El Paso Shooting Reaction: A Content Analysis

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On August 3, 2019, Patrick Wood Crusius, a 21-year-old white man, opened fire on a Walmart in El Paso, Texas, ultimately killing 22 people (Andone et al., 2019). In the aftermath of the attack, a racist manifesto written by the shooter and a confession by the perpetrator indicated that the shooter specifically targeted Latinos (Attanasio et al., 2019; Ura, 2019). The massacre and its motivation reverberated across the country, striking fear in Latinos around the United States (Carrasquillo, 2019; Mealer, 2019; Romero et al., 2019). On February 6, 2020, Patrick Crusius was indicted by a grand jury on capital murder charges, ultimately being sentenced to 90 consecutive life sentences (Al Jazeera, 2019; Lee & Weber, 2023; Murphy, 2019).

The discourse after the attack varied by messaging and actor. A notable theme that emerged after the tragedy was the use of white supremacy to explain the event, as well as its classification as domestic terror. For example, numerous entities, such as mainstream media outlets, law enforcement entities, and politicians across the aisle, labeled the shooting as an act of white supremacy and domestic terrorism (BBC, 2019; Samuels, 2019; Svitek, 2019). Interestingly, most entities that called the massacre a domestic terror attack also spoke of its white supremacist nature, alluding to their reciprocal relationship.

Gun access and reform also rose to the forefront of conversations after the El Paso shooting, reigniting the dormant gun control debate in the United States. For instance, numerous media outlets turned to Texas' relaxed gun laws to help explain how the perpetrator was able to commit his act of terror (Roldan & Stephens, 2019; Santhanam, 2019). Moreover, although several actors, such as community members and politicians, immediately demanded gun reform after the tragedy (Golshan, 2019; Gopnik, 2019), other individuals condemned these challenges against the state's gun culture, advocating for looser gun restrictions (Dart, 2019; Johnson, 2019).

While some focused on discussing the massacre as an act of terror and debated the next steps in gun control, others closely examined the perpetrator and his potential mental health issues. Notably, hours after the shooting, Texas Governor Greg Abbott emphasized the need to address mental health as a "large contributor to any type of violence," going as far as to verbally support legislation aimed at addressing children's mental health (McCullough & Stephens, 2019). Then-President Donald Trump followed suit as he highlighted "reform[ing] our mental health laws" as a key pillar to deter future similar acts of violence (Trump, 2019).

Several additional themes materialized in the wake of the El Paso shooting, including fact-focused media reporting, grieving for the lost lives, critiques of the government and government officials, and much more. While these topics can be subjectively identified through browsing news articles, blogs, social media, and other outlets, the true prevalence of these narratives remains to be determined. This paper addresses this gap in the literature by providing insight into how the public spoke about the El Paso shooting after it happened. By providing this insight, I aim to provide a paradigm to examine potential trends in political discourse regarding high-profile shootings.

Methodology

This study utilizes content analysis, a common method for analyzing social and political trends in social science (Grimmer et al., 2022; Holsti, 1969; Krippendorff, 2004). Content analysis has also become a cornerstone in research regarding sentiment analysis after high-profile shootings (Bland, 2022; Damiano et al., 2024; Miller, 2015; Iannuzzi, 2017). We derive our raw data from X, formerly known as Twitter, a public workspace, specifically tweets related to the El Paso shooting. Since the tweets are sourced from the public workspace, any user may be admitted into the sample so long as they include #ElPasoShooting in their tweet.

The TwitteR package scraped the public workspace between August 3, 2019, and August 10, 2019. This time frame was chosen as it is a week after the shooting, which occurred on August 3, 2019. The final raw dataset included 20,000 tweets, which was the maximum number of tweets the API could scrape.

Once we created a sample by hashtag and timeframe, we developed categories and themes to classify the tweets. Our process began by extracting a random sample of 200 tweets from the original dataset with R's sampling function. One coder read and hand-coded all 200 tweets, noting any recurring categories or themes that appeared. After the coder developed the categories and themes, they randomly sampled another 1,800 tweets from the original dataset, hand-coding them with the existing categories and themes for a combined total of 2,000 tweets.

Table 1.

Classification Categories and Descriptions

Category/Theme	Description
White Supremacy/Terrorism	Any tweet that explicitly uses the terms "White Supremacy" or alludes to the likely (e.g., White Nationalism, White Extremism, etc.). Any tweet that explicitly uses the term "Terrorism", including "Domestic Terrorism". These themes have been combined because they are normally used in tandem and are used to drive the same message.
Critique of Political Response	Any tweet that criticizes the response of any political actor or entity, regardless of the level (i.e., federal, state, local) or political affiliation
Calls for Gun Control	Any tweet that explicitly calls for any amount of ***restrictionist*** gun reform *OR* clearly alludes to the need for gun reform

Stochastic Terrorism	Any tweet that explicitly blames the violent act on a political actor's or entities directed, hostile public rhetoric
Personal and Community Grief	Any tweet that implies the original poster is experiencing a level of personal grief *OR* that they are feeling grief on behalf of the community *OR* on behalf of the victims/victim's families Grief is defined as "very great sadness, especially at the death of someone"*
Mental Health	Any tweet that explicitly mentions "Mental Health" *OR* clearly alludes to it (i.e., Mental Illness, Mental Sickness, etc.) as a factor in the shooting, either positive or negative
Discourse of Media Representation	Any tweet that supports *OR* criticizes a media outlet *OR* media reporters discourse on the violent act
Cynicism and Despair	Any tweet that expresses sentiments of inevitable failure or doom for the "state" because of the violent act
Racism	Any tweet that explicitly expresses racist sentiments toward the target population of the violent act
Media Reporting	Any tweet that reports the objective facts (e.g., Death toll, the number of people injured, information about the shooter, etc.) about the violent act
Liberal	Any tweet that explicitly uses the term "Liberal" *OR* alludes the left-wing as playing in role in the violent act
N/A	Any tweet that does not fit within the categories

*Note: * Cambridge Dictionary, s.v. "grief," accessed October 22, 2024, https://dictionary.cambridge.org/us/dictionary/english/grief.*

After hand-coding 2,000 tweets, the first coder collected a subsample of 100 tweets from the already coded tweets. A second coder received this subsample of 100 tweets, which had the thematic coding removed. The second coder then performed their coding for the 100-tweet sample. After the second coder completed the task, the original coder executed Krippendorff's alpha test to determine the intercoder reliability of the content analysis. After running Krippendorff's alpha test on the 100-tweet sample from both coders, the intercoder reliability for each category is provided in Table 1. After reviewing the intercoder reliability for each category, I decided to narrow down the remaining data analysis to the 'White Supremacy/Terrorism' category. I made this decision for two reasons. First, the alpha value of the 'White Supremacy/Terrorism' indicated strong intercoder reliability. Krippendorff's alpha test measures reliability "as 1.000 for perfect reliability and 0.000 for the absence of reliability" (Hayes & Krippendorff, 2007). With a score of 0.813, the 'White Supremacy/Terrorism' category exhibits strong intercoder reliability. Like this category, the 'Gun Reform,' 'Mental Health,' and 'Liberal' categories also scored high alpha values, all above 0.800. However, I decided not to include them in the final analysis for the second reason: the number of observations. Between both coders, a total of forty observations were labeled as 'White Supremacy/Terrorism,' while only twenty were classified as 'Gun Reform,' thirteen as 'Mental,' and two as 'Liberal.' The higher frequency of observations classified as 'White Supremacy/Terrorism' provides a more robust dataset for testing intercoder reliability, as the larger sample size increases the potential for disagreement and strengthens the case for agreement.

After narrowing the categories to 'White Supremacy/Terrorism,' I took a supervised learning approach to classify the remaining tweets in the original dataset. Supervised learning is a type of machine learning that uses training data to analyze how documents are classified and then predicts further assignments in a larger, uncategorized dataset (Grimmer et al., 2022; Nasteski, 2017). I used supervised learning to code my larger, uncategorized dataset for two reasons. First, supervised learning has been widely adopted by others in social sciences, especially in sentiment analysis (Go et al., 2009; Nielsen, 2017; Wang et al., 2016; Yadav et al., 2021). Second, the alternatives to supervised learning, such as hand coding and unsupervised learning, are less efficient or not appropriate for the goals of this paper, which are to describe how the public spoke about the El Paso shooting. Although hand-coding may provide the most optimal reliability because of its focused nature, hand-coding the remaining 18,000 tweets would prove a long, inefficient task. Unsupervised learning, a form of machine learning that extracts patterns from uncategorized data, is inadequate for this study because the process relies on artificial intelligence to identify patterns without human interference, while my study uses established categories to classify future documents (Gentleman & Carey, 2008; Grimmer et al., 2021). Human interference is important for this project because tweets are a unique communication method that requires context, which is best understood by humans, especially around the period I examine. In 2019, for instance, at a similar time to the El Paso shooting, the hashtag #MoscowMitch grew increasingly popular in public discourse, eventually being included in several tweets about the El Paso shooting. Although humans can use context to understand the meaning behind the hashtag, that being a node to Mitch McConnell being a Russian asset for blocking stronger election security measures, we cannot be certain that an unsupervised learning algorithm could discern this meaning from a context-absent hashtag (Hulse, 2019)

I adhere to the Naive Bayes supervised learning technique outlined by Grimmer et al. (2022) in *Text as Data: A New Framework for Machine Learning and the Social Sciences*. As mentioned, the model learns from already classified documents to predict how future uncategorized documents will be assigned by analyzing their text and classification. To best achieve this, the complexity of the text must be reduced as much as possible, which I completed by preprocessing the data. Using the Python programming language, I simplified the 2,000-handed coded tweets by setting all the words to lowercase, removing punctuation, numbers, white spaces, non-ASCII characters, and stop words. After preprocessing the data, I used R to conduct the supervised learning technique. I began by further tokenizing the text and constructing a Document-Term Matrix (DTM), a matrix indicating the frequency of terms occurring in each document, removing any terms that occurred in less than 1% of documents (Grimmer et al., 2022). After creating the DTM, the 2,000 hand-coded tweets were randomly split into training and testing sets. The Naive Bayes algorithm then used the training set, treating the 'White Supremacy/Terrorism' classification as the dependent variable and the other columns, or the terms, as conditionally independent predictors. Once I test the classifier, I use a confusion matrix to evaluate the performance of my prediction model. A confusion matrix is a matrix that helps visualize the performance of the learning algorithm by representing the intersection of actual and predicted classifications, providing a summary of the "most relevant performance information" (Grimmer et al., 2022). The confusion matrix indicates significant agreement between the actual and predicted classifications, as there is only one false negative and one false positive (See Appendix B). I also measured the model's accuracy along with the confusion matrix, which returns a near-perfect score of 0.996 (See Appendix C).

After verifying the accuracy of our confusion matrix, I applied my Naive Bayes classifier to the 20,000-tweet dataset. I created a Document Term Matrix (DTM) for the 20,000-tweet dataset, removing terms that occurred in less than 1% of documents. Once I produced the DTM, I added all the columns (terms) missing in the 2,000-tweet and 20,000-tweet datasets, assigning "No" to every row since they did not appear in the original text. When I verified that all the columns for both datasets matched, I applied the classifier model, which was trained using the original classifications in the 2,000-tweet dataset, to the 20,000-tweet dataset to predict how each tweet would be classified.

Results

Our results begin with the proportion of tweets classified as "White Supremacy/Terrorism" in the hand-coded 2,000-tweet sample and the machine-classified 20,000-tweet sample. Table 2 demonstrates the number of tweets classified as "White Supremacy/Terrorism" by either the hand-coder or the algorithm in the total sample. The data shows that roughly 18% of tweets in the hand-coded dataset were classified as "White Supremacy/Terrorism," while roughly 14% of the tweets in the machine-classified dataset were assigned as "White Supremacy/Terrorism," meaning 14% of general discourse surrounded "White Supremacy/Terrorism," a 4-percentage point difference between the datasets.

Table 2

Proportion of Tweets Classified as White Supremacy/Terrorism Across Datasets

Type of Dataset	Classified Tweets*	Sample Size	Proportion
Hand-Coded Dataset	355	2,000	0.178
Machine Classified Dataset	2,826	20,000	0.141

Note: * Classified Tweets refers to tweets classified as "White Supremacy/Terrorism."

After examining and comparing the proportion of tweets classified as "White Supremacy/Terrorism," I also inspect the tweets with the highest confidence of being labeled "White Supremacy/Terrorism" to further scrutinize the model. Table 3 reveals the top ten tweets with the highest confidence of being classified as "White Supremacy/Terrorism," according to our model. The closer a tweet's confidence is to 1, the more likely the tweet is to be classified as our theme of interest. The top ten tweets from our sample have a confidence of 0.999, indicating strong confidence that the tweets should be classified as our target category. Several

Table 3

Top 10 Tweets with Highest Confidence of White Supremacy/Terrorism Classification

Tweet #	Text	Confidence*
19992	Trump is a White Supremacist Terrorist! #Trump #WhiteSupremacist #WhiteSupremacistTerrorism	0.999
5948	#ElPasoShooting #walmartshooting #WhiteSupremacistTerrorism #massshooting #ElPasoTerroristAttack #TrumpsTerrorists	0.999
354	#ElPasoShooting #ElPasoTerroristAttack #Ohio #Dayton #WhiteSupremacistTerrorism #WhiteState terrorist organization	0.999
19126	#WhiteSupremacistTerrorism #ElPasoShooting #TrumpsTerrorists #GunControlNow #DomesticTerrorism #thoughtsandprayer	0.999
13930	#WhiteSupremacistTerrorism #TrumpsTerrorists #ElPasoTerroristAttack #ElPasoShooting #GunControlNow This is dire	0.999
15361	#TrumpsTerrorists #WhiteSupremacistTerrorism #massshootings #ElPasoShooting #DomesticTerrorism @realDonaldTrump SO	0.999
244	#ElPasoTerroristAttack #ElPasoShooting #WhiteSupremacistTerrorism #massshooting #GunControlNow	0.999
19975	The number one terrorist threat in America remains white supremacis tmales. #WhiteSupremacistTerrorism	0.999
6344	@tedcruz so what do you have to say about the white supremacist terrorist act in #elpaso #ElPasoShooting #terrorism	0.999
18231	#HomeboyIsNuts #DomesticTerrorism #massshooting #WhiteSupremacistTerrorism #ElPasoShooting #TrumpsTerrorists	0.999

Note: * Confidence refers to the algorithm's confidence in assigning a given instance to a category

themes within the ten tweets explain why they are and should be labeled as "White Supremacy/Terrorism. First, all the tweets include some mention of white supremacy or racial violence, shown through repeated references to "#WhiteSupremacist," "#WhiteSupremacistTerrorism," and "#WhiteState terrorist organization." Moreover, each tweet also contains an explicit remark about terrorism and domestic threats, such as "#ElPasoTerrorist Attack," "TrumpsTerrorists," and "The number one terrorist threat in America remains white supremacist males." The abundance of these themes, coupled with their clear meaning, signals that these tweets should be classified as "White Supremacy/Terrorism." Furthermore, we can be convinced that any tweets containing language like the ten tweets can assertively be classified as our target theme.

After examining the top ten tweets, I proceed to analyze the bottom ten. Usually, the closer a tweet is to a confidence of 0, the less likely a tweet is to be considered our theme of interest. However, since I am only evaluating tweets that were classified as "White Supremacy/Terrorism," then our baseline is 0.5, as any tweet that falls below that threshold is not classified as our theme. Therefore, I examine the ten tweets closest to 0.5. Table 4 represents the top ten tweets closest to the threshold, all having confidence of 0.500, suggesting a lack of confidence regarding whether they should be categorized as "White Supremacy/Terrorism" or not. Closely inspecting the tweets gives further insight into the lack of confidence when classifying the tweets and potential inconsistencies in the algorithm. For instance, there are a couple of tweets that are correctly classified, such as tweet 16358, which mentions "#ElPasoTerroristAttack" and tweet 14416, including usage of "#WhiteNationalistMedia." While these tweets are clearly connected to white supremacy and terrorism, others in the sample do not have such an explicit correlation. For example, several tweets, such as tweets 10158, 17201, 12344, and 8270, comprise several mentions of El Paso in general, including "#ElPasoShooting," "#ElPaso," and "#ElPasoStrong." Although the event-specific context of the El Paso Shooting being linked to white supremacy may have informed these classifications, every tweet we included in the sample included the #ElPasoShooting, so it is not clear why these

Table 4

Top 10 Tweets with Lowest Confidence of White Supremacy/Terrorism Classification

Tweet #	Text	Confidence*
2514	Relax everyone! False alarm! It was only an American born white male who committed the #ElPasoShooting not a Muslim	0.500
19754	Press conference going on now regarding #ElPasoShooting and it looks like @CNN has already abandoned ship! Support	0.500
16358	#GunControlNow #GunControl #GunViolence #gunreformnow #gun #guns #america #Violence #ElPasoTerroristAttack	0.500
14416	GeraldoRivera Shouldn't you be busy taking drunk pictures in a mirror. The #WhiteNationalistMedia mothership you w	0.500
10158	#ElPasoShooting #daytonshooting #JesusChrist #God #Bible	0.500
17201	Ayudenme a compartir por favor#ElPaso #ElPasoShooting #elpasostrong	0.500
12344	Jerehmiah 17:9 #ElPaso #ElPasoShooting #DaytonOhioShooting #ElPasoShooting #elpasoshooter #ElPasoStrong	0.500
5524	@thecjpearson Appears to me that Trump Supporters are harming others. #ElPasoShooting #ElPaso #FoxNews #CNN	0.500
8270	@AnoNQcue @marwilliamson @BryanCrusius #elpasoshooter #ElPasoShooting #ElPasoStrong #ElPaso #Texas #WWG1WGA	0.500
221	Save us, oh gubmint! Please prevent all death. #massshooting #walmartshooting #ElPasoShooting #daytonshooter	0.500

Note: * Confidence refers to the algorithm's confidence in assigning a given instance to a category

tweets are unique other than frequency. Finally, various tweets, including tweets 10158, 12344, and 221, utilize religious messaging, such as "#JesusChrist," #God," "#Bible," "Jerehmiah 17:9," and "Save us." Again, although a vague connection can be made between religion and white supremacy or terrorism as a potential motivator, this connection is unclear in the tweets, so we cannot be confident in the algorithm's classifications near the threshold. The analysis suggests the classification model displays inconsistency and uncertainty when assigning tweets near the classification threshold. While some tweets proximate the cutoff include explicit suggestions of white supremacy and terrorism, others lack a clear relationship between the tweet and the classification and instead seem to be assigned based on vague contextual factors.

Discussion

Although our results suggest a 4-percentage point difference in the proportion of tweets classified as “White Supremacy/Terrorism” between the datasets, this is still convincing evidence that the classifier performed well for two reasons. First, the classifier performed consistently across a much larger, diverse sample. Second, the hand-coder had access to context that the algorithm may not have had, leading to the hand-coder interpreting more tweets as “White Supremacy/Terrorism” than the machine classification. With the general consistency of the classification and the understanding that context may have influenced the discrepancies, we can be confident that the algorithm effectively emulates human coding patterns, assuring its ability to generalize classifications across larger datasets.

Moreover, although we can confidently classify tweets with explicit references to white supremacy or terrorism, the same is not valid for tweets near the assignment threshold. The algorithm seems to rely on vague factors with an ambiguous connection to white supremacy or terrorism to classify tweets. These tweets demonstrate a critical flaw in the model: the model has trouble differentiating between relevant and irrelevant contextual factors, causing possible misclassifications.

Despite the model’s inconsistencies, we can still use the results to draw out real-world implications pertinent to the future. For instance, the assertion that nearly 14% of public discourse on X, a popular social media platform, revolved around white supremacy or terrorism after the El Paso shooting echoes the real-world trend of increasingly classifying events as domestic terrorism. For instance, although the United States formerly defined domestic terrorism in 2001 through the PATRIOT Act, domestic terrorism-related investigations have notably increased in the last 10 years, growing by 357% (American Civil Liberties Union, 2002; U.S. GAO, 2023). Domestic terrorism-related investigations also remarkably spiked after 2018, which complies with the timeframe of the El Paso shooting, which occurred in 2019. While the increase in investigations related to domestic terrorism may have subsequently increased the public's use of the term in discourse, our results indicate that the opposite is also possible, as the public's growing use of white supremacy and domestic terrorism may lead to authorities further investigating cases as such. Moreover, the fact that white supremacy and domestic terrorism were closely associated in the public's discourse after the shooting reveals that the general population may view the concepts as synonymous, delineating domestic terrorism as a white act and general terrorism as an act committed by people of color.

Before drawing conclusions from the results, it is essential to acknowledge this study's limitations. The first potential limitation is the algorithm's lack of context and subsequent bias replication. Since the algorithm's understanding of the El Paso shooting is restricted to the tweets provided by the researchers, its comprehension of the event is incomplete. This means it cannot use context to classify tweets that do not explicitly reference white supremacy or domestic terrorism. Moreover, since the algorithm exclusively relies on hand coding to train itself, it may reproduce the coder's biases, if any are present. However, I address the potential limitation of coder bias by taking a two-coder process and selecting the most robust category with the highest reliability score.

Another possible limitation is the nature of tweets, which lack substance, and the scraping package's further removal of the substance by the scraping package. In most cases, tweets can only comprise roughly 300 characters, which is restrictive, so users turn to hashtags to maximize meaning while minimizing character count. This means that most X users' tweets contain hashtags rather than substance, leading to an analysis of tags rather than sentiment analysis. This study further exacerbated the lack of substance as the TwitteR scraping program only scrapes portions of tweets, resulting in incomplete documents. Although the algorithm can still extract meaning from incomplete tweets, partial scarping provides less data to train the model, which may hurt its ability to classify documents. While having more data may strengthen the model training, training the model with partial tweets does not necessarily erode its reliability since incomplete tweets are treated as complete documents, meaning the model can improve, but its current form is not unreliable.

The results from this study may also suffer from generalizability when applied to other high-profile shootings or acts of violence. The El Paso shooting was a unique event for several reasons, including the shooter's clear racial motive and connection to white supremacist organizations, its proximity to another high-profile shooting (the 2019 Dayton Shooting), and a massive international response. However, other high-profile acts of violence do not have these same characteristics. Several high-profile acts of violence, such as the 2017 Las Vegas Shooting, the Parkland High School shooting, and numerous others, had unclear motives, were relatively isolated, and remained domestic, so applying this algorithm to those types of shootings may prove inadequate.

Future research can take steps to address these limitations better and further improve the field of study. Regarding the sensitivity to context and potential bias replication, future researchers may provide the algorithm with a pool of documents (e.g., articles, headlines, speeches, etc.) to improve its understanding of the event. Moreover, although I took a two-coder approach to ensure the reliability of constructs, prospective work could increase the number of coders to ensure more substantial reliability. Furthermore, researchers in this field may want to utilize a scraping package that extracts the entire tweet rather than just a portion, ensuring that more data is available for training the model. Finally, regarding generalizability, subsequent researchers can either include tweets from multiple high-profile shootings in one study or separate other high-profile shootings into individual studies and then compare them.

Future researchers may also explore how frequently white supremacy and domestic terrorism appear in discourse between political actors, such as members of Congress. Members of Congress's speech is influenced by intrinsic motivators, party agenda, public pressure, and more, so their speech is often more curated. It would be interesting to explore whether certain factors, like party affiliation, change the rate at which politicians refer to white supremacy and domestic terrorism. I expect that Democrats are more likely to make references to these categories than Republicans since high-profile shooters are usually associated with the Republican party.

Conclusion

This study sought to provide insight into the way the public spoke about the El Paso shooting after it occurred. After developing categories by hand-coding a sample of tweets, I took a supervised learning approach to classify a larger sample of tweets. After applying the classifier to the uncategorized tweets, I found that roughly 14% of tweets were categorized as "White Supremacy/Terrorism." Although the model was able to classify tweets confidently with explicit references to white supremacy or domestic terrorism, it was inconsistent when assigning documents near the threshold that did not make explicit references to white supremacy or domestic terrorism.

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Appendix

Appendix A

Krippendorff's Alpha Reliability Scores for Theme Classifications

Category/Theme	Description	Alpha Value
White Supremacy/Terrorism	Any tweet that explicitly uses the terms “White Supremacy” or alludes to the likely (e.g., White Nationalism, White Extremism, etc.). Any tweet that explicitly uses the term “Terrorism”, including “Domestic Terrorism”. These themes have been combined because they are normally used in tandem and are used to drive the same message.	0.813
Critique of Political Response	Any tweet that criticizes the response of any political actor or entity, regardless of the level (i.e., federal, state, local) or political affiliation	0.345
Gun Reform	Any tweet that explicitly calls for any amount of restrictionist gun reform *OR* clearly alludes to the need for gun reform	0.889
Stochastic Terrorism	Any tweet that explicitly blames the violent act on a political actor’s or entities directed, hostile public rhetoric	0.271
Personal and Community Grief	Any tweet that implies the original poster is experiencing a level of personal grief *OR* that they are feeling grief on behalf of the community *OR* on behalf of the victims/victim’s families	0.162
Mental Health	Any tweet that explicitly mentions “Mental Health” *OR* clearly alludes to it (i.e., Mental Illness, Mental Sickness, etc.) as a factor in the shooting, either positive or negative	0.918
Cynicism/Despair	Any tweet that expresses sentiments of inevitable failure or doom for the “state” because of the violent act	0.591
Racism	Any tweet that explicitly expresses racist sentiments toward the target population of the violent act	0.000*

Media Reporting	Any tweet that reports the objective facts (e.g., Death toll, the number of people injured, information about the shooter, etc.) about the violent act	0.388
Liberal	Any tweet that explicitly uses the term "Liberal" *OR* alludes the left-wing as playing in role in the violent act	1.000

Note*: * The "Racism" category returned an Alpha Score of 0.000 because only one coder categorized one tweet as "Racism" while the other coder did not.*

Appendix B

Confusion Matrix for White Supremacy/Terrorism Classification Accuracy

Prediction	**No**	**Yes**
No	411	1
Yes	1	88

Note: *The confusion matrix is between the human coder and the algorithm's agreement on the white supremacy/terrorism classification. The top left panel indicates true positives, the top right panel indicates false negatives, the bottom left panel indicates false positives, and the bottom right panel indicates true negatives.*

Appendix C

Accuracy and Diagnostic Metrics for White Supremacy/Terrorism Classifications

Metric	Value
Accuracy	0.996
95% CI	(0.9857, 0.9995)
No Information Rate	0.8224
P-Value [Acc > NIR]	$< 2e - 16$
Kappa	0.9863
McNemar's Test P-Value	1
Sensitivity	0.9976
Specificity	0.9888
Pos Pred Value	0.9976
Neg Pred Value	0.9888
Prevalence	0.8224
Detection Rate	0.8204
Detection Prevalence	0.8224