations, Google Trends can be used in conjunction with social media data to assess the overall level of public attention in a disaster. Here, public attention was measured using the normalized search volume provided by Google Trends. It was calculated based on the hourly volume of searches for the term “derailment” during the disaster period starting from 02/03/2023 to 03/08/2023 EST, with values ranging from 0 and 1. We then compared the behavior of the trends on Google Trends with that on social media by graphing the time series data of Google Trends to identify similarities and differences in patterns over time.

4.2 Geographic Analysis

After designing a methodology to study the relationship between social media data and people’s attention towards the derailment, we need to shed light on how the contamination leaked and distributed from a spatial-temporary perspective. Only by recreating the chemical leak and relating the leak to public awareness are we able to study the timeliness and effectiveness of social media data during the derailment. Thus, this section mainly articulates how a spatial-temporary simulation for the PVC leak is developed, and how a temporal relationship between pollutant distribution and public attention is studied.

4.2.1 Modelling and Simulation.

The Lagrangian Particle Tracking is commonly used to model how concerned particles (pollen, dust, etc.) are suspended and mobilized within a turbulent flow field without relying on a significant amount of model constants [6]. The characteristic of the Lagrangian approach is to trace back the movement trajectory of dispersed particles, which is well suited to provide useful information like particle residence time [7]. The particle tracking starts with the basic differential equation below:

$$\frac{dX_p}{dt} = U_p \qquad [1]$$

where X_p is the location of the particle at certain time, dt is the time interval, and U_p is the speed of the particle. The key step of particle tracking is to define the particle moving speed U_p, whose value is usually determined by force balance under Newton's second law. Since there are various forces (fluid speed, gravity/buoyancy, etc.) that could contribute to particle movement, various particle tracking models exist. Sommerfeld et al. (2019) included fluid inertia, lift and rotation force, gravity, and buoyancy in their dry powder inhaler model. Rowe et al. (2016) mainly focused on wave velocity and turbulent diffusivity when forecasting the short-term distribution of Microcystis blooms in Lake Erie.

Considering our objective of visualizing PVC distribution in 2D (latitude and longitude), we decided to omit gravity and complex forces and adopted the most fundamental differential equation [1] to construct the simulation as below:

$$X_{t_{i+1}} = X_{t_i} + U_p \Delta t \qquad [2]$$

where U_p is simply the wind speed at the corresponding time stamp and location.

To calculate U_p, as mentioned in the data source section, we accessed Google Earth Engine to obtain wind data at required coordinates and time. Also, we encapsulated the API into a self-designed Google Earth class, so that the following API calls can directly generate required data in a succinct format based on customized input parameters.

Before describing the simulation process, we proposed the following assumptions:

Assumption 1. We group particles into "clusters" and track the movement of every cluster, assuming each cluster has the same amount of particles. This is because it is not computationally feasible and realistic to track every single pollutant particle released during the simulation. Also, through this form of abstraction, the idea of cluster will be treated as a proxy for the pollution concentration or what we call the "hazard level".

Assumption 2. Pollution particle clusters are assumed to diffuse at 10m altitude, and the impacts from gravity and buoyancy are ignored. The is because the wind data obtained from Google Earth Engine is fixed at 10m above ground, and we do not consider the vertical migration of the particles, since our simulation is in 2D.

Assumption 3. Particle clusters would follow the obtained trajectories within every hour, and only when they reach the next position can they obtain the new wind vector data. Again, this is limited by the nature of the data since Google Earth Engine provides wind data by every hour, which is the finest temporary resolution we can get.

Assumption 4. When particle clusters mobilize towards a certain direction, they would leave behind a "trail" along the path. This is our attempt to combat hourly wind data and provide more details and dynamics about how clusters move within every hour. For instance, if there is one particle cluster that has traveled from (x_0, y_0) to (x_2, y_2), then each (x, y) location along the straight path will uniformly receive $\frac{1}{3}$ of the cluster as a proxy of concentration.

Assumption 5. We only focus on air-born pollutant dispersal and do not consider any chemical or physical interactions as particle clusters disperse through space.

The detailed simulation process and related terminologies are described as follows. The longitude and latitude of the pollution source are set to be -80.52 and 40.84, respectively. Starting at 10 pm, February 3rd, 2023 EST, the source is designed to emit one pollution cluster every hour within the first two days. Meanwhile, the simulation iterates forward by every "iteration interval" (every hour) until it reaches the ending time, which is set to be 9 am, February 11th, 2023 EST. Note that the simulation's ending time is rather arbitrary and less important, and it is truly the time when particle clusters start to dissipate that is used to identify a time window where the pollution dispersal is prominent. Within every hour, we first filter out those coordinates that (1) have positive cluster numbers but are outside the US boundary and (2) have cluster numbers that are almost zero. Then, wind speed data is retrieved from the Google Earth engine based on respective cluster coordinates. Afterward, all current particle clusters update their coordinates based on obtained wind data. Furthermore, to inspect how particle clusters travel within every hour at the finer spatial and temporal resolution, we further proposed the idea of a "stepping interval", which breaks the clusters' traveling path during each hour into smaller footsteps. By every "stepping interval" (which is set to be 20 minutes), the geospatial distribution of particle clusters is recorded and carried over to the following iterations to achieve the cumulative effect. At the end, all of the locations with valid cluster numbers during every hour are aggregated at the metro/county level, where only the largest cluster number is kept. The pseudocode of the simulation algorithm is shown below:

$Source \leftarrow (-80.52, 40.84)$
$Start\ date \leftarrow 10pm, 02/03, 2023$
$End\ date \leftarrow 9am, 02/11, 2023$
$Iteration\ interval \leftarrow 1\ hour$
$Stepping\ interval \leftarrow 20\ minutes$
$Time \leftarrow Start\ date$

while Time < End date **do**
  $current\ geoconfiguration \leftarrow empty$
  if Time - Start date ≤ 2 days **then**
    source releases one cluster
    append source to $current\ geoconfiguration$

end if
for coordinate i in $old\ geoconfiguration$ **do**
  if coordinates out of US $\vee$ particle clusters ≈ 0 **then**
    remove such coordinate
  end if
  get wind & cluster number k at i
  calculate coordinates after $Iteration\ interval$ from i
  for every $Stepping\ interval$ **do**
    clusters travel from i along the wind
    clusters leave behind $\frac{k}{\frac{Iteration\ interval}{Stepping\ interval}}$ clusters
    append to $current\ geoconfiguration$
  end for
end for
$old\ geoconfiguration = current\ geoconfiguration$
Time $+=$ $Iteration\ interval$
end while

Lastly, the geospatial configuration of simulation was plotted with Matplotlib by every hour, and the mp4 format of simulation was exported with the cv2 package. We also recorded how metro level google search data changed over time and space, and we aligned it with our simulation to create the final pairwise visualization.

4.2.2 *R-square analysis.*

After the simulation is completed, we would identify a time period, during which a large number of metro areas are impacted by the pollutant. To relate the simulated hazard level back to public attention quantitatively, we recorded the largest pollutant cluster number (feature) and the Google search value (label) at each county/metro area. Then we performed a ridge regression between those two values and calculated the R-squared value. Lastly, we repeated this process for every hour before pollutant dissipated and plotted the change of R-squared to explore the relationship between public awareness and pollution hazard level over time.

4.3 GRU Model

The Gated Recurrent Unit (GRU) model is a type of recurrent neural network that has gained popularity due to its ability to model and learn dependencies in time series data. Unlike traditional RNNs, GRU models use a gating mechanism that allows them to selectively update and forget information from the previous time steps. This mechanism helps address some of the limitations of traditional RNNs, such as the vanishing gradient problem, enabling GRU models to effectively model long-term dependencies.

Compared to the more complex Long Short-Term Memory (LSTM) model, GRU models have a simpler structure that makes them computationally cheaper and easier to train. In this study, we used a GRU model to predict public attention towards disasters using time series features extracted from social media data.

Specifically, we trained our model using features and labels from data of the Ohio train derailment accident and evaluated its performance as well as feature importance in predicting the public attention trend of the Minnesota nuclear leak accident. The features were built from statistics data from Twitter and TikTok, including the count of all related tweets, related tweets from a popular domain, popular URLs, posted TikTok videos, video's play times, and the authors' popularity, measured by the number of their followers. By comparing the predicted attention trend with the actual attention trend, we can determine the predictability of our model and the importance of social media in capturing the public's attention.

Our assumption is that if our model is able to accurately predict the public attention trend for the Minnesota nuclear leak accident given social media data, we can infer that social media plays an important role in disseminating information and shaping public perceptions of disasters. This study demonstrates the potential of GRU models and social media data in predicting public attention toward disasters and can inform disaster response and communication strategies.

5 FINDINGS & DISCUSSION

5.1 Trends and Peaks of Online Discourse

Trends and peaks of derailment-related social media content and search behavior on Google Trends are shown in Figure 1.

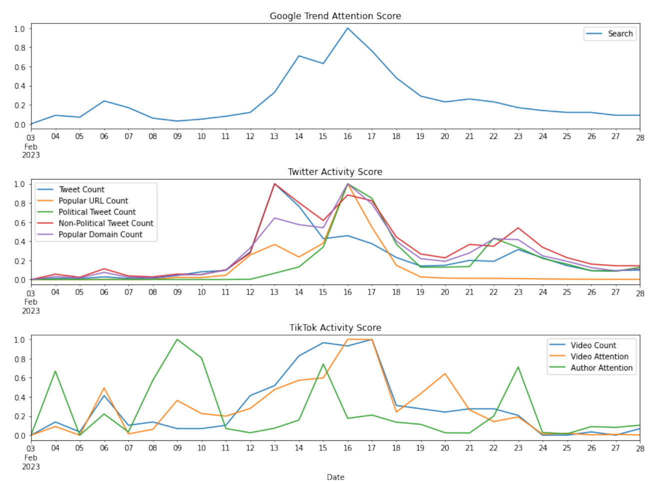

Figure 1: Trends and peaks of online discourse

We can observe that content related to the disaster was promptly created and shared on TikTok, emerging from the day after the derailment incident took place. We also notice that the peak of author attention on TikTok, which is the mean followers of video creators, precedes that of total video counts and aggregated video attention. Specifically, the author's attention feature rose to a high point on February 4th and demonstrated a peak on February 9th while the total video counts and aggregated video attention peaked at a later date, around February 17th. This suggests that the attention of influential video creators plays a crucial role in initiating discussions about the disaster.

Despite the quick generation of disaster-related content on TikTok, Google Trends did not adequately capture such a surge, especially in the early stage of discourse. One possible explanation for this mismatch could be the difference in the target audience of TikTok and Google. TikTok is particularly popular among the younger demographic while Google is used by a more diverse audience of different age groups. Thus, derailment-related videos on TikTok may be mainly created and shared among a specific group of young users initially. Another possible reason for this discrepancy might be that TikTok content tends to be more emotionally charged and reflective of individual experiences and viewpoints [23] [22]. This personal aspect of TikTok is different from Google, which typically offers a more objective representation of search behavior.

On the contrary, attention trends observed on Twitter and Google were more closely aligned. In general, there was a gradual increase in the relative volume of derailment-related discourse on Twitter and Google Trends after the day of the derailment. An initial uptick in discourse volume was both noted on Twitter and Google on February 6th, with the first peak occurring on February 14th and February 16th, respectively. Subsequently, the discourse volume continued to decrease and later experienced a minor surge during the latter half of February.

Timeline	Online Attention	Government Response
Feb 6th	The initial uptick in attention on Twitter and Google Trends.	Ohio and Pennsylvania governors took their first action by expanding the East Palestine evacuation zone and releasing toxic chemicals into the air from derailed tankers.
Feb 10th	Major attention on derailment started to take off across Twitter and Google Trends.	The Environmental Protection Agency (EPA) reported that about 20 rail cars had been carrying hazardous materials which were released into the air, surface soil, and surface waters.
Feb 14th	Twitter reached its first volume peak and Google Trends saw its first high point.	Ohio's Department of Natural Resources reported finding an estimated 3,500 dead fish in water systems.
Feb 16th	Twitter experienced a second peak in volume, while Google Trends reached its first peak.	EPA administrators visited East Palestine for the first time, addressing concerns about air and water quality.
Feb 21st - 23rd	A minor surge in volume was observed during the latter half of February.	EPA ordered Norfolk Southern to remediate polluted soil and water sources. National Transportation Safety Board released an initial report of an overheated wheel alert before the derailment.

Table 1: Online attention & government response timeline

Upon closer examination, we discovered that popular non-political tweets and embedded non-political news on Twitter first reached a peak in volume on February 13th. While tweets containing political-related content peaked later on February 16th, they were more frequently reflected in search volume on Google, which also peaked on the same day. A possible explanation for this echo might be that tweets with political content or embedded political news links may lead to increased exposure to additional information and perspectives of the derailment. This may bring more attention to the incident and potentially prompt people to search for related terms on Google, which could be reflected in the observed increase in search volume.

To further explore the relationship between attention towards a disaster and political inferences, we compared the timelines of content attention on Twitter and Google Trends to the timeline of the derailment and government intervention presented in Table 1. Our analysis shows that the peaks in attention on social media and Google Trends appeared to coincide with major disaster management efforts undertaken by the government.

5.2 Geography Analysis

With our simulation, it is clear that the general wind direction is from north west to south east, which is causing pollutant to migrate toward several coastal areas to the east (with snapshot of Feb 6th shown in Figure 2 below). However, although relatively more searches are appearing in eastern US, the geographical configuration of the Google search is rather sporadic throughout the country. Another important finding from the simulation is that after February 10th, the pollutant hazard levels were getting close to 0 among impacted areas in eastern US. This suggests that a major impact of the pollutant was observed from February 3rd to February 10th.

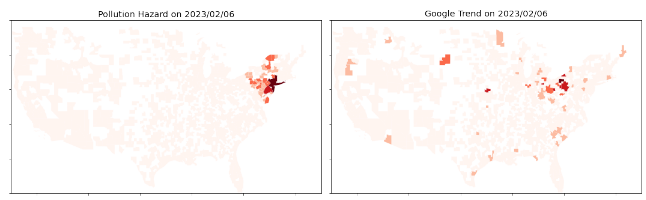

Figure 2: A snapshot of pairwise comparison between simulated pollution dispersal (left) and Google search (right) on Feb 6th, 2023.

From the results of the R-squared analysis (Figure 3), we can see that on February 6th, the R-squared in regression between public attention and the pollutant hazard level was the highest, but reaching only around 0.12. The small increase in R-squared surprisingly coincides with the initial uptick observed in the time series analysis in the previous section, which suggests that people at corresponding locations were aware of the pollution leak on that day, but such awareness was insignificant. Despite this small increased R-square, R-squared values on other dates are even lower. Those low R-squared values indicate that within the period when the impact of the pollutant was at its highest, there was a poor relationship between pollutant impact and public awareness over time. Such low R-squared values over time also deviated from our expectation, as we anticipated much higher R-squared values throughout the entire simulation and expected the attention towards the disaster to increase over time. There are several possible explanations for such a poor relationship. Firstly, Google search might not sufficiently capture how information spread among the public, which could influence how people became aware of the derailment. For instance, if local people tend to inform each other about the derailment, instead of searching for the event by themselves, then Google search may significantly underrepresent people's awareness. On the other hand, if local people were spreading the information to their relatives or friends in distant areas which drove them to search for the incident, then the searches recorded in those distant areas could generate a significant amount of noise. Secondly, it is possible that our simulation generated noise as well. The limitations mentioned above will be further elaborated on in the following limitation section.

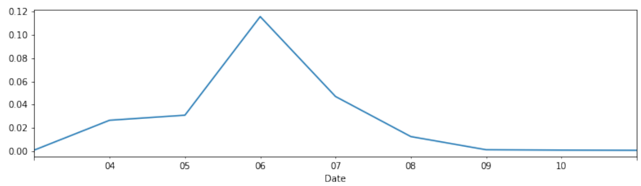

Figure 3: Change of R square for regressions between public attention and hazard level from Feb 3rd to Feb 10th.

Connecting to the time series analysis in the previous section, we can observe that major peaks in Google Trends and Twitter data occurred around February 14th. However, as shown in our simulation, the pollutant was showing its impact mainly from February 3rd to February 10th. Thus, there clearly exists a lag between pollutant dispersal and eventual awareness from the public. Given the importance of timely information regarding communicating and combating disasters, we proposed a few hypotheses behind the delayed reporting of the Ohio derailment to better understand the situation. First, people's perception of risk impacts the promptness of decision making, where a low risk is usually associated with delayed acting[1]. Second, there is a concern of social media infodemic, where rapid dissemination of various information is the main cause of feeling panic, fear, and anxiety among people [2]. We are able to peek into how the two factors above played their roles during the pollution leak from WCPO 9 News, Cincinnati [19]. It is reported that the Ohio Department of Health initially did not put much emphasis on the health risks caused by the pollutant, framing it as "a part of everyday life". Also, local government shown considerable sensitivity to the concerns and anxieties among local people, which may attribute to delayed response.

5.3 GRU Model - Social Media and Public Interest

To explore the relationship between social media activities and search behavior on Google with regards to the Ohio derailment, we trained GRU models on time series features extracted from social media data to predict attention trends on Google, labeled as the relative search volumes on Google Trends. The model performance was verified on the nuclear leak accident in Minnesota that took place in November 2022 with content extracted from social media data and Google Trends using the keyword "nuclear leak". Figure 4 shows the predicted and actual attention score of the nuclear leak incident. It is shown that the predicted attention trend adequately mirrors the actual attention toward the incident with a mean square error of 0.0086. Such a low mean square error appears to support our assumption that there is a time-series dependency between the public attention reflected in Google Trends and social media activities. Social media may be central to bringing about public interest in disasters. Besides, the predicated attention follows a smoother trend over time. It suggests that our GRU model can capture long-term dependency in time series data and smooths out short-term fluctuations that allow us to identify trends from noises. Interestingly, we can see that similar to the Ohio derailment incident, public interest in the Minnesota nuclear incident only reached its peak around 10 days after the incident, showing a lag in response to the disaster.

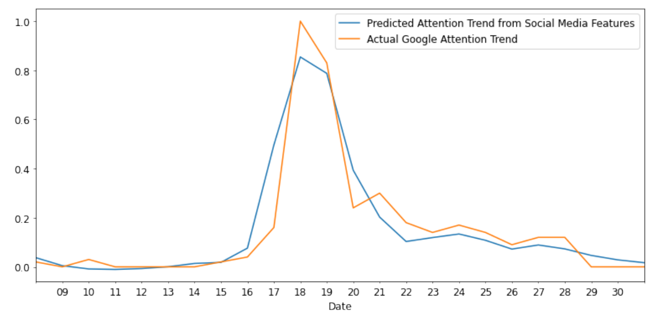

Figure 4: GRU model prediction vs actual attention in Minnesota nuclear leak

6 CONCLUSION

In this study, we explored the effectiveness of social media in information dissemination, with an emphasis on its timeliness and impact on public interest in disasters. We conducted a temporal analysis of disaster-related content on social media, such as TikTok and Twitter, and compared the timeline of social media activities to that of search behavior on Google. We show that social media represents an opportunity to initiate engaged discourse. It can provide relevant and timely information about disasters but its impact on public interest is not immediate, which requires government agencies' efforts to foster greater awareness among the public. To encourage citizen engagement, it is important to identify and highlight priorities that need to be addressed. This may involve identifying high-risk areas and showing timely care to those directly affected, which is demonstrated in our proposed method of estimating the impact of the derailment and the attention from nearby areas by using a 2D Lagrangian Dispersion model. Furthermore, government agencies can take proactive measures for more effective disaster response and communication. As shown in our GRU models, understanding when public interest in a disaster starts and the level of attention can help the government allocate response efforts. Particularly, the government can increase awareness by informing the public about the potential risks of disasters when public interest is low while providing frequent updates and engaging with the public more actively when public interest is high. In conclusion, our study contributes to the field of disaster management by providing a framework for understanding the role of social media in information spread during disasters and highlighting its practical implications in emergency response efforts.

7 LIMITATION AND FUTURE WORK

Our study has shown the role of social media in information dissemination and its potential practical implications in disaster management. Nonetheless, these results must be interpreted with caution and a number of limitations should be borne in mind. Specifically, there are three main limitations in this study that could be addressed in future research.

First, our temporal analysis of social media activities during a disaster primarily focuses on two social media platforms, namely Twitter and TikTok. However, there are other social media platforms such as Instagram, YouTube, and Facebook, that can be taken into account to better understand attention towards disasters in future research. When extracting time series features from social media data, future work can further investigate additional features and conduct statistical testing to determine significance.

Besides, we measured public interest in disasters in terms of search behavior reflected in Google Trends. But it is important to note that Google Trends may not adequately represent the views and opinions of the entire society. Although Google might be the most commonly used search engine, there are also other search engines, such as Bing and Yahoo, that are widely available and can be used to search for information online. Information related to disasters could also be obtained through offline sources, such as reports, newspapers, or face-to-face communication, which is hard to be quantified. On top of that, the attention provided by Google Trends refers to the search volume relative to the population within a particular region instead of the absolute search volume. This presents a potential inability to accurately estimate the actual number of searches made.

Due to the limitation of data sources that constrains the scope of our analysis mentioned above, the relationship between social media activities and search behavior on Google during a disaster must be approach with some caution. Further statistical testing is required to determine the causal relationship between social media activities and search behavior on Google and to determinate its significance.

Moreover, for computational feasibility and due to the limitation of geo-spacial data provided by Google Earth Engine, several assumptions were made during our geographic analysis. Our estimation may be limited to accurately reflects the actual disaster simulation as (1) we only considered air-borne pollution particle clusters diffused at 10m altitude without considering chemical or physical interactions as particle clusters dispersed through space and the effects of gravity and buoyancy due to the 2D nature of the simulation; (2) we assumed that particle clusters followed obtained trajectories within every hour, and updated their wind vector data only when they reached their next position after an hour due to the hourly data from Google Earth Engine; and (3) we assumed that when particle clusters mobilized towards a certain direction, they are modeled to leave behind a "trail" to mimic pollutant distribution at a finer resolution. Those assumptions may not fully capture the complexity of the real world, which can limit the generalizability of our research findings. To address those limitations, futures work can add complexity to the model by adjusting parameters or incorporating additional variables that were not initially considered.

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8 APPENDIX

The source code of our research is hosted at https://github.com/allmemes/study-of-media-and-diaster