Mapping Mourning: Computational Insights into Collective Grief After the Parkland Shooting

Gino Biasioli (255193), Virginia Di Mauro (255068), Matteo Massari (258355), Luisa Porzio (255069), Anthony Tricarico (254957)

Department of Sociology and Social Research, University of Trento

Abstract :

This study explores how collective grief unfolds over time on social media following large-scale public tragedies, using the 2018 Parkland school shooting as a case study. Drawing on a dataset of over 230,000 Reddit and YouTube comments collected between 2018 and 2025, we apply a combination of sentiment analysis, time series decomposition, and topic modeling to examine the emotional and thematic evolution of public discourse. Using a BERT-based classifier aligned with Plutchik's emotion taxonomy, we identify long-term trajectories for emotions such as sadness, fear, anger, and surprise, revealing distinct inflection points tied to major events like protests, legislation, and the shooter's trial. Additionally, we use Latent Dirichlet Allocation (LDA) to track shifts in thematic focus, from early expressions of grief and solidarity to later debates on justice and policy. Our findings show that online grief is neither static nor fleeting: it responds dynamically to real-world developments, varies across platforms, and reflects a dual discourse that mixes emotional intensity with ironic detachment. This research contributes to the growing field of computational social science by offering a longitudinal framework for analyzing how communities remember, process, and politicize tragedy in the digital age.

Keywords: *Affective Trajectory Modeling, Transformer-Based Sentiment Classification, Longitudinal Text Mining, LDA, Event-Centered Emotion Analysis, Cross-Platform Discourse Dynamics*

1 Introduction

Death and the following process of grief are two of the very few experiences that all human beings have in common. Several theories stemming from cognitive and social psychology have indeed identified some common stages through which the majority of people go during the grieving process (Tyrrell et al., 2025; Altschul, 1984; Bonanno et al., 2002). With the technological advancements of the last century and the increasingly central role acquired by social media, also the grieving process has gone "digital". Both personal and collective accounts related to mourning and grief find their way on media platforms, where users share personal experiences, thoughts and feelings in search of social support, allowing also for the "emergence of communities that could exist beyond the boundaries of physical distance" (Beaunoyer et al., 2021). Such phenomenon becomes even more evident when collective disasters and large-scale tragedies occur, leaving entire communities stricken and in shock. Such disasters receive massive media resonance in the first weeks or months following the event, and previous research has focused on establishing if collective grief experienced by communities follows regular patterns in response to different large-scale disasters, analyzing a 4-month period after the event (Maldeniya et al., 2023). However, it is less clear how collective grief and sentiment related to the disaster evolve when media attention decreases. Therefore, the aim of this paper is to analyze how online communities collectively express grief, loss, and trauma online after public tragedies or large scale disasters. Specifically, this paper will focus on understanding how grief-related sentiment trajectories evolve and change over time in response to specific public tragedy. In addition, the paper investigates also how sentiment related to a specific disaster is affected by other related events.

The paper will start by conducting a brief analysis of the literature background behind online collective grieving processes after massive disasters, through the lenses of computational social science methodologies and theories. Following that, the case study of the Parkland Stoneman Douglas School shooting will be introduced, in order to proceed with the project design and the three main core analyses of this paper. Finally, results will be accurately interpreted in order to draw informative conclusions.

2 Literature Review

When addressing the consequences of loss, it is necessary to give a definition of grief. The American Psychological Association (APA) defines grief as "the anguish experienced after significant loss, usually the death of a beloved person" (APA, 2018). On the other hand, there is not a specific definition of collective grief; however, when such phenomenon is experienced by an entire group of people, such as a community, the results can vary. Indeed, previous findings in disaster response theory have shown that in some cases relationships between community members improve, especially within close families, while other research show that post traumatic stress in the aftermath of disasters deteriorates both interpersonal relationships and sense of community (Bonanno et al., 2010). An element that is known to be constant for both interpersonal and collective bereavement is the need for social support, both physical and verbal, which is considered a coping mechanism (Scheinfeld et al., 2024). However, in 2020 with the advent of the Covid-19 global pandemic, people were experiencing unexpected losses while being unable to be physically close, which pushed them to share their experiences online, through forums or social networks, which allowed to keep enough anonymity while receiving support from others that were going through similar experiences (Scheinfeld et al., 2024). This practice has not stopped after the end of the pandemic, leading to a completely new scenario, where a topic that was treated intimately before, such as death and grief, can be now analyzed through social media (Scheinfeld et al., 2024).

One of the main studies on this topic has been conducted by Maldeniya and colleagues, who analyzed over 200 disaster-stricken U.S. communities, analyzing whether community responses on social media in the aftermath of several disasters showed a prototypical trajectory (Maldeniya et al., 2023). In addition, the authors investigated also the differences between online grief processing behaviors and offline behaviors (Maldeniya et al., 2023). Data were collected using the Twitter API, selecting 3200 tweets spanning on a 8-weeks timeline, starting from 4 weeks before the event ending 4 weeks after the event. Several events were chosen, focusing mainly on natural disasters such as fires, earthquakes and tornadoes (Maldeniya et al., 2023). The main methodology used by Maldeniya and colleagues was a lexicon-based clustering approach, which employed a previously validated list of themed lexicons to estimate disasters-response dimensions. The estimated dimensions were then used to build a multidimensional time series of disaster responses for each disaster, in order to then cluster together similar responses (Maldeniya et al., 2023). Results showed that the majority of the stricken communities analyzed in this study followed some regular patterns of social media behavior that also generalize well to different disasters; however, even if the analyzed trajectories resulted similar, there was still a lot of variability in the duration and intensity of such behaviors (Maldeniya et al., 2023). This study, despite being one of the few taking into account a large number of disasters and using data from before the events as baseline to compare disaster-responses, it still presents some limitations related to the short period of time taken into consideration after the event has happened. In addition, another limitation stems from the fact that only Twitter was used as social media, so this study lacks generalizability to other social networks.

Another main contribution to the topic of online disasters response comes from Burger and colleagues, who in 2019 introduced the term "Computational Social Science of Disasters" (Burger et al., 2019). This paper does not conduct a specific empirical study, but serves as theoretical framework for the current research, as it explores how computational social science's methodologies can be effectively applied to address the topic of social media-based collective disasters response. The authors start by analyzing the current literature in different social sciences, such as sociology, psychology, anthropology and economics, underlining how even though each one of these fields has contributed in building the literature on disasters response, focusing both on qualitative and quantitative research, they still remain limited by the "respective disciplinary approaches and methodologies that cannot manage the quantity of events and data available for collection and study in disasters" (Burger et al., 2019). Where classic social science approaches fail, new computational social science methodologies can succeed. Indeed, what Burger and colleagues suggest is the possibility of closing the gaps between different disciplines by using big data methodologies and computational methods, such as text mining and natural language processing on social networks' data, or suggesting the use of Agent-based modeling to simulate evacuations in case of disasters (Burger et al., 2019). More advanced methodologies focusing on geospatial elements are also suggested such as Geographic Information System (GIS) that can be used during disaster response to capture the areas needing priority, as showed by Hu and colleagues in another paper, where grid-based tessellation of space was developed, providing a systematic approach for prioritizing areas needing to be mapped by digital volunteers (Burger et al., 2019). Finally, also Graph theory is suggested in order to investigate information diffusion, and possible clusters of information. Even though this theoretical framework presented by Burger shows many valuable computational methodologies that could be employed when addressing disaster responses, it does not account for many limitations that could be encountered when applying these methodologies to real life events, with the main ones being ethical and privacy issues in data collection from social media, especially when dealing with sensitive topics such as disasters and large-scale tragedies.

Similarly to the previously analyzed study conducted by Maldeniya, also Malgaroli and colleagues focused on the use of trajectory modeling to understand the development of grief. Even though this paper focused on individual grieving process, it still provides valuable computational methods applicable to the topic, such as machine learning based trajectory modeling, network analysis of grief symptoms and natural language processing or predictive modeling (Malgaroli et al., 2022). The first methodology addressed is Latent Growth Mixture Modeling (LGMM), an unsupervised machine learning approach used for trajectory modeling, which tried to identify whether a sample is represented by one single common response trajectory or if it rather shows different patterns in which grief develops basing the analysis on large-scale longitudinal datasets (Malgaroli et al., 2022). Results from studies using LGMM trajectories showed, for example, that over time gender was an influential factor affecting the development of the grief process (Malgaroli et al., 2022). The second methodology analyzed is network analysis. Malgaroli and colleagues showed the strengths of using network analysis to identify the core symptoms of Prolonged Grief Disorder, a psychological disorder characterized by a dysfunctional and extremly prolonged period of grief. Network analysis results showed that some symptoms such as loneliness and sense of meaninglessness are more central to this disorder than others, helping in this way to correctly classify diagnosis. However, this also shows that such methodology could be effectively applied also to collective grief experienced by communities in response to disasters, possibly helping classifying more precisely the core symptoms that are experienced by a community in times of losses and grief.

2.1 Research Question

Based on the literature background on the topic and the computational methodologies presented before, this paper focuses on a precise and concise question: How does the expression of grief evolve over time on social media following a major public tragedy? To answer such question, the analysis will be split in 3 different sections, each one focusing on answering a specific side.

- RQ1: What are the main sentiments expressed by the stricken communities and how do these sentiments evolve over time?
- RQ2: What are possible factors that could cause a shift in sentiments?
- RQ3: What are the main underlying themes that are discussed by members of communities dealing with large-scale disasters?

3 Project Design

3.1 Case Study

The research here conducted is a longitudinal study ranging over a 7 years period, focused on a single case study. The case study selected is one of the many tragedies related to the issue of mass school shootings plaguing the US. Indeed, the Parkland Mass School Shooting was selected given the high media resonance and the sadly elevated number of losses. On February 14th, 2018, Nick Cruz attacked the Marjory Stoneman Douglas High in Parkland, Florida. He entered the high school armed with a gun and he managed to kill 17 people among teachers and students, injuring other 17. He had largely planned the shooting and he displayed violent behaviors with tendency to isolate himself from everyone else (BBC, 2022). The Parkland community was left in shock and the case has been since then remembered as one of the worse cases of school shootings. The shooter, Nick Cruz, has been arrested right after the event and has been processed after confessing his actions (BBC, 2022).

3.2 *Data Collection*

In order to create the dataset with YouTube data, we initially selected over 90 videos based on their relevance and view counts, using "Parkland school shooting" as the search keyword via API. From this collection, we can conceptualize a network structure (see Figure 1) in which nodes represent users and videos.

Each video receives comments from one or more users, and each user may comment on multiple videos. These comment interactions can be represented as edges connecting users to videos, forming a bipartite network. This structure allows us to draw on hub-based theories, which suggest that in such distributions, a small number of videos accumulate a disproportionately large number of comments, while the majority receive relatively few.

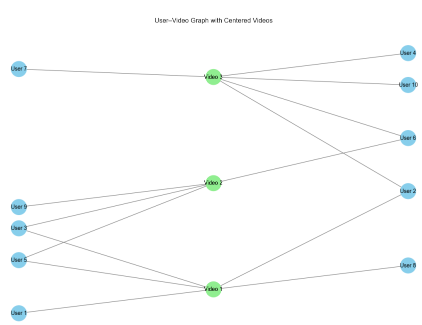

Figure 1. Illustrative bipartite graph showing synthetic interactions between 20 users (blue) and 3 videos (green). This example highlights the typical star-shaped structure of user–video networks, with videos in the center.

Generally, hubs are identified using the 95^{th} percentile as a threshold. However, based on the distribution shown in Figure 2 and the detailed breakdown in Table 1, this cutoff may be too restrictive. Considering both the shape of the distribution and the total number of comments preserved at each level, the 75^{th} percentile appears to be a more suitable threshold. It retains a sufficient number of videos (23 out of 92), while still capturing the majority of the comments' volume. This choice avoids excluding important discussions that would be lost under a stricter 95^{th} percentile cutoff.

Then we selected all posts and comments from the following subreddits: IAmA, PublicFreakout, Teachers, TrueCrime, florida, guncontrol, neveragainmovement, news, nextflevel, pics, politics

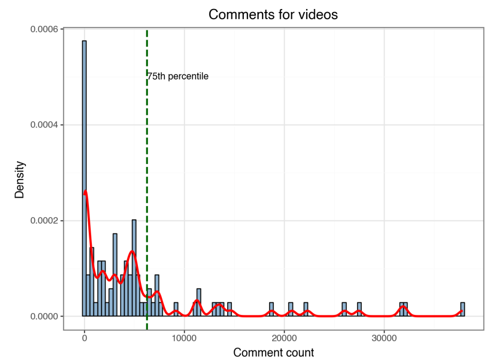

Figure 2. Distribution of videos by comment count. The plot highlights the skewed nature of the distribution and the concentration of comments in a small subset of highly active videos.

Percent	comments	Rem Vid	Tot comments
$\geq 25^{\text{th}}$	535	68	515,071
$\geq 50^{\text{th}}$	3,219	46	472,354
$\geq 75^{\text{th}}$	6,265	23	364,210
$\geq 90^{\text{th}}$	13,728	10	245,406
$\geq 95^{\text{th}}$	24,188	5	155,137

Table 1
Distribution of videos by comment count thresholds at different percentiles. The table shows how many videos remain above each threshold and the total number of comments they account for.

and teenagers. Using the query `Parkland AND school AND shooting`, we filtered for contents related to the topic. We included only data from the time of the event up to the present day, resulting in a total number of 15,897 entries gathered from Reddit. We joined the Reddit and YouTube datasets using shared attributes, and added a `source` field to indicate the origin of each data point (e.g., Reddit or YouTube). We further reviewed the data to ensure no comments prior to February 14th 2018 were collected and finalized data collection and cleaning with a dataset containing more than 230K observations (N = 231,308)

3.3 *Sentiment Trajectory Analysis*

In order to better understand the emotional impact that the Parkland Stoneman Douglas School shooting had on the community at large, in this paper we employ a technique based on Transformers to conduct a sentiment analysis across time. This methodology was preferred since it is flexible and allowed to analyze the data without treating it as an equally-spaced time series, thus increasing the employability and reusability of this approach also for future studies. The idea of using BERT was also suggested by the literature, with many studies employing it for analyzing the sentiment of different texts coming from social media platforms (Bello et al., 2023; Talaat, 2023). In our study, we used a lightweight yet top-performing version of BERT (Bidirectional Encoder Representations from Transformers) developed by Huggingface (DistilBart-MNLI).

Next, we selected the eight main emotions that can be conveyed through a text following the theoretical framework proposed by Plutchik which was also implemented in the reference literature

(Tromp et al., 2014). Selecting these emotions and having a theoretical framework for this step is fundamental since all the subsequent analyses will be based on the classification carried out by BERT on the assigned categories. In our case, we used all eight emotions (joy, trust, fear, surprise, sadness, disgust, anger, and anticipation) without truncating any of them to make sure that the whole variety of feelings expressed by each text could be captured accurately. Next, we ran BERT classification based on these eight emotions on our entire aggregated sample. This resulted in a structured dataset where eight new columns (one for each emotion) were added. Importantly, results coming from this classification can be interpreted as probabilities since the scores assigned to each emotion for any given text are guaranteed to sum up to one.

Having now provided all the details needed to understand the current work, it is now possible to dive into the analyses that were carried out. The first analysis that we developed was designed to understand how long-lasting each emotion would be in the context of the timeframe analyzed (Feb 2018 - June 2025). In order to do that, we aggregated the data computing the mean for each day and for each emotion in order to have a time series with a regular index. Then, we employed an STL decomposition (Cleveland, 1990) to extract the components out of the time series to understand if some emotions exhibited a specific trend or seasonality. We showcase the results from such decomposition for a selection of emotions.

As it is possible to observe from the second subfigure starting from the top in each plot, when using a method that is robust to outliers, there is a clear and observable trend and trajectory that is followed by such emotion. However, regardless of the approach, it was difficult to pinpoint whether a seasonal effect was actually present. While it may remain unclear why some of the observed shifts in the trend of each emotion happens, we will try to shed more light on this in a later section of the paper. For now, let us focus on interpreting the estimated trend from STL for each emotion.

- Sadness (Figure 3): there is a clear increase in the amount of sadness conveyed by the sampled texts in the immediate aftermath of the shooting. However, this slowly decreases until reaching a plateau with occasional small bumps more recently.
- Fear (Figure 4): there is a slow, but substantial, increase in fear in the years considered. Interestingly, this trend is upward sloping until 2022 and then this trend is inverted. Therefore, 2022 represented an inflection point for this emotion.
- Surprise (Figure 5): the overall trend shows a steady increase from 2018 through approximately 2022. This rise suggests that expressions of surprise have become more common over time, possibly reflecting a growing exposure to unexpected or attention-grabbing events on social media. After 2022, the trend appears to level off or slightly decline, indicating a possible stabilization in the intensity or frequency of this emotional expression.
- Disgust (Figure 6): This emotion follows a different trajectory. From 2018 through 2021, the trend shows a gradual decline, implying a reduced presence or expression of disgust in the content during those years. However, beginning in 2022, the trend reverses and rises again, pointing to a renewed or intensified emotional response in that direction.
- Anger (Figure 7): The overall trend indicates a mild increase

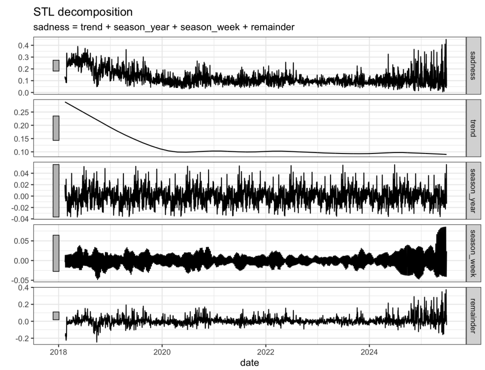

Figure 3. STL decomposition of Sadness

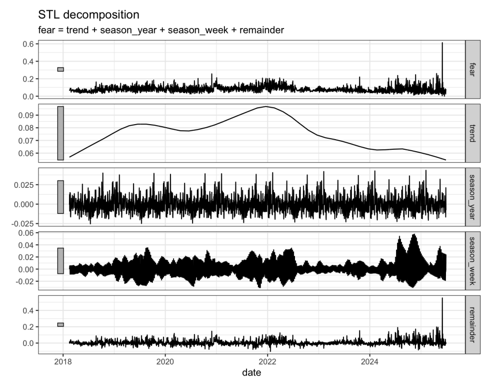

Figure 4. STL decomposition of Fear

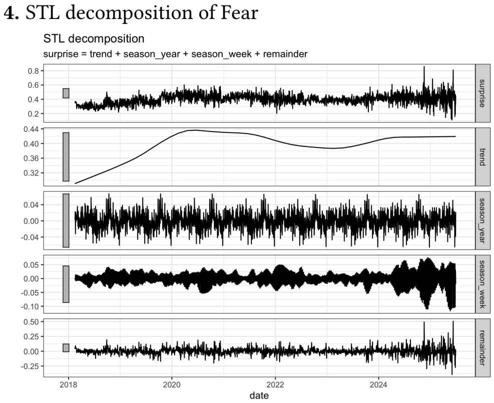

Figure 5. STL decomposition of Surprise

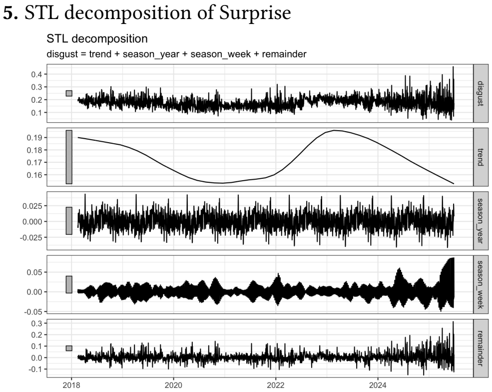

Figure 6. STL decomposition of Disgust

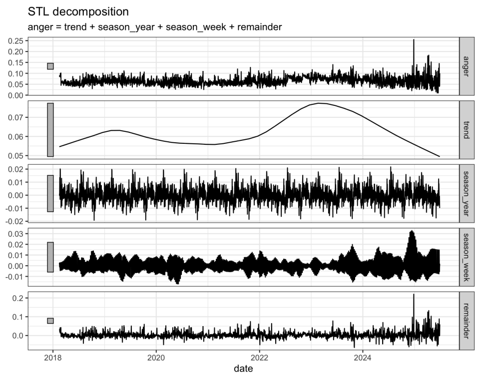

Figure 7. STL decomposition of Anger

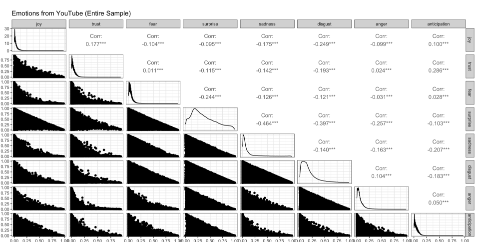

Figure 8. Distribution and correlation of emotions extracted from YouTube comments.

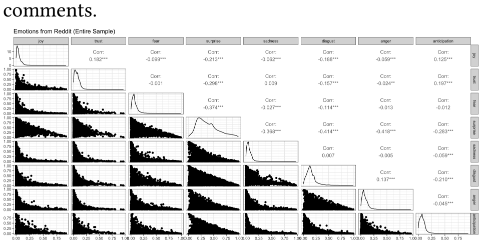

Figure 9. Distribution and correlation of emotions extracted from Reddit posts and replies.

from 2018, peaking around 2023, followed by a noticeable decline into 2025. This suggests that expressions of anger were gradually intensifying over several years, potentially in response to accumulating social or political tensions.

In the last part of this first analysis, we studied the co-occurrence of specific emotions across a variety of texts and investigated their correlation across time. We separated the results for both Reddit and YouTube to understand if there were differences between the two platforms and found out that among statistically significant correlations, the majority of them carried the same sign, thus indicating the presence of a correlation whose behavior is consistent across platforms, despite varying in magnitude. The results are shown in Figure 8 and Figure 9.

3.4 Sentiment Analysis related to specific Events

After conducting a general analysis of emotional trajectories over time, we focused our attention on specific key events related to the Parkland school shooting. The goal was to understand how public emotional responses evolved in direct connection to these events. This methodology isolates the short-term emotional impact by comparing emotions expressed in Reddit posts and comments under YouTube videos before and after each event, enabling us to assess whether external stimuli led to statistically significant shifts in collective sentiment. To quantify emotional expression, we relied on emotion classification scores generated using a fine-tuned BERT-based model, consistent with the approach used in our Sentiment Trajectory Analysis. For each selected date, we defined a symmetric time window of seven days before and seven days after the event, allowing us to capture temporal shifts in emotional expression. Posts and comments collected from Reddit and YouTube were segmented into two distinct groups: a *before* period, covering the week leading up to the event and an *after* period, covering the week following it. Within each time frame, we analyzed the predicted intensity scores for the eight emotions. To determine whether these scores significantly differed across the two periods, we first applied the Shapiro-Wilk test to assess normality. Depending on the outcome, we then selected the appropriate statistical test. If the emotion scores followed a normal distribution, we applied a Student's t-test or if normality was violated, we used the Wilcoxon rank-sum test, a non-parametric alternative suitable for skewed or non-Gaussian data. We considered results statistically significant when the associated p-value was below the conventional threshold of $\alpha = 0.05$. Emotions meeting this criterion were interpreted as having undergone a meaningful shift in response to the event under analysis.

To complement the statistical analyses, we also generated visual representations of the emotional trends surrounding each event. These visualizations consist of smoothed line plots showing the daily average of each emotion over the two-week interval, segmented by source (Reddit and YouTube). These plots provide an intuitive overview of how public emotions evolved over time, highlighting phenomena such as spikes in anger or sadness following highly publicized developments. We applied the statistical approach described above to a series of politically, legally and symbolically relevant events spanning from 2018 to 2025. For each event, we compared emotion distributions in the seven days before and after the selected date, examined statistical significance and visualized the results through smoothed temporal plots. The figures display the emotion trajectories in the week before and after the event, across Reddit and YouTube.

3.4.1 Platform Differences and Interpretation We noticed that on YouTube, emotional levels are overall more stable, which is consistent with the platform's comment dynamics and structure. YouTube's content is predominantly based on the video and comment discussions tend to reflect reactions to the video itself rather than to concurrent events in the real world. Additionally, the high comment volume can lead to opposing emotional expressions that neutralize each other, reducing the visibility of statistically significant shifts. In contrast, Reddit functions as a platform oriented to text where users engage in discussions that are more reflective, detailed and timely. This structure makes Reddit more sensitive to external events, allowing for clearer emotional fluctuations in response to key developments. These differences highlight the importance of platform analysis when studying digital emotional responses. Reddit tends to reflect immediate, collective sentiment shifts, while YouTube's emotional dynamics are more diluted, potentially masking underlying sentiment even when it exists.

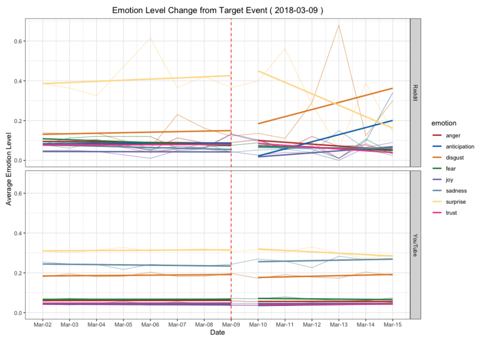

Figure 10. Average daily emotion scores across Reddit and YouTube for the period surrounding March 9, 2018.

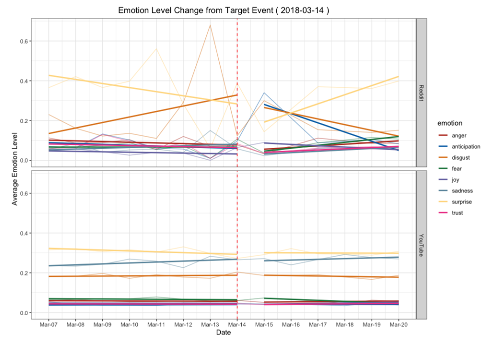

Figure 11. Average daily emotion scores across Reddit and YouTube for the period surrounding March 14, 2018.

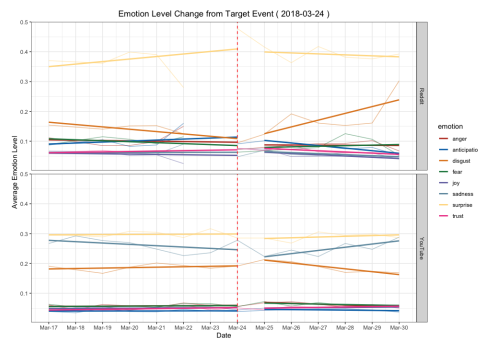

Figure 12. Average daily emotion scores across Reddit and YouTube for the period surrounding March 24, 2018.

3.4.2 March 9, 2018 - Marjory Stoneman Douglas Public Safety Act Signed On 9 March 2018, Florida enacted the Marjory Stoneman Douglas Public Safety Act, prompting us to examine public sentiment at that time. This legislation was one of the earliest policy responses to the Parkland school shooting, introducing new gun control measures and school safety protocols. Statistical tests revealed significant variations in five emotions: trust, surprise, sadness, anger and anticipation.

As shown in Figure 10 on Reddit, the most evident pattern is a sharp decline in surprise, indicating that the legislative response was expected or anticipated. Concurrent decreases in anger, trust and fear may reflect a calming of the initial emotional reaction. Meanwhile, increases in anticipation, joy and disgust point to mixed reactions maybe hope for change, cautious optimism but still persistent discomfort. On YouTube, emotional levels are more muted. Slight changes, such as a decrease in surprise and small increases in sadness and disgust, suggest lower engagement or emotional dilution due to comment structure.

3.4.3 March 14, 2018 - National School Walkout On 14 March 2018, exactly one month after the Parkland shooting, students across the United States took part in the National School Walkout, a coordinated protest demanding legislative action on gun control. This highly visible, symbolic event captured national attention, and the emotional impact can clearly be seen in the sentiment dynamics observed in social media discourse. Statistical analysis revealed significant differences in the expression of seven out of eight measured emotions before and after the event: joy, trust, fear, surprise, sadness, anger and anticipation. This comprehensive shift highlights the emotional significance of the walkout, indicating that it had a wide and deep resonance with the online public.

As shown in Figure 11 on Reddit, the emotional responses to this event were both intense and varied. Feelings such as trust, surprise, fear, anger and sadness all intensified in the days immediately after the walkout. This increase likely reflects a renewed sense of urgency, solidarity and political awareness, which were triggered by the protest. In particular, the increases in trust and sadness could signal admiration for the students' courage, as well as continued mourning for the victims. Conversely, there were noticeable declines in disgust, anticipation and joy. The drop in joy could indicate emotional fatigue or a temporary shift from hopeful optimism to more solemn, reflective states. The decrease in anticipation may suggest a waning belief in the likelihood of imminent policy change despite public mobilization. On YouTube, however, the emotional response was considerably more stable, with only a slight decrease in fear observed. Other emotions remained largely unchanged, consistent with earlier findings suggesting that YouTube's comment sections may be less reactive to immediate events. This could be due to the nature of comment engagement, the variety of video content that is not directly tied to the event or the sheer volume of unrelated discourse that effectively dilutes emotional responses to specific events.

3.4.4 March 24, 2018 - March for Our Lives Protest On 24 March 2018, the March for Our Lives protest took place in Washington, D.C. and numerous other cities around the world. Organized by students who survived the Parkland shooting, it was one of the largest demonstrations in US history led by students. It advocated for stricter gun control legislation and safer school environments. The emotional impact of this event is evident in statistically significant shifts in three key emotions: joy, fear and anticipation.

As shown in Figure 12 The emotion trajectories on Reddit illustrate a complex and dynamic emotional response. Post-event, anticipation and joy notably decreased, suggesting a potential deflation of emotional momentum after the protest. This decline could be interpreted as a return to realism, where initial optimism gave way to concerns about the long road ahead for policy change. Similarly, trust and sadness also declined, possibly reflecting tempered expectations or emotional fatigue after the heightened mobiliza-

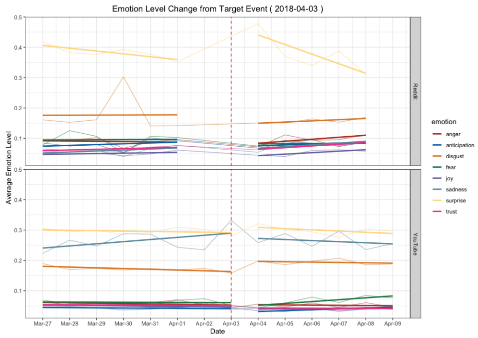

Figure 13. Average daily emotion scores across Reddit and YouTube for the period surrounding April 3, 2018.

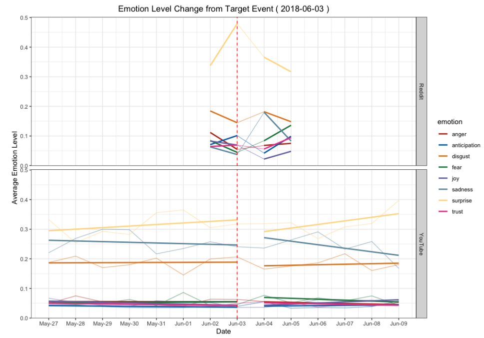

Figure 14. Average daily emotion scores across Reddit and YouTube for the period surrounding April 3, 2018.

tion. In contrast, fear and disgust showed a visible increase, indicating that even as hope and optimistic emotions diminished, concerns about violence and systemic issues persisted. The rise in disgust might reflect frustration in response to political inaction or polarizing media narratives in the aftermath of the protest. Interestingly, anger remained relatively stable, which may indicate that frustration was already high prior to the event and did not intensify further immediately after. On YouTube, emotional responses were more subdued but still showed subtle variations. Sadness and surprise slightly increased following the protest, possibly driven by reflective or reactionary comments on videos covering the demonstrations. Meanwhile, disgust, fear and anger decreased, which might be attributed to the platform's tendency to host pre-recorded content with less immediate emotional reactivity than platforms based on text like Reddit. The remaining emotions, including joy, trust and anticipation, stayed mostly consistent, suggesting a more stable affective baseline among YouTube users.

3.4.5 April 03, 2018 - School Reopening with Security Controls On 3 April 2018, Marjory Stoneman Douglas High School officially reopened under heightened security measures, marking a pivotal moment of transition for students, staff and the wider community. This day signified a shift from mourning and protest towards institutional adaptation, with the introduction of controlled access, clear backpacks and a visible law enforcement presence within the school environment. Emotional analysis reveals that this transition back to routine schooling under security constraints elicited statistically significant shifts in all eight core emotions, suggesting an emotional response that was widely felt across social platforms.

As shown in Figure 13 the most evident trend on Reddit was a marked decrease in surprise, which may indicate a reduction in emotional volatility or unexpectedness as users became aware of and accepted the institutional measures. Meanwhile, all other emotions, anger, anticipation, fear, sadness, trust, joy and disgust, showed modest increases, even if to different extents. These parallel increases suggest that the event triggered a complex mixture of feelings, including a renewed sense of anger and disgust, possibly directed towards systemic issues. There was also fear and sadness associated with returning to a site of trauma, as well as a subtle rise in trust or anticipation, perhaps reflecting cautious optimism about efforts to enhance safety. By contrast, YouTube displayed a different pattern. Although emotional shifts were generally less pronounced, some notable trends emerged. Surprise, sadness and disgust decreased, which may indicate a decline in active emotional engagement or an adaptation effect among commenters. Meanwhile, fear and anticipation increased slightly, reflecting Reddit's emotional profile, even if less intensely. Other emotions remained relatively stable, reflecting the nature of YouTube content, which is less conversational and reactive than that on Reddit, and the fact that many comments were probably unrelated to the reopening itself.

3.4.6 June 03, 2018 - Graduation Ceremony Honoring the Victims On 3 June 2018, Marjory Stoneman Douglas High School held its graduation ceremony. While traditionally a day of celebration and achievement, this year's ceremony took on a deeper and more solemn significance as it honoured the students who lost their lives in the shooting in February. The ceremony attracted national attention, including a speech by comedian Jimmy Fallon, who praised the resilience and activism of the student body. From a statistical standpoint, no emotions exhibited significant changes before and after the event. This may be partly attributed to the relatively limited sample size, which can reduce statistical power and mask subtler shifts in emotional expression. However, the lack of statistically significant results does not equate to the absence of emotional impact.

As shown in Figure 14, when examining the emotion trajectories, a number of meaningful trends emerge, especially on Reddit, despite some incomplete daily data coverage. In fact, not every day in the time window surrounding the event is represented in the dataset and the available data shows a clear spike in user interaction in conjunction with the graduation ceremony event, suggesting increased engagement. On Reddit, we observe decreases in surprise, disgust and sadness, while anger, anticipation, fear, trust and joy show a modest upward trend. These patterns may reflect a shift away from the initial shock and grief, toward an emotional landscape characterised by remembrance, hope and a reaffirmation of community values. The increase in trust and joy, even if moderate, suggests that many users perceived the event as a moment of symbolic healing and collective resilience. Conversely, YouTube exhibited a different emotional profile. Here, surprise, disgust and joy increased, likely in reaction to emotionally charged content such as video tributes, speeches and public statements. By contrast, sadness and fear both decreased, suggesting a subdued

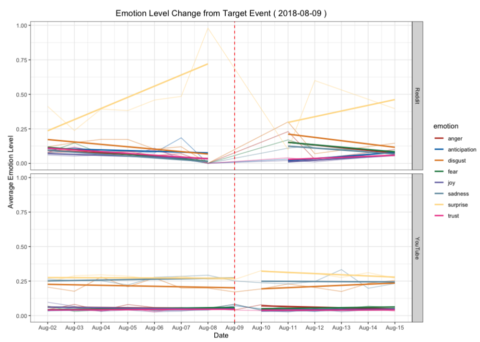

Figure 15. Average daily emotion scores across Reddit and YouTube for the period surrounding August 9, 2018.

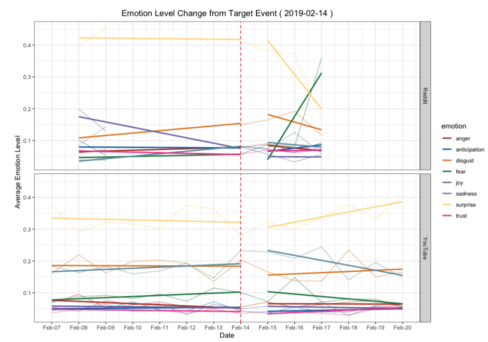

Figure 16. Average daily emotion scores across Reddit and YouTube for the period surrounding February 14, 2019.

or reflective emotional response from the audience, possibly due to the ceremonial nature of the event. Other emotions also remained steady throughout the observation period, which further highlights YouTube's comparatively muted emotional dynamics.

3.4.7 August 09, 2018 - Interrogation Video Release On August 9, 2018, a significant development in the Parkland shooting case emerged when footage of the police interrogation of Nikolas Cruz was made publicly available. The video, which included moments of emotional breakdown and confession, drew widespread attention and sparked renewed debate online about Cruz's state of mind, the legal process and broader issues related to justice and responsibility. From a statistical perspective, the emotional reactions surrounding this event were modest but notable. Out of the eight Plutchik emotions, three showed statistically significant changes in their expression across the Reddit and YouTube datasets: joy, trust and anticipation.

As shown in Figure 15, examining the Reddit data revealed a clear pattern of emotional divergence on the platform. Following the video release, emotions such as surprise, trust, anticipation and joy increased. This suggests that users responded to the transparency of the interrogation process with relief, curiosity or validation of their existing beliefs. Conversely, disgust, fear, sadness and anger decreased, potentially indicating a shift away from intense emotional reactions. In contrast, YouTube comments remained generally stable, with only a few notable changes. Surprise and anger decreased slightly, possibly suggesting a more muted response or one that was more focused on the content of the video than the broader narrative. Interestingly, disgust increased, possibly reflecting viewers' discomfort with Cruz's behaviour during the interrogation or the public nature of the footage itself. All other emotional trends remained relatively flat, reinforcing the idea that YouTube's comment sections are more heterogeneous and reflect engagement with the video format.

3.4.8 February 14, 2019 - First Anniversary The first anniversary of the tragic Parkland school shooting on 14 February 2019 marked a solemn moment of reflection across the media and online platforms. This milestone served as both a memorial and an opportunity to assess progress in terms of justice, safety reforms and collective healing. Such anniversaries often reactivate grief and remembrance, while offering space for solidarity and commemoration. In terms of statistical significance, only joy showed a notable change in emotional intensity when comparing the week before and the week after the event. Although this may seem counterintuitive in the context of mourning, it can be seen as a complex emotional signal. It may be connected to commemorative actions that celebrate the lives of victims, demonstrate community strength or symbolise resilience. A more nuanced pattern emerges from the visual analysis of emotion trajectories, especially when disaggregated by platform.

As shown in Figure 16 in the days following the anniversary on Reddit, surprise, disgust, sadness and anger all decreased, possibly reflecting a quietening of more intense emotional expression as the community moved into a phase of remembrance and solemnity. Interestingly, joy declined in the days leading up to the anniversary and then plateaued. This pattern may suggest anticipatory sorrow as the date approached, followed by emotional stabilisation. Disgust initially increased before falling after the day of the anniversary. Meanwhile, fear and anticipation increased around the anniversary, possibly signalling continued anxiety over gun violence or anticipation of reform discussions being reignited by the commemoration. The emotional profile on YouTube differs slightly. Here, surprise, disgust, trust and anticipation all increased after the anniversary, suggesting renewed emotional engagement. Sadness and fear revealed an increase prior to the anniversary, followed by a decline afterwards. This suggests that emotional intensity may have built up in anticipation of the date, and then been released or diffused following public acts of remembrance. In contrast, anger decreased before the anniversary and then increased afterwards, potentially reflecting renewed frustration with unresolved political or systemic issues that resurfaced in the aftermath of the commemorations. Other emotions remained relatively stable.

3.4.9 November 02, 2022 - Sentencing of Nikolas Cruz On 2 November 2022, Nikolas Cruz was sentenced, marking a significant milestone in the aftermath of the Parkland shooting as the legal process reached its conclusion. Cruz was sentenced to 34 consecutive life sentences without the possibility of parole, a decision which sparked widespread public discussion, particularly given the controversial absence of the death penalty. The event prompted intense emotional responses online, reflecting both relief at the closure of the case and frustration or dissatisfaction with the outcome. For this event, it is important to note that our analysis is based solely on YouTube comments, as no Reddit data was

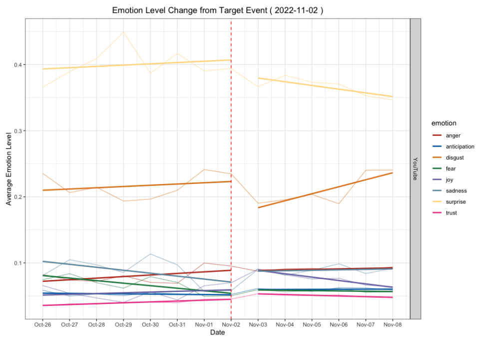

Figure 17. Average daily emotion scores across Reddit and YouTube for the period surrounding November 2, 2022.

available during this period. Despite this limitation, the YouTube dataset is substantial. This large volume enables us to gain meaningful insights into public sentiment and emotional trends. From a statistical perspective, significant changes were observed in all eight Plutchik emotions across the 14-day period, indicating an intense and widespread emotional response to this event.

A visual analysis of emotional trajectories as shown in Figure 17 reveals several notable patterns. Surprise increased in the lead-up to sentencing, reflecting rising anticipation and uncertainty, before declining sharply once the outcome was made public. Disgust increased steadily throughout the period, rising more sharply after the verdict, suggesting growing negative sentiment likely tied to the absence of a capital sentence or resurfaced courtroom details. Sadness follows a slight U-shaped curve, dipping before the event and rising afterwards, indicating renewed emotional engagement and grief as the case returned to public discourse. Anger grows more sharply in the days leading up to the event and continues to slightly rise afterwards, highlighting frustration and unresolved emotional reactions to the perceived justice delivered. Fear declines in the lead-up to the event and then slightly levels off, possibly due to reduced uncertainty once the sentence was known. Trust increases before sentencing, perhaps due to faith in the legal process, but then decreases slightly afterwards, potentially reflecting disappointment in the verdict. Joy shows only a mild increase before the event, followed by a decline afterwards, consistent with a complex mix of relief and dissatisfaction. These trends suggest that, even though the legal case had reached its formal conclusion, the public's emotional response was far more complex. While some individuals may have felt relieved, the prevalent emotions after the event, disgust, sadness and anger, suggest that many believed the outcome to be emotionally inadequate or even unjust.

3.5 Context Analysis with LDA

In order to understand the underlying themes, we first need to identify some macro groups that help define the overall topic. To perform this kind of analysis, we rely on Latent Dirichlet Allocation (LDA). LDA is a topic modeling technique used to uncover hidden themes or topics within a collection of documents (Blei et al., 2003). It is an unsupervised machine learning model grounded in a generative probabilistic framework. The LDA assumes that each document is a mixture of multiple topics, and each topic has a distribution over words. Given a predefined number of topics, LDA can effectively identify and cluster the main themes discussed across various posts, enabling the extraction of underlying semantic structures from the text. As with every machine learning model, there are some hyperparameters that need to be chosen *a priori*:

- alpha (α): Controls how many topics are assigned to each document (lower = fewer topics per document).
- beta (β): Influences how many words define each topic (lower = more specific topics)
- number of topics: Sets how many themes the model will extract from the data.
- Learning Rate: determines how quickly the model updates its parameters during training.

These hyperparameters have to be tuned to asses the best performance of the model. To tune these parameters we have performed a full grid search evaluating performance on this possible parameter set:

- number of topics: `1, 2, 3, 4, 5, 6, 7, 8, 9`
- alpha (α): `0.001, 0.005, 0.01, 0.05, 0.1, 0.2, 0.5`
- beta (β): `0.001, 0.005, 0.01, 0.05, 0.1, 0.2`

for a total of 378 combinations. To identify the best combination of hyperparameters, we used perplexity as the evaluation metric. A lower perplexity indicates a better model, as it means the model is more confident in predicting unseen data. Conversely, a high perplexity suggests that the model is more uncertain or "confused" in capturing the underlying structure of the text. In this case the best LDA configuration, as shown in Figure 18, found four main topics, with $\alpha = 0.1$ and $\beta = 0.2$, achieving a perplexity score of 2285.85. The plot below showcases how the best number of topics was chosen. The heat map (Figure 19) shows the best combination of alpha and beta for the number of topics set to four.

3.5.1 Global topic analysis The topic extracted via the fine-tuned LDA where:

- Topic 0: `sorry | god | sad | feel | hope | love | people | heart | families | know`
- Topic 1: `school | shooting | like | kids | day | shooter | people | know | got | going`
- Topic 2: `judge | like | kid | children | guy | defense | court | lawyers | cruz | said`
- Topic 3: `people | gun | guns | death | need | like | america | penalty | think | stop`

Given this result we can understand what are the evolution of the discussed themes during the years. The line plot in Figure 20 shows the temporal evolution of the four topics identified by the LDA model, plotted on a monthly basis and faceted by year from 2018 to mid-2025. The y-axis indicates the percentage of posts associated with each topic for a given month. As we can see from Figure 20, for each topic we have a different dominance in different months:

- Topic 0 (red) shows an early peak in mid-2018, followed by a gradual decline and stabilization at lower levels.
- Topic 1 (green) becomes dominant from 2019 to 2021, maintaining a relatively stable presence above 40%, before decreasing in 2022 and beyond.

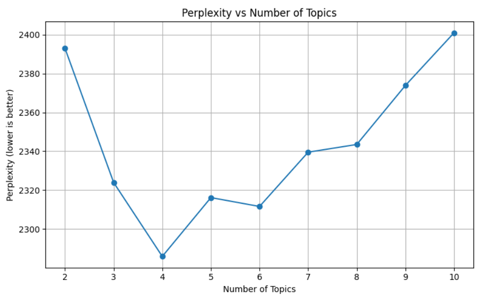

Figure 18. Perplexity scores for different numbers of topics obtained through grid search. The optimal number of topics was selected based on the lowest perplexity value.

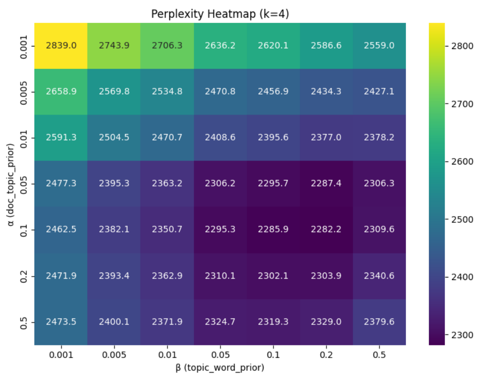

Figure 19. Grid search heat map showing perplexity scores for different combinations of α and β values, with the number of topics fixed at 4. The combination $\alpha = 0.1$ and $\beta = 0.2$ yielded the lowest perplexity.

- Topic 2 (cyan) remains marginal until 2022, after which it steadily increases and becomes the most prominent topic in 2023 and 2024.
- Topic 3 (purple) fluctuates over time without a clear long-term trend, showing local peaks in 2018 and 2022.

To determine the most prevalent topic in each month, we visualized the distribution of post counts (Figure 21), with each bar colored according to the dominant topic. The temporal evolution of topic dominance offers a compelling narrative arc of how public discourse unfolded around the tragic event. In the initial months, the dominant topics are emotionally charged, reflecting raw and immediate reactions of grief, compassion, and solidarity. Keywords such as "sorry", "god", "sad", "feel", "hope" and "families" indicate a collective mourning and an attempt to express empathy toward the victims and their loved ones. As the months progress, the discourse shifts toward a more analytical and descriptive register. The emergence of terms like "school", "shooting", "kids", "shooter", and "day" suggests that users began reconstructing the event, recounting what happened, sharing details, and collectively processing the trauma.

Later on, particularly around key legal milestones such as the sentencing of Nikolas Cruz in November 2022, the focus of discussion turns toward the judicial process. The prominence of words like "judge", "defense", "court", "lawyers", and "Cruz" reflects increased public engagement with the trial and its outcome. This final phase of discourse reveals not only a concern with justice but also a reactivation of emotional and ethical debates, potentially

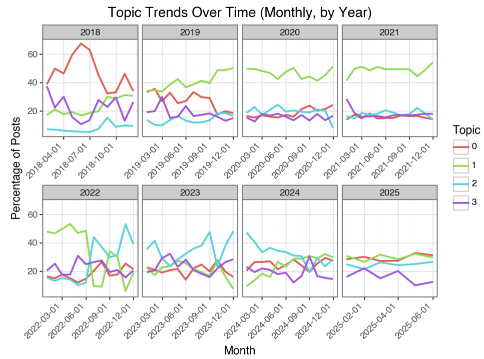

Figure 20. Monthly trends of the four identified topics from 2018 to mid-2025. Each subplot corresponds to a calendar year and shows the percentage of posts assigned to each topic. Topic 1 (green) dominates between 2019 and 2021, while Topic 2 (cyan) becomes more prominent starting in 2023.

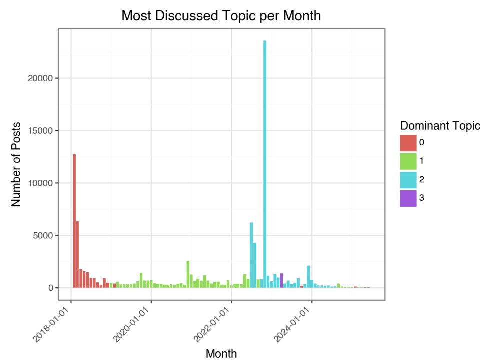

Figure 21. Monthly distribution of the most discussed topic from 2018 to 2025. Each bar represents the number of posts for the dominant topic in a given month, with colors indicating which topic was most prevalent. Topic 0 (red) was dominant in the early years, followed by Topic 1 (green) during 2020–2022, and Topic 2 (cyan) showing a sharp spike in early 2023.

highlighting polarization in public opinion regarding the sentence. The progression from mourning, to sense-making, to judgment illustrates how collective attention evolves in response to traumatic events, shaped by both emotional resonance and institutional developments.

3.5.2 Peak analysis By observing the distribution, we can clearly identify two distinct peaks: the first corresponding to the event itself, and the second aligning with the trial. Knowing the broader context of the discussion, we can now zoom in and explore these peaks (in the predominant topic) in greater detail by performing a dedicated LDA analysis focused on each time window.

First peak (School shooting) Performing a fine-tuned LDA the context words suggest us two narratives:

- Topic 0: `people | kid | guy | kids | good | cruz | got | wrong | said | ass | shooter | know | make | going`. This topic seems to capture a more serious and emotionally engaged narrative. Users are referring to the shooter ("cruz", "shooter"), expressing opinions and judgments ("good", "wrong", "ass", "said") and possibly recounting

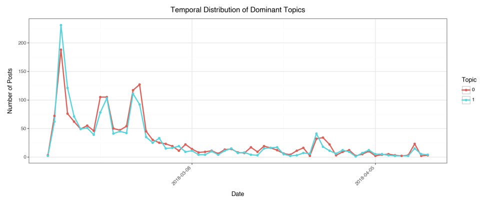

Figure 22. Temporal distribution of dominant topics over time. The line plot shows the number of posts per day for Topic 0 (red) and Topic 1 (cyan). Both topics exhibit sharp spikes in early 2018, followed by a gradual decline and periodic fluctuations. This suggests that both topics were highly discussed at the beginning of the observation period before stabilizing.

what happened ("got", "know", "make", "going"). It reflects a direct engagement with the tragedy and its implications, often discussing individuals involved and their moral responsibility.

- Topic 1: `gone | lol | man | watch | really | video | children | people | say | comment | damn | guy | know`. This second topic appears to convey a more detached or ironic tone, possibly sarcastic. The frequent use of informal expressions ("lol", "damn", "watch", "man") and references to media consumption ("video", "comment", "say") suggest a reaction mediated through online discourse, where humor or cynicism may be used to cope with or comment on the situation.

As shown in Figure 22, the two narratives are not sequential but rather represent two coexisting perspectives through which users process and evaluate the tragedy. While their intensity varies over time, both topics emerge in parallel from the early stages of the event and continue to be discussed throughout the following weeks, suggesting that people engage with grief through different discursive lenses one more emotionally direct and judgmental, the other more ironic or mediated.

Second peak (Cruz trial) Zooming in on the second peak, we find that it aligns precisely with the sentencing date of Nikolas Cruz, November 2nd, 2022. This sharp increase in comment volume coincides with a highly mediatic and emotionally charged legal moment, offering a unique opportunity to examine the public's reaction to the trial and its outcome. To uncover the topics discussed within this phase, we performed a dedicated LDA focused exclusively on the posts published around this date.

The fine-tuned LDA model for this window extracted the following two dominant topics:

- Topic 0: `judge | children | like | said | kids | judges | court | lawyers | sit | way`. This topic appears to represent a neutral or procedural narrative. It reflects users describing the legal proceedings, roles of the actors involved (judges, lawyers), and the courtroom atmosphere. The tone remains largely observational and descriptive, without overt emotional or evaluative content.
- Topic 1: `defense | like | lawyers | court | families | disgusting | people | victims | team | lawyer`. In contrast, this topic conveys a strongly opinionated and emotionally charged stance, focused particularly on Cruz's legal defense team. The presence of negative terms such as disgusting , and references to victims and families , indicate a moral rejection of the defense's strategies or arguments. This topic embodies an indignant narrative, possibly reflecting public outrage over perceived injustices.

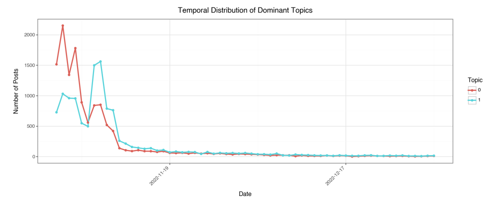

Figure 23. Temporal distribution of dominant topics between late 2022 and early 2023. The plot displays the number of posts per day for Topic 0 (red) and Topic 1 (cyan). Topic 0 initially shows higher activity, but is rapidly overtaken by Topic 1, which peaks and then gradually declines. Both topics stabilize at lower volumes towards the end of the period.

From Figure 23, it is evident that the initial spike in posts corresponds to users trying to comprehend the details of the trial, focusing on the legal procedures, the roles of the judge and lawyers, and the courtroom dynamics. As time progresses, the conversation gradually shifts toward more opinionated and emotional responses, where users start to express their personal views, criticisms, and support for the parties involved. This transition reflects a collective process of sense-making followed by engagement and judgment.

4 Summary of Results

The following presents the main findings from the study's three core analyses, providing a clear picture of how collective grief developed and changed in online spaces after the Parkland school shooting.

The first component of the analysis examined the long-term evolution of emotional expression using sentiment classification based on Plutchik's eight core emotions, applied to over seven years of Reddit and YouTube data. By decomposing the daily emotional signals through STL, we identified distinct trajectories for each emotion. Sadness was the most immediate and dominant response following the tragedy, reaching its peak shortly after the event and then gradually stabilizing over the years. Fear, on the other hand, grew slowly and quietly over time, rising until around 2022, when it started to go down, suggesting a slow-burning anxiety that eventually found partial resolution or redirection. Surprise mirrored this trend, growing consistently until 2022 before staying more or less the same. Disgust declined in the earlier years but rose again after 2021, indicating renewed emotional engagement likely triggered by developments in the public narrative. Anger showed a steady upward trajectory, peaking in 2023 and subsequently declining, a pattern that reflects the long-term accumulation of frustration and its eventual release. These trajectories not only confirm that grief-related emotions remain active and responsive over time but also demonstrate that they are shaped by meaningful social and political developments rather than by passive decay or seasonal cycles.

The second analytical section focused on how specific real-world events, ranging from legislative responses and protests to commemorations and courtroom decisions, produced statistically significant shifts in collective emotional expression. By analyzing the emotional dynamics in the days before and after each event, we were able to detect consistent patterns of reactivation, intensification, or recalibration of sentiments, particularly on Reddit where discursive formats lend themselves to rapid affective engagement. While the degree and direction of change varied, events tied to direct political action or institutional decisions, such as the National School Walkout, the sentencing of Nikolas Cruz, or the school's reopening with heightened security, elicited the most pronounced emotional responses. These findings underscore the temporal sensitivity of collective grief and reveal that it is not only continuous but also punctuated by sharp affective inflection points tied to symbolic or high-impact moments in the public sphere.

The final component, a topic modeling analysis using Latent Dirichlet Allocation, revealed a parallel evolution in the thematic structure of online discourse. Initially, conversations centered on expressions of shock, solidarity, and emotional support, dominated by language associated with mourning and empathy. As time progressed, these discussions gave way to more descriptive and analytical narratives that sought to reconstruct the event, interpret its causes, and share factual information. From 2022 onwards, in correspondence with the trial and sentencing of the shooter, the discourse shifted again, this time toward legal interpretation, justice, and public accountability. A particularly revealing insight was the consistent presence of two parallel discursive registers: one emotionally intense and morally evaluative, the other marked by detachment, irony, or sarcasm. This duality illustrates the diversity of affective and cognitive strategies that online users employ to process tragedy, some expressing pain and moral urgency, others using humor or critique as a way of coping. Together, these thematic shifts and tonal contrasts highlight how the digital space becomes a site not only for mourning but also to help people understand what happened, reflect on it, and make sense of it together after the traumatic event.

5 Conclusions

This study addressed three main research questions concerning the emotional, temporal, and thematic dimensions of online collective grief. First, in response to the question about which sentiments are most present and how they evolve, we found that emotions such as sadness, fear, and anger were especially prominent. These emotions followed distinct and long-lasting trajectories, demonstrating that grief-related sentiment remains active for years and adapts in response to the broader social and political context.

The second question considered what factors might cause shifts in these sentiments. Our findings show that emotional responses were clearly shaped by real-world events: protests, legal rulings, symbolic anniversaries, and institutional decisions often triggered significant emotional changes, especially on Reddit, where discourse is more immediate and reflective.

Lastly, regarding the themes that characterize online conversations in the aftermath of tragedy, our topic modeling revealed a progression from early expressions of mourning and solidarity to more descriptive accounts, and eventually to legal, political, and moral debates.

In sum, the study shows that collective grief expressed online is dynamic, event-sensitive, and shaped by evolving emotional and discursive patterns. Each research question contributed to understanding how people process shared trauma in a digitally mediated public space.

6 Critical Analysis

One of the main strengths of this analysis is its longitudinal design, which spans a period of seven years. This timeframe allowed for the observation of long-trends in both emotional expressions and thematic discourse, offering insights that could not have been obtained in shorter studies. Another strenght is the implementation of event-based sentiment analysis, which added further value to the project design. By examining emotional responses around specific real-world events, the study was able to identify statistically significant short-term emotional shifts and connect them directly to external triggers.

This project also presents some limitations. One key weakness is the restricted platform scope. While Reddit and YouTube provided valuable insights, the exclusion of other important platforms, such as Facebook or X, limits the generalization of the findings. These platforms have large and active communities where grief and public discourse are also expressed. Their absence means that the emotional and thematic patterns observed in this study may not fully represent the broader digital response to the Parkland tragedy. Another limitation is the imbalance in data volume between the platforms. The data from Reddit and YouTube used for this analysis, not only differ in the quantity, but also in the nature of user interaction, as it has been already mentioned. Reddit fosters threaded, text-based discussions with a focus on dialogue and debate. In contrast, YouTube comment sections are typically flatter, more fragmented, and often shaped by the content of the video rather than ongoing discussion. With this, a possible improvement arises, expanding the platform scope would allow a more comprehensive and representative analysis of online grief. Adding social medias such as X, or TikTok, would capture a wider variety of emotional and discursive expressions, as this platform differ not only in user demographics but also in communications styles and interaction dynamics. Finally, applying this framework to other types of public tragedies, such as natural disasters, terrorist attacks or global pandemics, would provide a valuable comparative research. Studying whether emotional and thematic patterns observed in the Parkland case also appear in responses to different types of crisis would help determine the extent to which online grief follows generalizable patters or varies depending of the nature of the event.

7 Additional Resources

The complete code used to develop the statistical analyses employed in this paper is freely available and can be found at the following GitHub repository[1] for replicability purposes.

References

Altschul, Sol (Feb. 1984). "Attachment and Loss, Vol. 3. Loss, Sadness and Depression. By John Bowlby." EN. In: *Journal of the American Psychoanalytic Association* 32.1. Publisher: SAGE Publications Inc, pp. 216–218. ISSN: 0003-0651. DOI: 10.1177/000306518403200125. URL: https://doi.org/10.1177/000306518403200125 (visited on 06/30/2025).

APA (2018). *APA Dictionary of Psychology*. en. URL: https://dictionary.apa.org/ (visited on 06/30/2025).

BBC (Oct. 2022). "Parkland shooting: How the attack unfolded". en-GB. In: URL: https://www.bbc.com/news/world-us-canada-43071281 (visited on 06/30/2025).

[1] https://github.com/CrispyCocaBoy/css_analysis

Beaunoyer, Elisabeth and Matthieu J. Guitton (Sept. 2021). "Cyberthanathology: Death and beyond in the digital age". en. In: *Computers in Human Behavior* 122, p. 106849. ISSN: 07475632. DOI: 10.1016/j.chb.2021.106849. URL: https://linkinghub.elsevier.com/retrieve/pii/S0747563221001722 (visited on 06/30/2025).

Bello, Abayomi, Sin-Chun Ng, and Man-Fai Leung (Jan. 2023). "A BERT Framework to Sentiment Analysis of Tweets". en. In: *Sensors* 23.1, p. 506. ISSN: 1424-8220. DOI: 10.3390/s23010506. URL: https://www.mdpi.com/1424-8220/23/1/506 (visited on 06/29/2025).

Blei, David M., Andrew Y. Ng, and Michael I. Jordan (Mar. 2003). "Latent dirichlet allocation". In: *J. Mach. Learn. Res.* 3.null, pp. 993–1022. ISSN: 1532-4435.

Bonanno, George A. et al. (2002). "Resilience to loss and chronic grief: A prospective study from preloss to 18-months postloss". In: *Journal of Personality and Social Psychology* 83.5. Place: US Publisher: American Psychological Association, pp. 1150–1164. ISSN: 1939-1315. DOI: 10.1037/0022-3514.83.5.1150.

Bonanno, George A. et al. (Jan. 2010). "Weighing the Costs of Disaster: Consequences, Risks, and Resilience in Individuals, Families, and Communities". EN. In: *Psychological Science in the Public Interest* 11.1. Publisher: SAGE Publications Inc, pp. 1–49. ISSN: 1529-1006. DOI: 10.1177/1529100610387086. URL: https://doi.org/10.1177/1529100610387086 (visited on 06/30/2025).

Burger, Annetta et al. (Apr. 2019). "Computational Social Science of Disasters: Opportunities and Challenges". en. In: *Future Internet* 11.5, p. 103. ISSN: 1999-5903. DOI: 10.3390/fi11050103. URL: https://www.mdpi.com/1999-5903/11/5/103 (visited on 06/30/2025).

Cleveland, Robert W., ed. (1990). *STL: a seasonal-trend decomposition procedure based on loess*. eng. ISSN: 0282-423X Issue: 1 Pages: 3–33 Place: Stockholm Publication Title: Journal of official statistics : JOS ; an international quarterly Series: Journal of official statistics : JOS ; an international quarterly. - Stockholm : Statistics, ISSN 0282-423X, ZDB-ID 629930-1. - Vol. 6.1990, 1, p. 3-33 Type: Aufsatz in Zeitschrift, Article in journal Volume: 6.

Maldeniya, Danaja et al. (Oct. 2023). "Pulling through together: social media response trajectories in disaster-stricken communities". en. In: *Journal of Computational Social Science* 6.2, pp. 655–706. ISSN: 2432-2717, 2432-2725. DOI: 10.1007/s42001-023-00209-8. URL: https://link.springer.com/10.1007/s42001-023-00209-8 (visited on 06/30/2025).

Malgaroli, Matteo, Fiona Maccallum, and George A. Bonanno (Feb. 2022). "Machine yearning: How advances in computational methods lead to new insights about reactions to loss". en. In: *Current Opinion in Psychology* 43, pp. 13–17. ISSN: 2352250X. DOI: 10.1016/j.copsyc.2021.05.003. URL: https://linkinghub.elsevier.com/retrieve/pii/S2352250X21000683 (visited on 06/30/2025).

Scheinfeld, Emily, Chinasa Elue, and G.B. Wilcox (May 2024). "Grieving Online: A Text Analysis of Narratives of Grief on Reddit". In: *The Journal of Social Media in Society*.

Talaat, Amira Samy (June 2023). "Sentiment analysis classification system using hybrid BERT models". In: *Journal of Big Data* 10.1, p. 110. ISSN: 2196-1115. DOI: 10.1186/s40537-023-00781-w. URL: https://doi.org/10.1186/s40537-023-00781-w (visited on 06/29/2025).

Tromp, Erik and Mykola Pechenizkiy (Dec. 2014). *Rule-based Emotion Detection on Social Media: Putting Tweets on Plutchik's Wheel*. arXiv:1412.4682 [cs]. DOI: 10.48550/arXiv.1412.4682. URL: http://arxiv.org/abs/1412.4682 (visited on 06/29/2025).

Tyrrell, Patrick et al. (2025). "Kubler-Ross Stages of Dying and Subsequent Models of Grief". eng. In: *StatPearls*. Treasure Island (FL): StatPearls Publishing. URL: http://www.ncbi.nlm.nih.gov/books/NBK507885/ (visited on 06/30/2025).