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Public discourse in the aftermath of the 2022 mass shooting in Buffalo, NY: Insights from social media data and ChatGPT

Li Yin [a,*], Jiao Dai [b], Robert Mark Silverman [a], Liang Wu [a], Henry Louis Taylor. Jr. [b]

[a] Department of Urban and Regional Planning, University at Buffalo, The State University of New York, United States of America
[b] School of Geography and information Engineering, China University of Geosciences, China

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ABSTRACT

Recent studies highlight the importance of transformative changes in planning and policymaking to enhance collaboration and effectiveness using new data sources and advanced tools. This study examines the potential of the NLP application in urban planning and the limitations of social media data in capturing local community concerns. Mass shootings have surged dramatically in the U.S., becoming alarmingly common, a troubling trend that is also evident globally. We investigated the dominant semantic topics and sentiments on Twitter about Buffalo's racially segregated East Side neighborhoods since the 2022 mass shooting, using natural language processing (NLP) and ChatGPT. The findings reveal a shift in discussions toward the shooter and broader issues of racism, rather than structural inequalities and local conditions in the Black community. Tweets primarily expressed sadness and anger, but also advocacy. Effective policy-making, such as post-massacre gun control, may have influenced social media discussions. At the same time, the government's failure to address structural racism and deliver promised improvements may create a disconnection between community needs and their online representations.

1. Introduction

> "Somehow this has become routine. The reporting is routine. My response here at this podium ends up being routine, the conversation in the aftermath of it … We have become numb to this."[1]
>
> President Barack Obama, October 2015

The frequency of mass shootings[2] in the United States has surged dramatically since 2012 (Mother Jones, 2024), becoming alarmingly common, increasingly deadly, and almost routine, as President Obama remarked. This troubling trend is not unique to the United States; it is also evident on a global scale (Crothers & O'Brien, 2020; Everly-Palmer et al., 2021; Kertcher & Turin, 2025; Silva & Lankford, 2024).

Obama's victory in 2008 ignited an increase in racial tension (McDermott & Belcher, 2014), marked by incidents of hate speech and racial slurs. His 2012 reelection intensified fears among some white Americans about a perceived "racial replacement". This sentiment resonated with the broader, global conversation on "white replacement" theories. In the years following Obama's election, there was a significant rise in violence linked to this racial anxiety (Lowery, 2023). The rise of extremism and hate speech on social media further fueled violent movements, contributing to lethal outcomes such as mass shootings driven by white nationalist rhetoric (Everly-Palmer et al., 2021).

One particularly tragic example is the racially motivated supermarket mass shooting in Buffalo, New York, on May 14, 2022, where 10 black shoppers and workers were killed, and three others were wounded. The 18-year-old shooter, an avowed white supremacist radicalized online, drove hundreds of miles to target this Buffalo East Side neighborhood's only full-service grocery store with the intent to kill "as many Blacks as possible", according to his manifesto. The Office of the New York State Attorney General (2022; p.2) noted that "it is hard to ignore the correlation between the rise in mass shootings perpetrated by

* Corresponding author.
E-mail addresses: liyin@buffao.edu (L. Yin), xndaijiao@cug.edu.cn (J. Dai), rms35@buffalo.edu (R.M. Silverman), wuliang@cug.edu.cu (L. Wu), htaylor@buffalo.edu (H.L. Taylor. Jr.).

[1] Statement by the President on the Shootings at Umpqua Community College, Roseburg, Oregon, delivered on October 1, 2015.

[2] Although there are numerous definitions of mass shooting applied in scholarly literature and media coverage, for this analysis, we adopt the definition of a mass shooting used by the U.S. Federal Bureau of Investigation (FBI). That definition classifies mass shootings as events where one or more individuals are actively engaged in killing or attempting to kill people with firearms in populated areas.

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young men and the prevalence of online platforms where racist ideology and hate speech flourish".

Social media platforms play a crucial role in the flow of information in today's interconnected world (Mattila & Nummi, 2022; Puri et al., 2020; Schweitzer, 2014; Wang & Yin, 2023). Following the Buffalo shooting, witnesses filed a lawsuit in the New York Supreme Court, naming several social media platforms, including YouTube and Reddit, as defendants. The National Association for the Advancement of Colored People (NAACP) has called for holding corporations accountable for their roles in spreading bigotry and racism through news and social media.

In response to the massacre, Governor Kathy Hochul pledged changes in the $50 million East Buffalo investment to support the development of this Black community. This approach aligns with situational crime theory, which posits that modifying physical and social environments can play a crucial role in reducing crime opportunities (Eck & Clarke, 2019). Additionally, Governor Hochul enacted legislation to strengthen New York's gun laws. This was similar to the adoption of gun reforms in New Zealand after the Christchurch Mosque shooting in 2019 (Everly-Palmer et al., 2021). The racial attack in Buffalo's predominantly black neighborhood also drew support from activists nationwide.

However, questions remain about the nature of social media discussions regarding this massacre. The framing of the events on social media platforms can significantly influence public understanding and interpretation of the causes and consequences of mass shootings, as informed by social representation theory (Marková, 2003). This, in turn, shapes social and political reactions. How was this event communicated? How did the public perceive and process information related to this strategic event? Was there public concern about racist ideologies driving racial and gun violence? Did the public sentiments reflect the actual realities that Black Buffalo faced? Would these public sentiments be useful to urban planners and policy makers?

Gathering and analyzing information from social media can help answer these questions, as they offer "a new way of supplementing traditional methods of public participation that are often face-to-face and engage small groups of participants" (Lin & Geertman, 2019, p.77). While traditional research methods like surveys remain valuable, big data from social media has become a valuable tool for studying public concerns and sentiments (Hu et al., 2021; Schweitzer, 2014; Yin et al., 2015). This data has increasingly been used to gauge public opinions and inform decision-making (Hu et al., 2021; Mattila & Nummi, 2022; Yin, Han, & Nie, 2024).

While urban planners increasingly recognize social media as one valuable source for gaining insights into public behavior and opinions, and for enhancing communication and participation (Nummi, 2017; Schweitzer, 2014), social representations from engagements on these platforms can be complex and fragmented, as informed by social representation theory, making them challenging to interpret effectively (Moscovici, 1988; Yin, Yin, & Silverman, 2024). This study employs natural language processing (NLP) and Large Language Models (LLM) to analyze the vast amount of unstructured information shared on Twitter. By extracting and analyzing this data, we can gain insights into public thoughts and perspectives about the Buffalo mass shooting that would otherwise be costly and time-consuming to collect and analyze using traditional methods (Evans-Cowley & Griffin, 2012; Wang & Yin, 2023). Techniques such as sentiment analysis and topic modeling can assist in interpreting unstructured data generated on social media platforms. These NLP methods provide valuable insights by extracting relevant topics and sentiments, enabling researchers to understand public opinion and concerns more effectively (Li et al., 2022).

This paper investigates the prevailing semantic topics and sentiments that have garnered the most discussion about Buffalo's East Side neighborhoods on Twitter since the mass shooting. We aimed to identify the major topics discussed in relation to the mass shooting in this racially segregated neighborhood (Yin, 2009) using NLP and LLM. What are the dominant topics that the public is interested in? Are Twitter discussions focused on the community's struggles with racial segregation, gun violence, poverty, and limited grocery options to reduce crime opportunities? Was there public concern about racism? Whether and how did these topics change over time? What are the prevailing sentiments and perceptions? How useful are these prevailing sentiments and perceptions to urban planners? Does social media provide us with the answers we need to guide public policy formation? These results can help inform effective policymaking to address mass shootings globally.

2. Literature review

Mass shootings, where multiple victims are injured or killed in a single incident, have become disturbingly frequent and a significant concern not only in the U.S. but also in many other countries (Everly-Palmer et al., 2021; Silva & Lankford, 2024; Stier, 2024). While the causes of these tragic events are complex and multifaceted, certain theories can help inform the development of policies to address crime and violence. For instance, situational crime prevention theory (Eck & Clarke, 2019) and social representation theory (Moscovici, 1988) offer valuable insights.

2.1. Racially motivated mass shooting in a black-dominated community

Situational Crime Prevention theory informs efforts to reduce crime opportunities through changes in physical and social environments, thereby making criminal acts more difficult to commit (Eck & Clarke, 2019). Long before the tragic racially motivated mass shooting, the predominantly Black and underdeveloped neighborhood in Buffalo's east side had been struggling for generations with poverty, property abandonment, low walkability, food apartheid, and unemployment (Silverman et al., 2013; Taylor Jr, 1991, 1996; Yin, 2009; Yin et al., 2020; Yin et al., 2023; Yin & Silverman, 2015). These root causes of violence are intertwined, and addressing them is crucial, especially in this case where racial and residential segregation and economic disparities played a significant role (Taylor Jr, 1991, 1996).

According to his own writings, the Buffalo shooter specifically chose that Top's Friendly supermarket because it served a predominantly Black clientele, highlighting the racial segregation in the area. The great replacement theory has been linked to various mass shootings and racially motivated violence in Western countries (Everly-Palmer et al., 2021; Lowery, 2023). Perpetrators often express racist views centered on preserving the white population and frequently cite this ideology as motivation for their attacks. The shooter targeted the only full-service grocery store in the predominantly black neighborhood, scouting the location at least three times in the months and days leading up to the attack, with the intent to kill Black individuals. This incident underscores how racial segregation and food apartheid (Reese, 2019) can make certain communities more vulnerable to targeted racist attacks.

Since World War II, Buffalo has been consistently ranked among the most racially divided cities in the U.S. (Taylor Jr, 1996; Yin, 2009; Yin et al., 2023). According to five decennial censuses from 1980 to 2020, Buffalo experienced significant levels of segregation, particularly in many East Side census tracts where over 90 % of the population identified as African American or Black in 2020 (U.S. Census Bureau, 2020). This racial disparity that has persisted for decades contributed to economic and social inequities in the city. Like other Rust Belt shrinking cities, Buffalo has grappled with deindustrialization, depopulation, and out-migration. The city faces some of the highest poverty rates and vacancy rates in the country (Silverman et al., 2013; Yin, Han, & Nie, 2024). Massey and Denton (1993) suggested that racial residential segregation is a significant contributor to poverty in urban areas of the U.S. Yin et al. (2023; p2267) concluded that "policies embedded in the types of racialized markets … reinforce segregation and inequality". Studies have also found long-term abandoned properties persistently in Buffalo's landscape with elevated poverty rates in the highly blackconcentrated census tracts in the east side as a function of the racialized market (Imbroscio, 2021; Silverman et al., 2013; Taylor, 2020; Yin et al., 2023; Yin & Silverman, 2015).

In addition, the East Side neighborhood has faced challenges in accessing affordable and healthy food. As documented by Reese (2019), food apartheid is the result of decades of discriminatory planning and urban policies that have led to residential segregation and underinvestment in black communities by both public and private organizations. This racial segregation and uneven investment have created systemic food inequity, significantly shaping the daily experiences of people living in these black communities (Huang & Yin, 2025). These situational factors can stimulate crime, but adopting situational crime prevention strategies to address them may reduce crime opportunities (Eck & Clarke, 2019). This approach is vital for revitalizing neighborhoods in shrinking cities around the world like this that have struggled with poverty and segregation (Brown & Cropper, 2001; Yin et al., 2020).

2.2. Analyzing social media data for topics and sentiments to reduce crime

The swift evolution of information and communication technology has led to the global proliferation of social media networks (Kertcher & Turin, 2025). Social media data has been instrumental in enhancing our understanding of human behavior and society (Chen et al., 2024). Social representation theory provides a lens for understanding how mass shootings and crimes are portrayed and processed on social media, shaping collective perceptions, influencing social movements, and reinforcing societal divides (Crothers & O'Brien, 2020; Kertcher & Turin, 2025).

Engagements on social media platforms can influence both thinking and behavior, shaping how people perceive, interpret, and interact with the world around them. The anonymity provided by social media platforms facilitates the spread of unfiltered, and sometimes violent or criminal, content (Duncombe, 2020). According to his own writings, the shooter was radicalized online, highlighting the role social media platforms can play in spreading racist ideologies and facilitating such violent acts. As noted by the Office of the New York State Attorney General (2022; p.1) that the "disturbing reality is that this attack is part of an epidemic of mass shootings often perpetrated by young men radicalized online by an ideology of hate."

On the other hand, social media data has become a valuable resource for understanding public perceptions of spaces, events, and policies and sparked a growing number of studies that applied social media data content for planning and decision making (Schweitzer, 2014; Plunz et al., 2019; Roberts et al., 2019; Shin, 2019; Yin, Yin, & Silverman, 2024). Social media platforms play a central role in shaping social representations of mass shootings, as informed by social representation theory (Marková, 2003). Different users can frame these events in ways that influence public perception and shape collective understanding. Discussions on social media can lead to collective actions. For instance, Hashtags like #NeverAgain, which emerged after the Parkland shooting, mobilized youth activists and sparked real-world movements calling for gun reform (Holody & Shaughnessy, 2020).

As one of the most widely used global social media platforms, Twitter allows users to access and share information through text and photos. There is an expanding body of literature utilizing Twitter data across various planning or planning related fields, including transportation planning (Rahim Taleqani et al., 2019; Schweitzer, 2014), smarty cities (Molinillo et al., 2019), and public health to enhance public participation and inform policymaking (Yin, Han, & Nie, 2024).

However, social representations from interactions on social media platforms can be complex and appear "as a 'network' of ideas, metaphors and images", according to social representation theory (Moscovici, 2000: 153). These representations can include fragmented and contradictory thoughts and ideas, embedded in communicative practices such as media discourses and social media discussions (Marková, 2003). The vast amount of information can make these communications difficult to understand and interpret.

Natural Language Processing (NLP) techniques and Large Language Models (LLM) (Nadkarni et al., 2011; Ouyang et al., 2022) offer advanced analytical capabilities, enabling the analysis of vast amounts of unconventional and unstructured data generated by social media platforms, such as Twitter. The latent Dirichlet Allocation (LDA) model (Blei et al., 2003; Wang & Chen, 2023a, 2023b) is a commonly used unsupervised machine learning method and is widely used for text analysis. It provides a probability distribution of topics within a collection of documents, enabling effective topic clustering and classification. It has been widely used to extract topics from social media data (Al-Sahar et al., 2024; Gao et al., 2016). Term Frequency-Inverse Document Frequency (TF-IDF) is another topic modeling approach (Rahim Taleqani et al., 2019), which takes into account the frequency of a word's appearance in a document and across multiple documents. Combining LDA and TF-IDF can improve classification because LDA can extract topics while TF-IDF can extract frequently occurring keywords (Kim & Gil, 2019).

In analyzing social media data for sentiments and emotions, researchers are continually exploring advanced techniques to go beyond simple positive vs. negative categorizations. NLP can categorize sentiments into a broader range of emotions by evaluating the wider context within a tweet. This method assesses the score and intensity of various sentiments, providing a more realistic analysis of real-world emotions (Hu et al., 2021; Singh et al., 2021; Wang & Chen, 2023a, 2023b; Yin, Han, & Nie, 2024).

In summary, analyzing social media data, such as tweets, can inform the development of policies aimed at altering environments to change how offenders perceive available opportunities, as guided by situational crime prevention theory (Eck & Clarke, 2019). This type of analysis can also provide insights into how the public perceives and discusses various issues related to mass shooting on social media, as informed by social representation theory (Marková, 2003), including gun control, community engagement, and improvements to both physical and social environments to foster safer interactions and reduce violence (Eck & Clarke, 2019; Moscovici, 1988; Stier, 2024).

3. Method

3.1. Data collection, processing, and analysis workflow

Fig. 1 illustrates our data collection, processing, and analysis workflow. As depicted in the leftmost box on the top, we gathered nearly 55 K English-language Tweets about the 2022 Buffalo shooting over one year following the tragedy, specifically from May 14, 2022, to June 1, 2023. The data was reformatted by standardizing all text to lowercase, removing links and emoji, and assigning a unique ID to each comment for identification. Duplicate comments are flagged, and only unique tweets are included in the analysis followed. We then proceeded with topic modeling and sentiment analysis.

3.2. Topic modeling and sentiment analysis

We carried out topic modeling and sentiment analysis on the processed tweets using two methods: LDA and ChatGPT, as illustrated in Fig. 1. LDA was employed to analyze and group discussion topics on Twitter. The topic summary was based on the word cloud visualization, researchers' experiences and interpretations, and ChatGPT summary based on keywords and their distribution. Additionally, we used ChatGPT to conduct sentiment analysis with human oversight to gain insights into the range of emotions expressed in the tweets.

3.2.1. Topic modeling

Topic modeling using LDA requires a text corpus and a determined number of topics to be clustered. For model training, this study used a

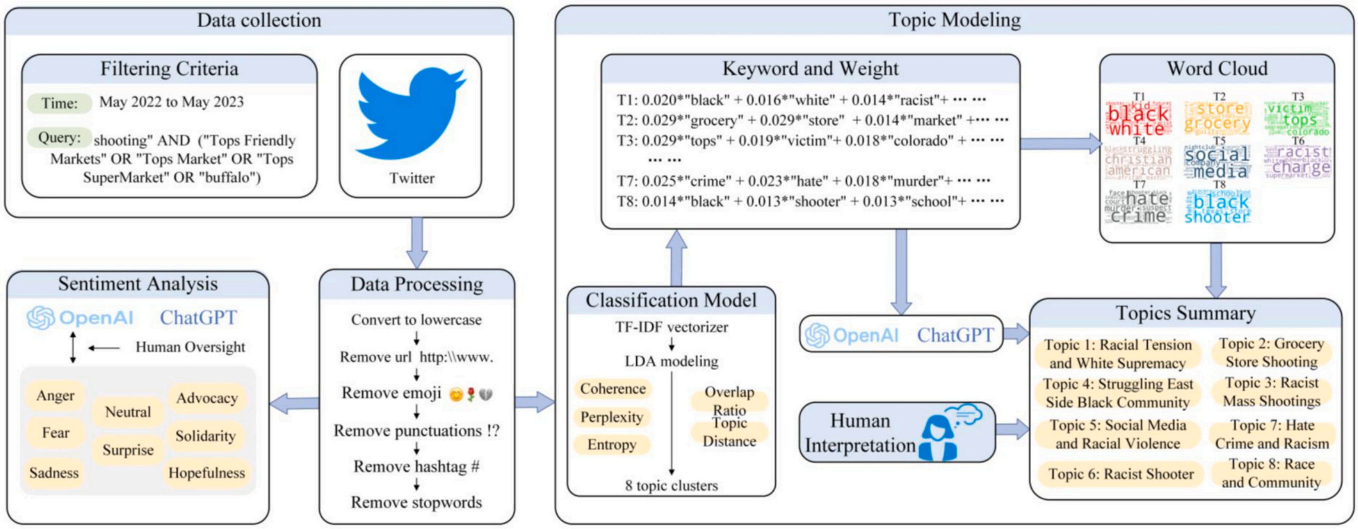


Fig. 1. Analysis flow chart.

document corpus weighted with Term Frequency-Inverse Document Frequency (TF-IDF), which highlights keywords and reduces the impact of noisy vocabulary, thereby enhancing model performance and interpretability.

We evaluated the model's performance using five indicators: coherence score, entropy, perplexity, overlap word ratio, and topic distance. The coherence score represents the correlation and consistency between topics. The higher the coherence score, the stronger the vocabulary correlation with the topic. Entropy assesses the uniformity of vocabulary distribution in topic modeling. High entropy indicates a more dispersed word distribution of a topic, probably because some words dominate while other words have lower weights. This may decrease the interpretability and understandability of the topic, resulting in lower-quality topic clustering. Perplexity indicates the predictive ability of the topic model on new documents. A lower perplexity implies that the model is more capable of predicting the topic distribution, indicating that the model is more robust and accurate. The overlap word ratio demonstrates the degree of lexical overlap between topics. A lower overlap word ratio implies that the lexical variability between topics is greater, and there are more differences and uniqueness between topics. Topic distance measures the similarity between topics. A higher topic distance implies more differentiation between topics with better interpretability.

Fig. 2 illustrates the changes in the five indicators as the number of topics (K) increases. Please note that for illustration clarity, the coherence and perplexity lines are reversed in the first graph. In this context, lower coherence and perplexity indicate better model performance. A higher entropy suggests a more even word distribution. The coherence score curve exhibits some fluctuations, whereas the other two lines gradually stabilize. Notably, the model performs relatively better across all three indicators when the number of topics is set to 5, 6, and 8. In the second graph, the overlap word ratio decreases once the number of topics exceeds 5, and the topic distance increases with more topics, indicating greater topic differentiations. All indicators perform relatively well when the number of topics is set to eight. Therefore, we decided to use eight topics for our further analysis.

We used Word Cloud to visualize the keywords according to their frequency for all eight topics (Fig. 1). Our team then evaluated and discussed potential titles for each topic based on our review of sampled tweets grouped within those eight topics and the word clouds. Additionally, we asked ChatGPT to generate titles for the eight topics based on the key words and their frequencies in each topic. The final topic titles were determined through these two processes.

3.2.2. *Sentiment analysis using Open AI*

We used the OpenAI ChatGPT-4o API to perform multi-class sentiment analysis on the tweet dataset. To provide context, the model was initially supplied with background information of the Buffalo mass shooting. After reviewing the preliminary results, the research team met to refine the analytical framework and established eight emotion categories based on relevant literature (Yin, Yin, & Silverman, 2024): anger, fear, sadness, surprise, neutral, solidarity, advocacy, and hopefulness. These categories guided ChatGPT in identifying the predominant sentiment expressed in each tweet. Each tweet was then assigned a single emotion that best represented its overall tone, based on the sentiment with the highest detected probability.

To assess the reliability of the model's outputs, we conducted a validation exercise. A random 3 % sample of tweets was independently coded by three researchers who were blinded to the ChatGPT results. Despite known limitations of large language models—such as potential variability in responses—the comparison revealed over 90 % agreement between the human coders and ChatGPT, suggesting strong alignment in sentiment classification.

4. Findings

Fig. 3 illustrates three distinct peaks in tweet activity during our study period: 1) May 2022, corresponding to the date of the mass shooting (May 14) and the initial charge of first-degree murder against the perpetrator (May 19); 2) November 2022, when the shooter publicly admitted to being motivated by racial hatred and domestic terrorism; and 3) February 2023, marking the court's sentencing of the perpetrator to life imprisonment without the possibility of parole, effectively concluding the legal proceedings. Notably, the one-year anniversary of the incident did not generate a significant increase in tweet volume.

Fig. 3 demonstrates a general decline in tweet activity over the year following the mass shooting, with three notable peaks corresponding to major developments in the case. This trend aligns with the concept of attention decay, as described in the literature, which refers to the gradual decline in public attention and engagement with content over time. Even when content continues to be cited—such as academic publications (Parolo et al., 2015)—its visibility and interaction on platforms like social media tend to diminish.

4.1. *Results from topic modeling*

Fig. 4 shows the word clouds for the eight topics that we grouped,

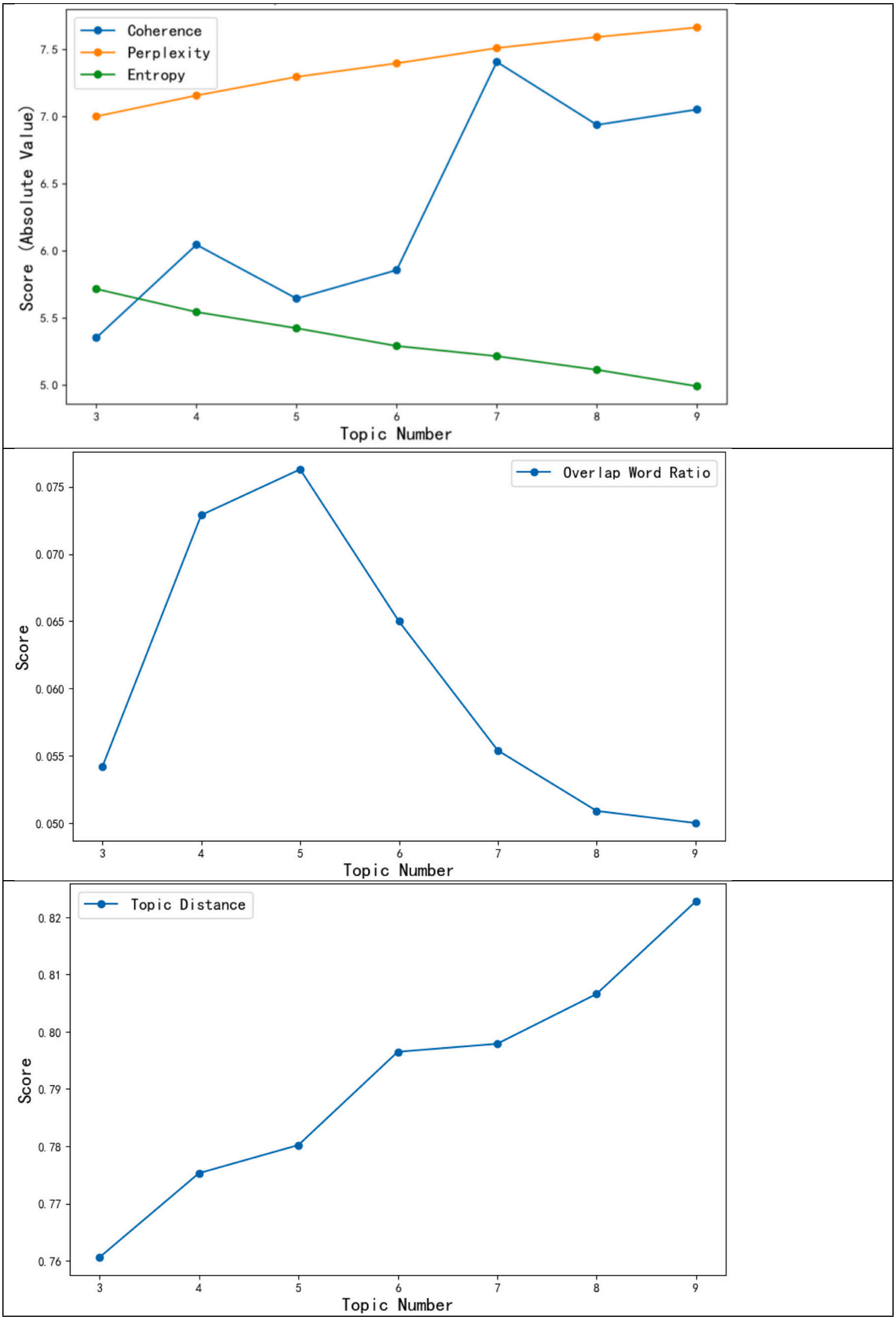


Fig. 2. Selection of number of topics.

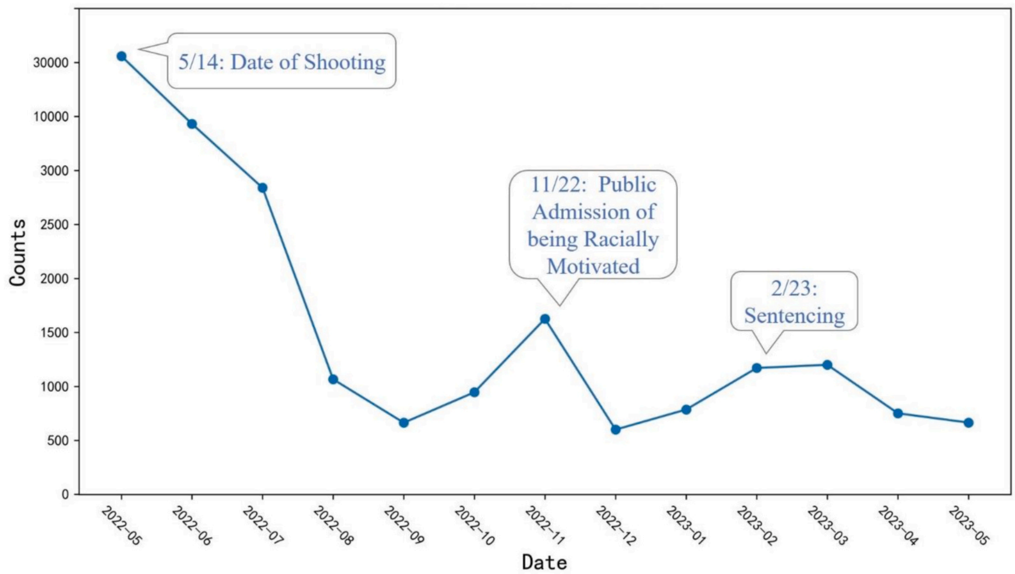


Fig. 3. Twitter counts: 05/2022–05/2023.

together with some example tweets. Results from word clouds visually represent the topics, each showcasing the top 40 words with the highest frequency for the corresponding topic. The larger the font size, the higher the frequency of the word is. The important terms or words associated with each topic offer insights into the main themes found within the tweet data. The topics that we identify are 1) racial tension and white supremacy; 2) grocery store shootings; 3) racist mass shootings; 4) struggling East Side black community; 5) social media and racial violence; 6) racist shooter; 7) hate crime and racism; 8) race and community.

Gun control did not emerge as one of the eight primary topics, likely due to the swift action taken by the New York State government to regulate gun use immediately following the mass shooting. This prompt response may have influenced the direction of policy discussions on Twitter. The prominence of the word "black" in the word cloud highlights the racial component present in nearly all topics of discussion. That further emphasizes the need to address systemic racism and segregation in the community, which made it a target for the shooter.

The choice of the grocery store as the shooting location, identified as one of the eight topics, is particularly significant, as it was the only full-service grocery store in the area. This underscores the existence of food apartheid and economic disparities in the community. Unsurprisingly, social media and hate crime also emerged as topics #5 and #7. The word cloud for the topic #8 has words like "school", "food", "grocery", "healing", and "church", representing both locations of mass shooting and sources of support in communities.

Fig. 5 presents the monthly distribution of topics throughout the study period, expressed as percentages. The heights of the bars represent the total number of tweets, with the percentages of each topic marked for each month. To facilitate clearer side-by-side comparisons across months and highlight changes over time, we adjusted the y-axis by compressing tweet counts exceeding 1100. This adjustment primarily affects the months of May through July, when the mass shooting initially occurred and generated a surge in online discussion. The modification enables clearer observation of topic distribution trends over time without allowing the early spike in tweet volume to overshadow later patterns.

Immediately after the mass shooting, in May, June, and July, discussions focused more on topic #8 (race and community). In May, other topics followed were topic #2 (grocery store shooting), topic #1 (racial tension and white supremacy), and topic #5 (social media and racial violence). About half a year later, in November, when the shooter admitted his racial motivation (identified as the second peak in Fig. 3), the discussions focused on topic #2 (grocery store shooting) and topic #6 (racist shooter). In February (the third peak in Fig. 3), following the shooter's sentencing, a significantly higher percentage of discussions centered on topic #6 (racist shooter). In March, discussions were still primarily about topic #6 and topic #2. The intensity of discussions about race and community wanes over time across the three peak periods.

These results suggest that while the East Side community continued to grapple with the same issues related to racial segregation, poverty, and health disparities, discussions about race and community diminished shortly after the mass shooting. Instead, the focus shifted more to the general discussion of the shooter's ideology and his motivations. This suggests a concern over the ideologies driving the increase in racialized violence or hate crimes.

4.2. *Results from sentiment analysis*

Fig. 6 summarizes the tweet sentiment distribution in eight emotion categories: anger, fear, sadness, hopefulness, solidary, advocacy, surprise, and neutral. The results show that the dominant emotion is sadness (62.81 %), followed by anger (26.89 %), as expressed by words like "grief-stricken", "tragic", and "grief". The third most expressed emotion is advocacy (5.57 %).

Fig. 6 shows that while discussions predominantly revolve around sadness and anger, there are also tweets about community building, reflected by the emotions of advocacy, solidarity, and hopefulness. Instead of showing binary sentiments of positive and negative, our findings showed more categories of emotions expressed in Twitter discussions.

Fig. 7 illustrates that sadness and anger are the predominant sentiments over the months. During the three peaks identified in Fig. 1 – May 2022, November 2022, and February 2023 – the percentages of sadness and anger are similar. The advocacy emotion declined after the initial months following the tragedy, both in the total number of tweets and percentage of tweets. This trend aligns with the patterns displayed in Fig. 6 on topics, as advocacy efforts are more locally oriented.

4.3. *Discussion*

Following the Buffalo mass shooting, the New York State government acted promptly to implement stricter gun control regulations. This

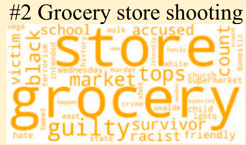
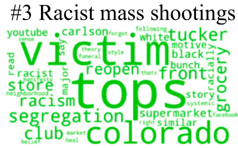
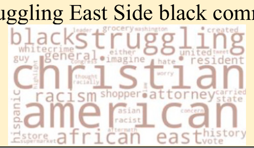
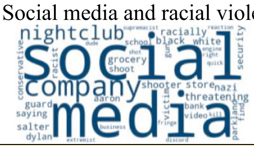
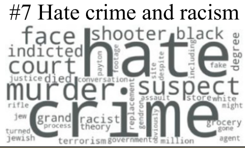
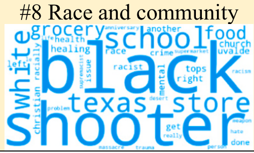
Topic	Example Tweets
#1. Racial tension and white supremacy 	➢ I'm seeing a lot of White people talk about what happened in Buffalo as Gun violence without mentioning the anti-Black racism, White supremacy, and hatred that drove it. Don't pretend this is another shooting.
#2 Grocery store shooting 	➢ I live in NY just a few hours from Buffalo where the horrific grocery store shooting happened last week and I haven't spoken out on it but it makes me sick. This shit gets closer to home every day for SO many people. When will it be enough for our government to do something?
#3 Racist mass shootings 	➢ Transphobes and homophobes @TuckerCarlson and @laurenboebertC0 should be charged as accessories to the Colorado Q-Club night club murders -- just like Carlson should have been charged in the Buffalo supermarket shooting for his racism ...@CarlsonTonight ...
#4 Struggling East Side black community 	➢ "Nothing changed": Buffalo's East Side still struggling a year after mass shooting - The Guardian ➢ For many Black residents of Buffalo, George Floyd's murder and the racist mass shooting at the Tops grocery store are two sides of the same coin.
#5 Social media and racial violence 	➢ Loved ones sue social media companies over Buffalo massacre. Massey Mapps stands on the porch of her sister Katherine "Kat" Massey's home in Buffalo, New York. Her sister was among 10 Black people killed in a racially motivated mass shooting at a Buffalo...
#6 Racist shooter 	➢ Charged With Hate Crime, Payton Gendron Facing Life Without Parole For Racist Buffalo Shooting https://...
#7 Hate crime and racism 	➢ UPDATE: Officials say the Buffalo supermarket mass shooting was a "racially motivated" hate crime. ➢ Because the shooting in Buffalo was a hate crime where the shooter's objective was to kill black people.
#8 Race and community 	➢ The Buffalo Public Schools Scholars of CLRI Programs holding community forum and food drive for healing following May 14 mass shooting

Fig. 4. Word Cloud for the eight topics and example tweets.

action aligns with situational crime theory, which suggests that measures like stricter gun control can reduce crime opportunities by limiting access to firearms. It is noteworthy that this immediate policy actions by the state government did not dominate the Twitter conversation to potentially sidelining other important discussions about community building and healing. This was similar to the emergence of consensus around gun control legislation that emerged in New Zealand after the Christchurch mosque shooting in 2019 (Everly-Palmer et al., 2021). In both New York and New Zealand, reform to gun control was not a contested issue following a mass shooting. The consensus and action on gun control created space for a greater focus on community building and healing in both cases. Future research is needed to compare these results to other places where gun control reforms were not adopted following a mass shooting. Tentatively, this finding suggests that adopting policies immediately following a mass shooting and addressing the root causes of violence in the community is important, particularly in cases where racial segregation and economic disparities played a significant role (Taylor Jr, 1991, 1996).

Over the one year following the mass shooting, Twitter discussions about the Buffalo incident have increasingly centered on the shooter, particularly during the peak tweet periods. This shift has overshadowed the struggles and difficulties faced by the local Buffalo community. It is possible that the adoption of gun reforms reduced the degree to which debates about gun control clouded discussions about the mass shooting; the focus of Twitter discussions was less focused on local conditions in the Black community. Despite millions of dollars being invested in the community that followed the principles of situational crime theory to reduce crime, these efforts have not attracted attention on social media. One possible reason for this is that social media platforms have users from all over the world, whose concerns and knowledge of the local community may not represent those of the local residents. Although there is some overlap between the local physical community and the online community, platforms like Twitter cannot adequately reflect the specific struggles of the local residents. This may explain the shift in discussion away from community building and healing to more general dialogue about the shooter and overt racism, particularly social media's

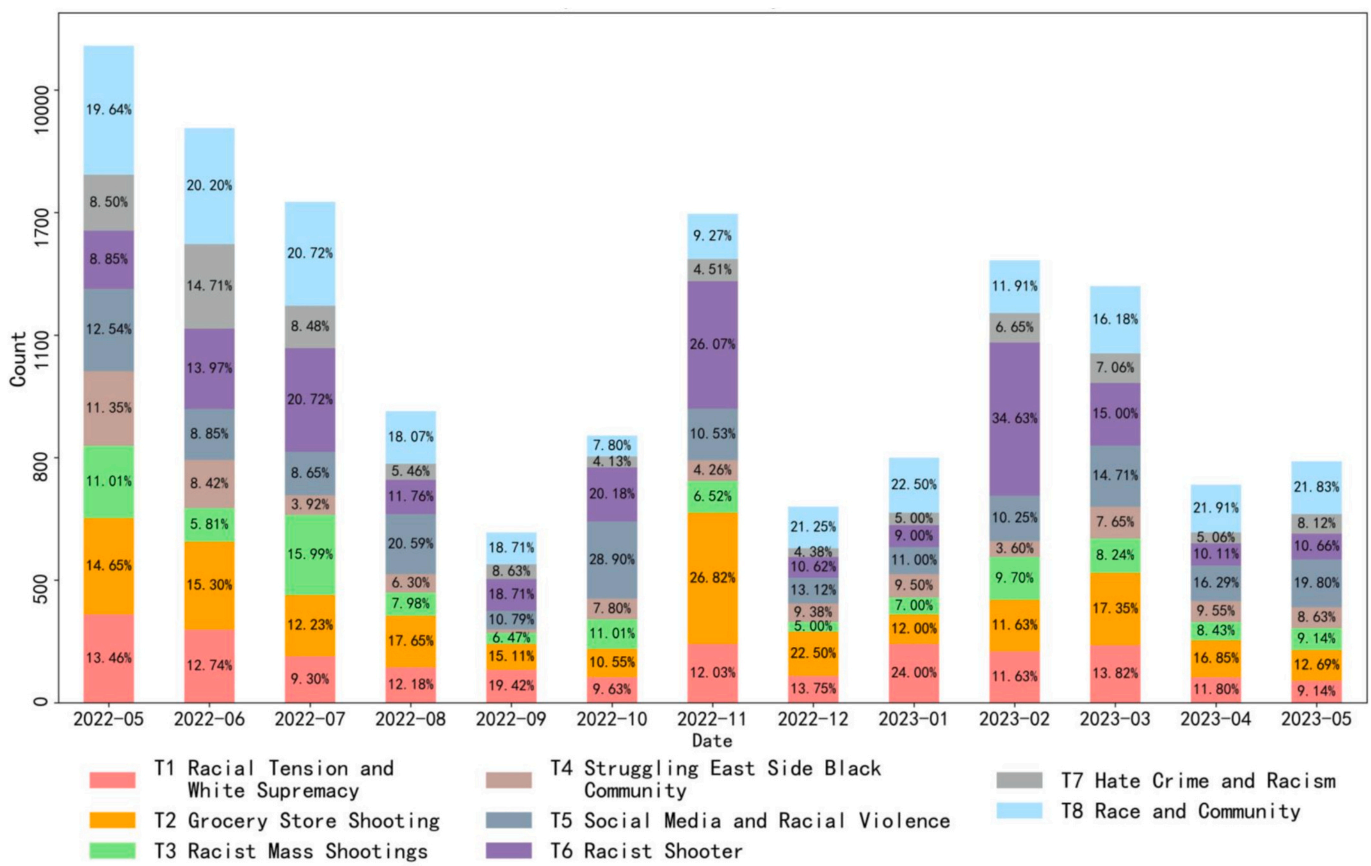


Fig. 5. Distribution of the eight topics by month (by percentage).

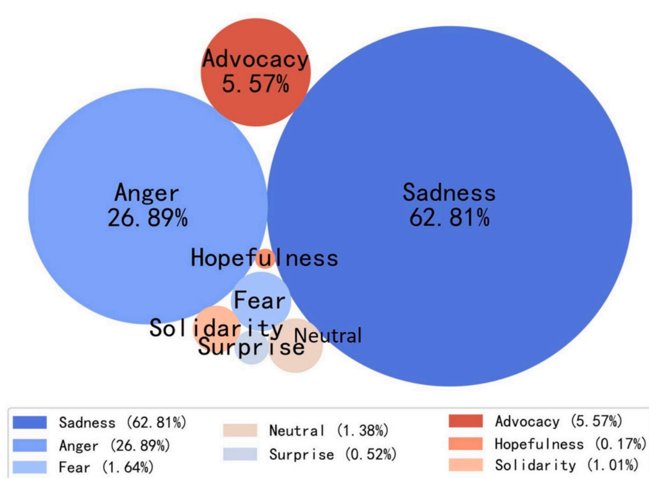


Fig. 6. Results from the sentiment analysis.

role, and racial violence.

Additionally, the shift is likely due to the lack of materialized improvement promised by the mayor and governor, their focus on overt racism, and their limited acknowledgement of structural discrimination, and distrust from the public. Instead, social media users may be taking cues from elected officials and traditional media, which frame mass shootings in terms of the racist motives of mass shooters and overt acts of racism, while paying less attention to structural forms of inequality. Additionally, there is less concern about the white supremacy ideologies (topic #1, racial tension and white supremacy) driving the increase in racial tension, racialized violence, and hate crimes. A comparison of traditional media and statements of public officials with social media conversations would illuminate how such framing influences public discourse. While changes in the community are crucial to address the issues rooted such as a racial segregation poverty, property abandonment, and food apartheid that this Black community has long struggled with (Silverman et al., 2013; Taylor Jr, 1991, 1996; Yin, 2009), it appears that the promised improvements have not spurred discussions on social media significantly.

5. Conclusion

This paper investigates the prevailing semantic topics and sentiments that have dominated discussions about Buffalo's East Side neighborhoods on Twitter since the 2022 mass shooting.

While the tweets predominantly revolve around sadness and anger, there are also tweets about community building, reflected in emotions of advocacy, solidarity, and hopefulness. The topic analysis results suggest that, despite the East Side community's ongoing struggles with issues like racial segregation, underdevelopment, and health disparities, discussions about these issues diminished shortly after the tragedy. Instead, the focus shifted more to the shooter, particularly during the peak tweet periods. This shift might be partly attributed to the lack of noticeable positive developments and opportunities in East Buffalo that correspond with the promises made by the mayor, the State, and the Erie County prosecutor, which could help to reduce crime opportunities, as suggested by situational crime theory. It might be reinforced by the framing in the traditional media and by elected officials, which emphasizes individual motivations of mass shooters over underlying structural inequalities. It could also be due to the swift changes in New York's gun laws following the shooting, along with a swift guilty plea and sentencing.

Effective policy-making, such as the implementation of gun control

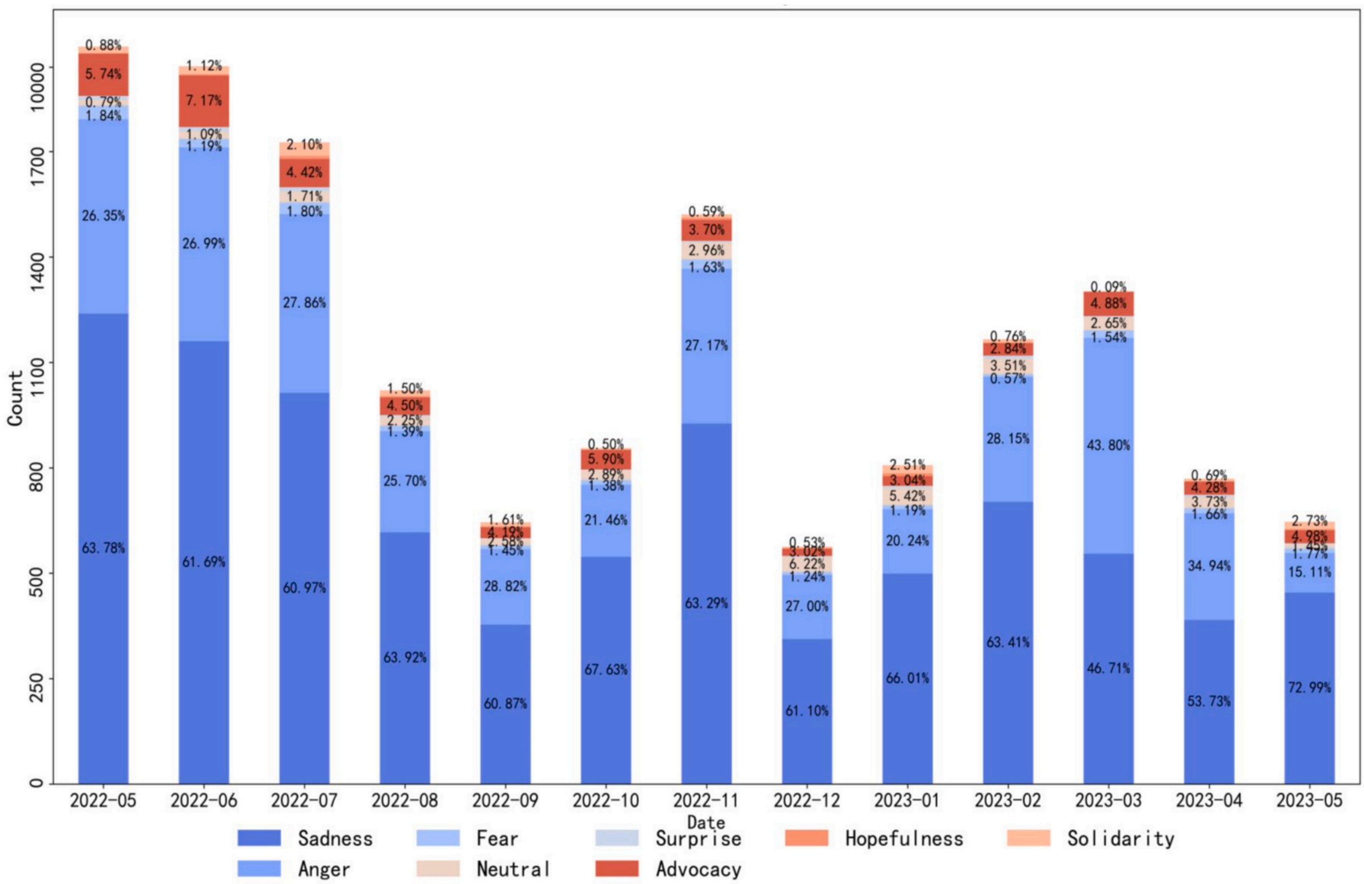


Fig. 7. Sentiment distribution by month.

regulations following the massacre, may have influenced discussions on social media platforms like Twitter. Conversely, the government's failure to acknowledge structural racism and deliver on promised materialized improvements within communities often goes unnoticed on social media. This lack of attention underscores a disconnect between community needs–such as changes to physical and social environments to reduce crime–and their representation in online discussions. Good decision-making not only shapes public discourse but also ensures that critical issues remain at the forefront of social media conversations. In contrast, inactive or ineffective policies fail to generate the same level of engagement and awareness, demonstrating the crucial role of responsive governance in influencing public interest and discussion.

Analyzing social media discussions offers valuable insights into public interest and the perceived impact of policies, as supported by

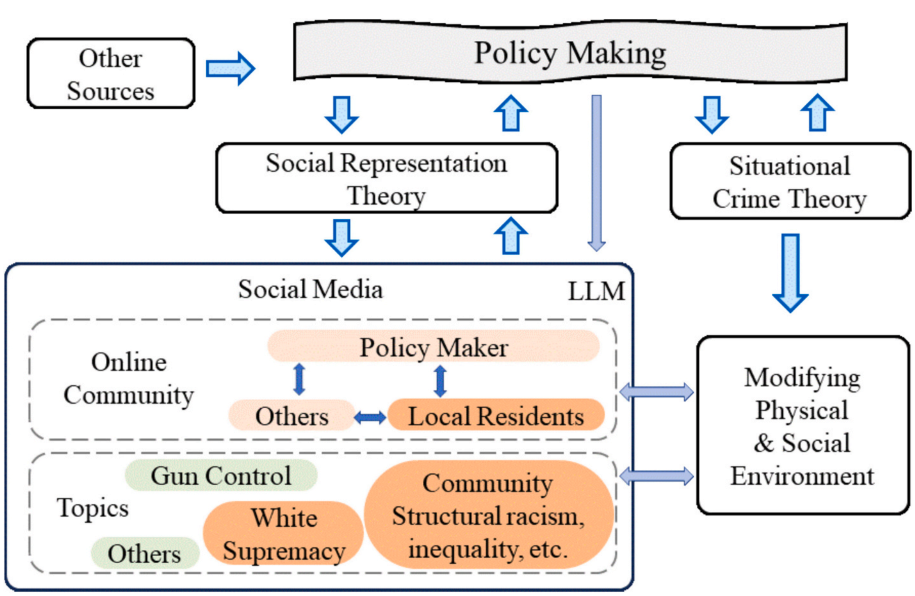


Fig. 8. Theoretical insights and policy development framework.

social representation theory and demonstrated in our study (see Fig. 8). The application of NLP and LLM in this context proves effective for gathering public comments and understanding the stakeholder concerns. Findings from our multi-class sentiment analysis and topic modeling shed light on the community apprehensions, particularly within Buffalo's predominantly Black neighborhoods, which have faced decades of systemic challenges.

The findings from this study have important implications not only for understanding public discourse surrounding the Buffalo mass shooting but also for analyzing social media responses to similar events in other communities. While social media data can offer valuable insights into public discourse, it carries inherent limitations in representativeness and reliability. One concern is selection bias, as individuals voluntarily choose to engage with platforms like Twitter. This self-selection results in a user base that is disproportionately younger, wealthier, more educated, and more digitally savvy than the general population (Mislove et al., 2011).

Geographic limitations further constrain the ability of social media data to reflect the nuanced and specific concerns of local communities. Our findings underscore these limitations. Although online discussions are widespread, they often involve participants from geographically dispersed locations whose perspectives may be too generalized to capture specific local issues effectively—particularly those rooted in structural racism, such as segregation and food apartheid. These issues are critical to understanding the full impact of events like the Buffalo mass shooting, and similar dynamics are likely to be present in other regions experiencing mass violence or community trauma. As noted in prior research, this broad focus can reduce the relevance of social media conversations for informing local decision-making and policy development (Mattila & Nummi, 2022; Nummi, 2025).

Although there is some overlap between the local physical community and the online community, the two are not synonymous. Social media discussions often shift toward generalized or sensational topics, such as national debates on gun control or the identity of the perpetrators, rather than sustained engagement with the specific, structural, and localized issues that matter most to the communities directly affected. These include concerns such as racial segregation, economic inequality, and community trauma. This shift in focus can obscure critical concerns and hinder efforts to evaluate the effectiveness of policy responses and promised improvements. To address this, researchers, policy makers, and practitioners must take a more proactive role in shaping the social media ecosystem to ensure that discussions and information dissemination are grounded in the structural realities of the communities most impacted.

In line with previous studies, scholars and practitioners across geographic contexts should exercise caution when interpreting social media data and consider supplementing it with other sources to gain a more comprehensive understanding of local issues (Nummi, 2025). This underscores the need for multi-source approaches in both research and policy development. Policymakers and practitioners should avoid relying solely on social media analysis when designing interventions or communicating policy responses. Instead, social media should be used not only to monitor public sentiment but also as a platform for disseminating evidence-based information and framing policy interventions within the broader context of structural inequality in communities targeted by such violence.

There is also a need for greater dissemination of academic research and more intentional framing of social media discourse around structural conditions. Academic researchers can play a vital role in this process by translating research findings into accessible formats and actively engaging in online conversations. By doing so, they can help bridge the disconnect between online discourse and local realities, ensuring that discussions remain grounded in the realities of marginalized communities—whether in Buffalo or in other regions facing similar crises.

Moreover, the intentional framing of social media narratives can contribute to addressing the psychological distress, heightened anxiety, and long-term impacts–such as post-traumatic stress– that may follow mass shootings (Peterson et al., 2025). In this context, academic engagement on social media can support broader community-level mental health interventions by fostering informed, empathetic, and constructive dialogue.

This study demonstrates the potential of NLP applications in urban planning and contributes to advancing discussions around their use in planning and designing more responsive and inclusive cities and communities. While some of the nuances in the analysis are particular to the city of Buffalo, this approach to examining public sentiment and applying these insights to inform policy making is broadly applicable. Given the global reach of social media platforms, this methodology holds relevance for both U.S. and international contexts.

By interpreting complex social representations engaged on social media through tools like NLP and ChatGPT, planners can gain insights into public behavior and opinion. Given the value of examining social media systematically to inform the policy process, schools of urban planning and policy should expand more continuing education opportunities and provide resources for professionals and scholars to learn how to apply this type of data in policy analysis and evaluation.

During the preparation of this work the author(s) used ChatGPT in order to finish part of the analysis. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Li Yin: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jiao Dai:** Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Robert Mark Silverman:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Liang Wu:** Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Henry Louis Taylor. Jr.:** Writing – review & editing, Validation, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. LDA sensitivity checks

K-values	Topics (top2 keywords)	Coherence	Perplexity	Overlap Word Ratio	Entropy	Topic Distance
3	Topic 1: 0.018*"racist" + 0.017*"white" Topic 2: 0.032*"store" + 0.029*"grocery" Topic 3: 0.021*"black" + 0.014*"white"	-5.354	-7.0022	0.0542	5.7172	0.7606
4	Topic 1: 0.021*"black" + 0.018*"white" Topic 2: 0.033*"store" + 0.030*"grocery" Topic 3: 0.015*"black" + 0.014*"tops" Topic 4: 0.012*"black" + 0.012*"media"	-6.0468	-7.1582	0.0729	5.5457	0.7753
5	Topic 1: 0.017*"christian" + 0.016*"white" Topic 2: 0.031*"store" + 0.029*"grocery" Topic 3: 0.018*"racist" + 0.017*"guilty" Topic 4: 0.016*"black" + 0.014*"court" Topic 5: 0.015*"black" + 0.014*"victim"	-5.6458	-7.2966	0.0763	5.425	0.7802
6	Topic 1: 0.017*"guilty" + 0.016*"black" Topic 2: 0.034*"store" + 0.032*"grocery" Topic 3: 0.024*"black" + 0.020*"shooter" Topic 4: 0.022*"american" + 0.020*"prison" Topic 5: 0.017*"supermarket" + 0.016*"tops" Topic 6: 0.026*"charge" + 0.020*"east"	-5.8578	-7.3977	0.065	5.2927	0.7965
7	Topic 1: 0.017*"white" + 0.016*"synagogue" Topic 2: 0.033*"store" + 0.032*"grocery" Topic 3: 0.017*"black" + 0.015*"tops" Topic 4: 0.030*"black" + 0.020*"history" Topic 5: 0.026*"east" + 0.014*"healing" Topic 6: 0.032*"charge" + 0.028*"social" Topic 7: 0.019*"racist" + 0.017*"crime"	-7.4083	-7.5114	0.0554	5.2168	0.7979
8 (Selected)	Topic 1: 0.020*"black" + 0.016*"white" Topic 2: 0.029*"grocery" + 0.029*"store" Topic 3: 0.029*"tops" + 0.019*"victim" Topic 4: 0.027*"american" + 0.025*"christian" Topic 5: 0.020*"social" + 0.019*"media" Topic 6: 0.030*"charge" + 0.024*"racist" Topic 7: 0.025*"crime" + 0.023*"hate" Topic 8: 0.014*"black" + 0.013*"shooter"	-6.939	-7.5932	0.0509	5.1154	0.8066
9	Topic 1: 0.033*"guilty" + 0.018*"white" Topic 2: 0.040*"store" + 0.039*"grocery" Topic 3: 0.017*"colorado" + 0.017*"racism" Topic 4: 0.034*"black" + 0.022*"supermarket" Topic 5: 0.024*"death" + 0.021*"victim" Topic 6: 0.025*"guard" + 0.018*"shooter" Topic 7: 0.024*"crime" + 0.021*"hate" Topic 8: 0.022*"christian" + 0.016*"east" Topic 9: 0.032*"media" + 0.031*"social"	-7.0536	-7.6646	0.05	4.993	0.8228

The shaded cells present information about the selected K value used in the analysis in the paper.

Data availability

Data will be made available on request.

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