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Domestic Terrorism Offender-Level Database (DTOLD): A Data-Driven Analysis of US Domestic Terrorists' Life Histories

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Abstract

In recent years, there has been a growing effort among scholars and practitioners to design and implement effective domestic violent extremism prevention and intervention programming. One major obstacle to this work is the lack of data needed for a nuanced understanding of the individuals who commit such acts. The Domestic Terrorism Offender-Level Database (DTOLD) is the first publicly available offender-level terrorism database that prioritizes psychosocial, trauma-related, and life history variables. It aggregates open-source data on 319 domestic violent extremists who committed attacks in the United States between January 1, 2001, and December 31, 2020, as documented by the Global Terrorism Database. This report provides a detailed discussion of analytical findings drawn from DTOLD, including the relevant literature we drew from, the analytical techniques we used, and instances in which we returned a negative result.

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The research team can be contacted at dtold@cna.org with questions about accessing or using DTOLD data.

Executive Summary

The Domestic Terrorism Offender-Level Database (DTOLD) is the first publicly available offender-level terrorism database that prioritizes psychosocial, trauma-related, and life history variables. Loosely modeled on the publicly available Mass Shooter Database (MSD) of the Violence Prevention Project Research Center (VPPRC), DTOLD was constructed with three goals: avoiding duplication of Profiles of Individual Radicalization in the United States (PIRUS) data, ensuring integration with other datasets, and prioritizing psychosocial, trauma-related, and life history variables. The final dataset aggregates data on 319 domestic violent extremists (DVEs) who met the following inclusion criteria:

1. The attack is included in the Global Terrorism Database (GTD);
2. The attack occurred in the US;
3. The attack occurred between January 1, 2001, and December 31, 2020;
4. The perpetrator was 18 or older at the time of the attack;
5. If charges were filed, the case did not result in acquittal or mistrial, nor were the charges dismissed; and
6. The attack meets the Federal Bureau of Investigation's (FBI's) definitions of DVE and terrorism.

Research questions and key findings

This report provides a detailed discussion of our findings, including the relevant literature we drew from, the analytic techniques we used, and instances in which we returned a negative result. To preface that discussion, we highlight key takeaways from the study here:

1. **Affiliation.** What variables are strongly correlated with how violent actors are affiliated with groups?
    a. Inspired by Borum, Fein, and Vossekuil (2012), we created a **composite affiliation variable** instead of using a binary (lone actor versus group actor) framework. The **distribution of affiliation scores across the dataset validates what Borum et al. proposed (i.e., loneness is not a binary variable)** insofar as the result is not a U-shaped graph with clusters around low and high affiliation.
    b. We found a **statistically significant relationship between affiliation and lethality**, confirming prior research suggesting that lower levels of affiliation (inclusive of lone actors) are correlated with higher levels of lethality.
    c. We found **a statistically significant relationship between affiliation and target type** such that offenders with higher rates of affiliation were the most likely to attack hardened targets (including industrial facilities, college/university laboratories, and government facilities). Much of this relationship can be attributed to environmental and animal rights extremists, who tend to have high levels of affiliation and who conducted more than half of the attacks on industrial facilities and colleges/universities.
    d. We recognized that a person might not have a formal diagnosis of a mental health issue for a wide range of reasons, including lack

of access to affordable behavioral health care, geographic inaccessibility of behavioral health care, and stigma around help-seeking behaviors. To account for this issue, we constructed a **composite mental health variable** to allow for a broad range of inputs. Using this variable, **we found a statistically significant relationship between a history of mental health issues and low affiliation scores**, in alignment with previous research.

2. **Lethality.** What variables are strongly correlated with lethality?
    a. Consistent with previous research, we found that **far-right violent offenders are significantly overrepresented in the group of perpetrators who killed or injured one to three people**.
    b. We found **no significant statistical evidence that lethality differs across specific ideologies**.
    c. We found **significant differences in the types of attacks committed by offenders of each ideology**. Some, but not all, of these differences are likely attributable to the beliefs and practices within each ideology (e.g., anti-abortion terrorists embrace an ideology that places a premium on life, which likely explains why they more frequently attack infrastructure instead of persons).
    d. We found no statistically significant relationship between lethality and mental health issues, but we did find that **those with mental health issues both commit more very-lethal attacks and commit attacks that are comparatively more lethal than the lethal attacks committed by offenders without mental health issues**.
3. **Leakage.** Do domestic terrorists of different ideologies or types share information about their plans (or "leak") differently?
    a. Building on Meloy & O'Toole's (2011) conceptualization of leakage, we constructed **two composite binary variables for leakage: narrow leakage and broad leakage. We found statistically significant differences in both narrow and broad leakage rates across ideological groups**.
    b. We found a **positive relationship between both narrow and broad leakage and suicidality**, such that the odds are higher that suicidal offenders will leak details related to their plans. However, in both cases, suicidality accounts for less than 2 percent of the variation in leakage, suggesting that other variables would have more explanatory power regarding variations in leakage between offenders.
    c. We found a **positive relationship between affiliation and leakage**, such that when an offender is more affiliated, the odds of leakage occurring increase. However, this relationship accounts for only about 3 percent of the variation in leakage, suggesting that other factors may be more influential in explaining variations in offender leakage.
4. **Profiles.** What constellation of psychosocial, trauma-related, and life history variables are most strongly correlated with domestic terrorists of different ideologies?
    a. We used a partitioning around medoids clustering algorithm to create 10 distinct clusters that we could use to explore the question of terrorist profiles, but we found **no unique life history profiles** among offenders.

b. We found **no practically or statistically significant relationships between the 10 clusters and offender ideologies**. However, environmental/animal rights extremism and conspiracy theory extremism did have relationships with specific clusters.

5. **Offender types.** Are lethal lone actor domestic terrorists more like mass shooters or lethal non-lone domestic terrorists in terms of psychosocial, trauma-related, or life history variables?

   a. We found that **lethal lone domestic terrorists are more like mass shooters in terms of age**.

   b. We found that **lethal lone domestic terrorists are more like non-lone lethal domestic terrorists in terms of suicidality, adult trauma, and narrow leakage**.

   c. We found that **lethal lone domestic terrorists fall between mass shooters and lethal non-lone domestic terrorists in terms of having a mental health issue**, and we found that they leak broadly at lower rates than either lethal non-lone domestic terrorists or mass shooters.

   d. We found that **the three groups are not statistically distinct in terms of sex or rates of childhood trauma**.

As captured in companion documents to this final report, we also found the following:

1. Domestic terrorists in general may be more suicidal than the general population but are significantly less suicidal than mass shooters, except when domestic terrorists kill four or more people (fatality requirement to qualify as mass shooter).

2. Of the individuals in DTOLD, 61.5 percent had contact with a system stakeholder (e.g., law enforcement officials, mental health providers, education professionals) before committing an act of domestic terrorism.

3. Individuals with unclear ideological motivations are less affiliated (i.e., less integrated into extremist communities) and less likely to leak (i.e., share information about their violent intentions), which may increase the challenge of identifying and preventing the acts of violence that they are planning.

Implications

There are three implications for researchers that merit highlighting. First, the finding on affiliation suggests that a binary distinction between lone and group actors may have limited utility. Second, the aggregate findings related to ideology suggest that ideologically based taxonomies have limited explanatory power (particularly when considering offender life histories and attack outcomes). Third, the existence of an ideology-less cohort within the dataset, and the similarities between domestic terrorists and mass shooters, suggest that distinctions between domestic terrorists, mass shooters, school shooters, etc. may be quite porous. In each case, though, additional research is needed.

For practitioners, the finding related to system stakeholder contact suggests a need for renewed focus on improving training for, and communication between, allied professionals most likely to encounter those at risk for committing acts of domestic terrorism. In addition, the finding of a correlation between suicidality and lethality has implications for both threat assessment and risk assessment efforts. Finally, the documented similarities between the life histories of domestic terrorists and mass shooters are relevant to policy-makers and practitioners seeking to design and implement intervention programming.

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Summary of the Project

Major goals and objectives

CNA's Domestic Terrorism Offender-Level Database (DTOLD) is the first publicly available offender-level terrorism database that prioritizes psychosocial, trauma-related, and life history variables. The database consists of 217 variables sorted into 13 subcategories capturing a range of risk and protective factors (see Table 1).

The CNA project team loosely modeled DTOLD on the publicly available Mass Shooter Database (MSD) of the Violence Prevention Project Research Center (VPPRC), but we also referenced the Profiles of Individual Radicalization in the United States (PIRUS) dataset and the Global Terrorism Database (GTD). Building from these, we constructed DTOLD with three goals:

1. Ensuring that it would not duplicate the PIRUS data (or near-term planned additions to the PIRUS data)
2. Ensuring that it could integrate with other datasets (GTD, VPPRC's MSD, and PIRUS) by including relevant record IDs when applicable and leveraging the codebooks of the other datasets to build a compatible schema
3. Ensuring that it would prioritize psychosocial, trauma-related, and life history variables vetted by terrorism scholars, criminologists, and psychiatrists familiar with this population

Table 1. Data subcategories

Data Type	Number of Variables
Record identifiers	4
Relevant dates	3
Type of attack	9
Location of attack	17
Weapons and methods	9
Offender demographics at time of attack	38
Life history variables, childhood	22
Life history variables, adulthood	13
Health and mental health	17
Previous crime and violence	22
Pathway toward radicalization	20
Grievance and motivation	12
Social contagion and warning signs	31

Source: CNA.

Inclusion criteria

For an individual to be included in DTOLD, the case must meet six criteria:

1. The attack must be included in the GTD.
2. The attack must have occurred within the US.[1]
3. The attack must have occurred between January 1, 2001, and December 31, 2020.
4. The perpetrator must have been 18 or older at the time of the attack.
    a. Because DTOLD is an offender-level database that includes the names and life histories of individuals, the DTOLD team made every effort to respect individual privacy, especially of minors. As a result, we excluded nine individuals whom we identified via news reporting and court records because they were under the age of 18 at the time of their attack.
5. If charges were filed, the case did not result in acquittal or mistrial, nor were the charges dismissed.
    a. We excluded 22 individuals who we identified via news reporting as being responsible for an attack in the GTD but whose trials resulted in acquittal or mistrial or whose charges were dismissed.
6. The attack must meet the Federal Bureau of Investigation's (FBI's) definitions of *domestic violent extremist* (DVE) and *terrorism*, provided here:
    a. **DVE**: Public Law 116-92 states that "the FBI and DHS [the Department of Homeland Security] use the term Domestic Violent Extremist (DVE) to describe an individual based and operating primarily within the territorial jurisdiction of the United States who seeks to further their ideological goals wholly or in part through unlawful acts of force or violence" (United States House of Representatives, 2019).
    b. **Terrorism**: The FBI website defines *terrorism* as "violent, criminal acts committed by individuals and/or groups to further ideological goals stemming from domestic influences, such as those of a political, religious, social, racial, or environmental nature" (FBI, 2016).

    We determined that because it does not derive from domestic influences, Islamist extremism does not meet this definition. Therefore, we excluded 53 individuals who we identified as being responsible for an attack in the GTD but who were motivated at least partially by Islamist extremism. We further excluded one individual whose attack was clearly motivated by a desire for personal revenge and not by any ideological goal.

Methodology

DTOLD aggregates data on 319 DVEs who committed GTD-documented attacks in the US between January 1, 2001, and December 31, 2020. The database excludes attacks for which a perpetrator has not been identified.[2]

To ensure a high-quality dataset, we ensured that 100 percent of the cases selected for inclusion were double coded by coding research assistants, who populated the database using only publicly available information such as newspaper reporting,

[1] Events must have occurred within the 50 United States, the District of Columbia, or a US territory.

[2] We were unable to locate a perpetrator identity for 237 of the 599 attacks that occurred within the time frame for inclusion in the dataset.

court records, and primary source content (including archived social media posts, manifestos, and videos).

Each of the DTOLD cells contains one variable. Coders entered text (e.g., the city name), a number indicating a specific response (e.g., 0 = no), multiple numbers when prompted to select all that apply, or a brief textual response when additional detail was necessary. Unfortunately, we were frequently unable to find the desired data via publicly available sources. In order to capture the types of missing data, coders were prompted to indicate whether (1) the answer to a question is negative (i.e., no), (2) a variable is not applicable (i.e., N/A), or (3) the information is not publicly available (i.e., NPA). These distinctions reflected an effort to avoid the ambiguity of empty cells. The following are examples of proper applications of these responses using the example variable "military deployment":

- N/A: This code should be selected if the variable is not applicable to the individual (e.g., they were not a member of the military).
- No: This code should be selected if the variable is applicable to the individual, but the research returned a definitive no (e.g., the individual was a member of the military, but research found that they never deployed).
- NPA: This code should be selected if the variable is applicable to the individual, but the research did not reveal a definitive answer (e.g., the individual was a member of the military, but researchers could not determine whether they deployed).

The CNA team practiced routine quality control throughout the data collection period. In addition to double coding 100 percent of the cases in DTOLD, we randomly selected 5 percent of the cases in the database and recoded them a third time (Pew Research Center, n.d.). In addition, a data collection manager reviewed every cell in DTOLD to improve standardization and ensure that no personally identifiable information had been included. Finally, the principal investigator reviewed every cell in the spreadsheet to evaluate accuracy and address logical inconsistencies.

In conducting the data analysis for this project, we used a range of statistical techniques, including comparative descriptive statistics, linear and logistic regressions, robust linear regressions, Wilcoxon signed-rank testing, Kruskal-Wallis H testing, Dunn testing, and Gower distance clustering. Given that most data fields did not fit a normal distribution, we used nonparametric and robust variations for testing and regression. In our analysis of the affiliation variable, we applied mode imputation to compensate for missing data. In all other areas, we used techniques capable of handling missingness or of incorporating the lack of data into analysis and conclusions.

Limitations

Unlike the data for some types of illegal violence, for which official and standardized data collection practices improve accessibility,[3] there is no centralized or official mechanism mandating the collection of data on violent extremism or violent extremists (LaFree & Dugan, 2007). If the perpetrator of an attack is not associated with a group that is on the US State Department's list of foreign terrorist organizations (i.e., if they are a domestic terrorist), there is no mandatory reporting requirement for local, state, or tribal law enforcement agencies (FBI & DHS, 2023). As a result, there is no federally

[3] Such as the Federal Bureau of Investigation's Uniform Crime Report (UCR) and the National Crime Victimization Survey (NCVS). The UCR includes data submitted through the National Incident-Based Reporting System from municipal, county, state, tribal, campus, and federal law enforcement agencies. The NCVS collects self-reported data on victimization from people aged 12 and older.

collected or maintained publicly available dataset that captures domestic terrorist attacks. Pursuant to Section 5602(a) and (b) of the National Defense Authorization Act for Fiscal Year 2020 (NDAA FY 2020), the FBI and DHS jointly produce reports on DVE in consultation with the Office of the Director of National Intelligence. Although NDAA FY 2020 requires that these reports be prepared for the purposes of internal recordkeeping, they have been criticized for providing an incomplete and "random" set of incidents.[4]

Moreover, large-scale data collection is prohibitively difficult for most nongovernmental researchers. To begin, public records (e.g., arrest records, incident reports) do not offer a means to fill the gap. Since 9/11, 992 terrorism defendants have been prosecuted by the US Department of Justice (Aaronson & Williams, 2023). However, this figure accounts for only those prosecuted for *federal* terrorism-related crimes. In addition, because there is no specific federal charge for *domestic* terrorism, those involved in DVE are prosecuted in both federal and state court systems (meaning that records are spread over 50 jurisdictions), and the charges—particularly at the state level—are often for related offenses and not for violent extremist activities, making it difficult to identify perpetrators (Berris et al., 2021; Neumann & Kleinmann, 2013). For instance, in one study examining extremists' perspectives on reintegration programs, researchers interviewed 17 former extremists: eight were involved with Islamist groups, eight were White supremacists or involved in other far-right groups or movements, and one was involved in the incel[5] community (Stern et al., 2023). Consistent with these issues, all eight of the individuals involved with the Islamist groups reported that they were charged with terrorism-related offenses, while the nine individuals involved with the far-right and incel groups reported being convicted of non-terrorism-related charges, such as selling narcotics, shoplifting, and domestic violence (Stern et al., 2023). Another factor complicating data collection is that the population of terrorists—compared to the population of those committing offenses such as murder or hate crimes—is relatively small and difficult to access.

One approach to this challenge is to use secondary sources (e.g., court records, newspapers, books, journals, and media publications) to populate a database that facilitates quantitative analysis (LaFree & Dugan, 2007, pp. 186–187). This methodology has been used by the creators of numerous DVE or DVE-adjacent databases and has resulted in a robust literature on issues including radicalization (Jensen et al., 2016), radicalization within the military and law enforcement (Jensen et al., 2022; Jones et al., 2021), changes in political violence over time (Kishi et al., 2021; Kleinfeld, 2021), changes in terrorism tactics over time (Jones et al., 2020a), and inconsistencies in criminal charges and case outcomes (Gruenewald et al., 2022; Jensen et al., 2023).[6] Unfortunately, such an approach is imperfect; therefore, we offer three notes of caution concerning DTOLD.

First, some of the included variables are inherently subjective. We worked to address this subjectivity by providing clear guidance to the coders, having each team member code a set of baselining cases, meeting weekly to discuss difficult cases, and ensuring that 100 percent of cases were double coded. The reality, though, is that human beings are complicated, and their lives rarely fit neatly into a set of standardized columns.

[4] For example, see Hughes & Kurup (2021).

[5] *Incel* is a portmanteau for "involuntary celibates" and refers to a mostly online community of individuals who embrace male supremacism and use their frustration with sexual or romantic rejection to justify violence against women (Lindner, 2023).

[6] Nonterrorism databases using this methodology include Bias Incidents and Actors Study and the Social Networks of American Radicals. See Jensen et al. (2020) and Jensen & LaFree (2022), respectively.

Second, DTOLD was created between fall 2022 and spring 2023. Additional information may have been released about these individuals since the coding process was completed. If you find a potential inaccuracy in the data, please contact the research team at dtold@cna.org, and we will work to correct the error.

Third, DTOLD relies on publicly available information. The availability of data, however, is often correlated with the infamy of the attack. We typically found less data on the individuals who committed low-profile attacks that resulted in relatively modest news coverage than we found on the individuals who committed high-profile attacks that resulted in robust news coverage. In addition, no data sources are fully impartial, and not all data were available. Research is clear that media coverage of terrorist violence contains a set of specific biases that can introduce error into the social science research that relies on it as a data source (Ackerman & Pinson, 2016; Franzosi, 1987). Such biases include more extensive media coverage of terrorist attacks that produce casualties (Mitnik et al., 2018; Ghazi-Tehrani & Kearns, 2023), more extensive coverage of bombings or attacks on infrastructure than armed or unarmed assaults (Mitnik et al., 2018), an increased likelihood of labeling an attack "terrorism" if the perpetrator is Muslim (Betus et al., 2020; Dolliver & Kearns, 2022), and a tendency to attribute White-perpetrated terrorist violence to mental illness while categorizing other types of terrorism as ideologically motivated (Kunst et al., 2018). Moreover, although court documents often provide information regarding the offender's life history variables, they are imperfect data sources for several reasons. Not all documents exist or are available in all cases, so the team often worked with a subset of these documents. For offenders charged at the state level, court records may be inaccessible (at the time of collection, North Carolina court records could be accessed only by self-service terminals physically located in clerk of court offices in each North Carolina county).[7] Many states do not allow remote access for sensitive cases such as divorce, child custody, and certain criminal cases.[8] And some states require payment to search or access their court records, which has made them inaccessible due to resource limitations.[9] Finally, although officers of the court often have access to better information than journalists do, records from trials are often influenced by the fact that both the defense and the prosecution have explicit agendas that shape how they present the available data.

Given these limitations, we note that DTOLD data cannot be used for predictive modeling.

[7] As of October 2023, North Carolina began transitioning to eCourts, which allows online access to North Carolina court records.

[8] For example, see https://www.courts.ca.gov/42512.htm.

[9] For example, see https://www.utcourts.gov/en/court-records-publications/records/xchange/subscribe.html.

Outcomes

Results and findings

Dataset

Analysis of DTOLD revealed that most of the offenders who met the inclusion criteria engaged in nonlethal activities: 182 did not kill or injure anyone, 73 injured at least one person, and 64 (approximately 20 percent) killed at least one person. In sum, the offenders in DTOLD were responsible for 303 attacks, 236 deaths, and 1,237 injuries (Figure 1).[10]

The subjects in the database were overwhelmingly male (89 percent), were primarily White (78.1 percent), and had a median age of 30 at the time of their attack. Just 14 percent of the individuals in the database completed only high school or a GED, while a further 17 percent completed some college or trade school (including an associate's degree). The majority were regularly employed (46.3 percent), 6.4 percent were underemployed, and 18.1 percent were long-term unemployed (Figure 2).

Most offenders planned their attacks (71 percent)—that is, they did not "snap" but instead committed premeditated acts of violence. For 172 offenders, we know the outcome they expected from their attack; the majority (58 percent) expected to escape.

More than 52 percent of offenders in DTOLD had a criminal record, had experienced prior police contact, or were previously criminally investigated. Thirty percent had no prior criminal record or police contact. Of the offenders with a criminal record or prior police contact, 45 percent also had a conviction leading to imprisonment.

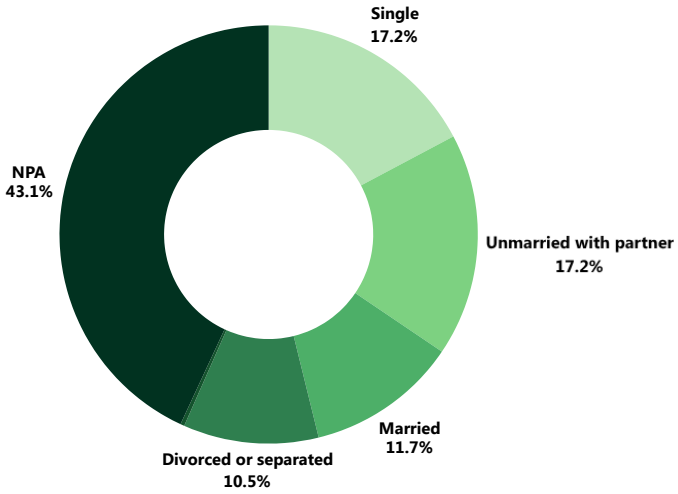
Figure 1. Database contents

Source: CNA.

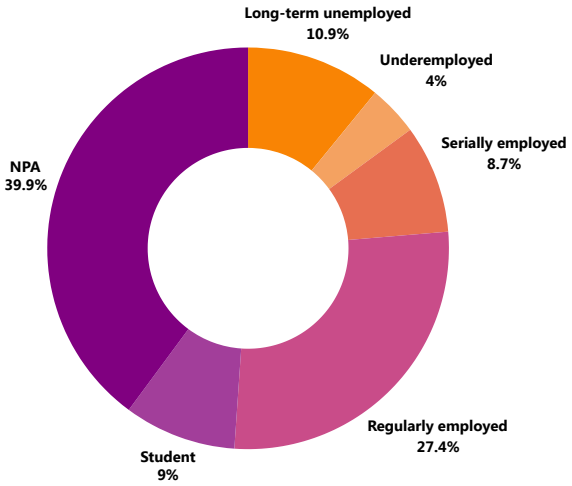
[10] Although the final version of DTOLD contains information on 319 perpetrators, the analysis in this report is based on either 320 or 321 offenders. We began with 320 offenders, but mid-analysis, we identified and added an additional offender to the dataset (thus increasing the number from 320 to 321). After all analysis was completed, we removed two offenders from the dataset, bringing the total down to 319: we found that one was acquitted of all charges related to the attack after a trial, and one was motivated to commit his crime by a personal grievance, not an ideological component.

Figure 2. Offender demographics

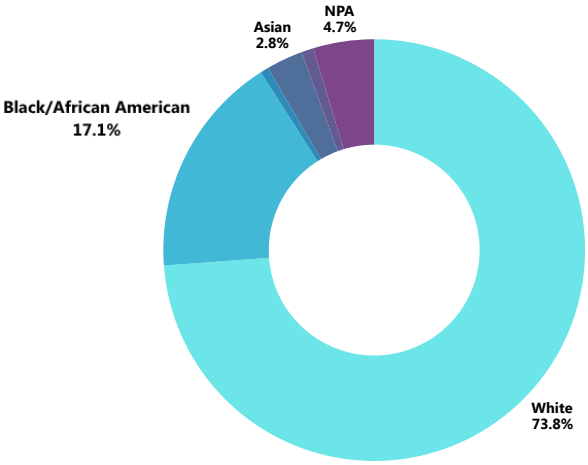
Relationship Status



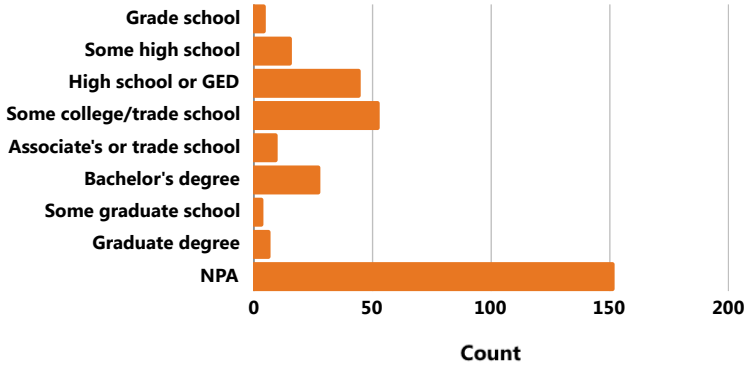
Employment



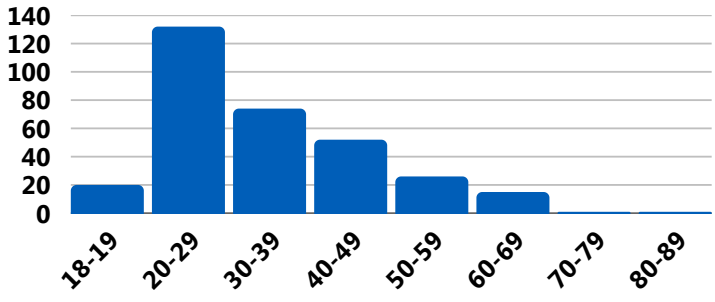
Race



Education



Age



Source: CNA.

Of the 141 offenders with a known mental health history, 60 percent had a mental health issue within one year of attack. Although data on suicidality were not publicly available for most offenders in the dataset, just over half of those for whom data were available (37 of 65) did have a history of suicidality.

In the following subsections, we present findings from DTOLD that address our key research areas: affiliation, lethality, leakage, terrorist profiles, and offender typologies.

Question 1: Affiliation

Research question: What variables are strongly correlated with how violent actors are affiliated with groups?

Terrorism scholars have long struggled with the challenge of defining a terrorist group, and a 2015 study noted that conceptual confusion about the term *terrorist group* undermines researchers' ability to conduct research that could meaningfully inform policy development (Phillips, 2014). Moreover, over the past 20 years—particularly with the creation of social media networks—concepts such as "group membership" have shifted considerably. Policy-makers, scholars, and practitioners now agree that lone actor terrorists—those acting with minimal direction or support from a terrorist group (Ellis et al., 2024)—present a unique challenge to law enforcement and a threat to public safety because of their relatively unaffiliated nature and, consequently, more limited "paper trail" compared to operators who are part of a group (Hewitt, 2002; Bakker & de Graaf, 2010; Phillips, 2017). At the same time, experts disagree on how to define *lone offenders* or even whether to use this term. Some researchers use *lone offenders* (Borum et al., 2012), *lone actor terrorists* (Smith et al., 2015; Gill et al., 2021; Schuurman & Carthy, 2023), *lone wolves* (Pantucci, 2011; Phillips, 2017) (although this term is increasingly being avoided), and *freelance terrorists* (Hewitt, 2002; Kushner, 2003). Some scholars also include small, isolated groups, such as dyads or triads, in their analysis (Gill et al., 2013; Corner & Gill, 2015). This lack of consensus—similar to the earlier lack of consensus around the term *terrorist group*—has made efforts to analyze the characteristics of lone actors challenging, limiting the development of a shared understanding.

Faced with these definitional challenges, Borum, Fein, and Vossekuil (2012) propose a "dimensional approach" to the concept of loneness. They build upon efforts by Pantucci (2011), who developed a typology of loneness to break terrorists into four categories and propose a "continuum" of loneness that looks at an offender's behavior across three dimensions. Borum et al.'s (2012) continuum of loneness informed the creation of the composite variable in DTOLD that we call "affiliation."

Rather than identifying someone as a lone or not lone actor, we produced "affiliation scores" for each offender in DTOLD. We reviewed all 217 variables in the database, considering whether the variable had implications for someone's degree of isolation or connection to other extremists or extremist communities. Ultimately, we selected 20 variables, assigning values to each based on the degree to which it implied affiliation or isolation. For example, if someone acted alone, we added zero points to their affiliation score; if they had one co-offender, we added two points to their affiliation score; and if they had more than one co-offender, we added three points. The full list of variables and their assigned values can be found in Table 2.

In DTOLD, there is a higher proportion of NPAs (i.e., not publicly available) coded for those offenders who did not engage in lethal attacks. When coding affiliation, we originally planned to deal with NPAs by treating them as zero. However, doing so could artificially deflate affiliation scores. For example, an individual for whom little data is available publicly (and a high proportion of NPAs) could be inaccurately

Table 2. Affiliation variables and values

Variable	Scores	Mode
Co-offender	Zero co-offenders: +0 One co-offender: +2 More than one co-offender: +3	
Recruited by extremist group	No: +0 Yes: +3	0
Role in extremist group	No: +0 Member: +2 Leader: +3	N/A[a]
Received training or resources from group	No: +0 Yes: +3	N/A
Friends or family previously radicalized	No: +0 Yes: +2	2
Gang affiliation	No: +0 While juvenile: +1 While adult: +2 Both juvenile and adult: +2	0
Role in gang	Leader: +1 Otherwise: +0	N/A
Militia membership or interaction	No: +0 While juvenile: +1 While adult: +2 Both juvenile and adult: +2	0
Role in militia	Leader: +1 Otherwise: +0	N/A
Known affiliation with prison gang	No: +0 While juvenile: +1 While adult: +2 Both juvenile and adult: +2	N/A
Violent extremist group interaction	No: +0 While juvenile: +1 While adult: +2 Both juvenile and adult: +2	0
Direct contact with a member of a violent extremist group	No: +0 Yes: +2	0

Variable	Scores	Mode
Source of initial introduction to extremist ideology	*These variables were coded identically.* If there were multiple values in cell, we added the corresponding values together.	12
Source of continued engagement with extremist ideology	Relative: +2 Friend/roommate: +2 Coworker: +2 Partner: +2 Religious or spiritual leader: +2 Stranger (in-person): +1 Social media networks, etc.: +2 Independent research: +0 Books, newsletters, manifestos, etc.: +0 Prison cohabitants: +2 Flyers, etc.: +1 Other: +0	7
Verified or claimed relationship with another extremist individual	No: +0 Yes: +1	0
Group linkage claims	Not claimed: +0 Claimed by individual: +1 Claimed by group: +1 Claimed by individual and group: +2	1
Notable interest in extremist individual	No: +0 Yes: +1	0
Claimed inspiration from attack	No: +0 Yes: +1	0

Source: CNA.
[a] In this table, "N/A" indicates that the most common entry (mode) for that variable was N/A. For these variables, we added no points to the affiliation score.

classified as a person who had low affiliation, when the reality would be that we simply could not find enough information to make a determination. As such, to better paint a picture of the average affiliation of a domestic terrorist in our database, we decided to use mode imputation. Notably, we separated DTOLD into two subsets—lethal actors and nonlethal actors—and imputed missing values for each separately.

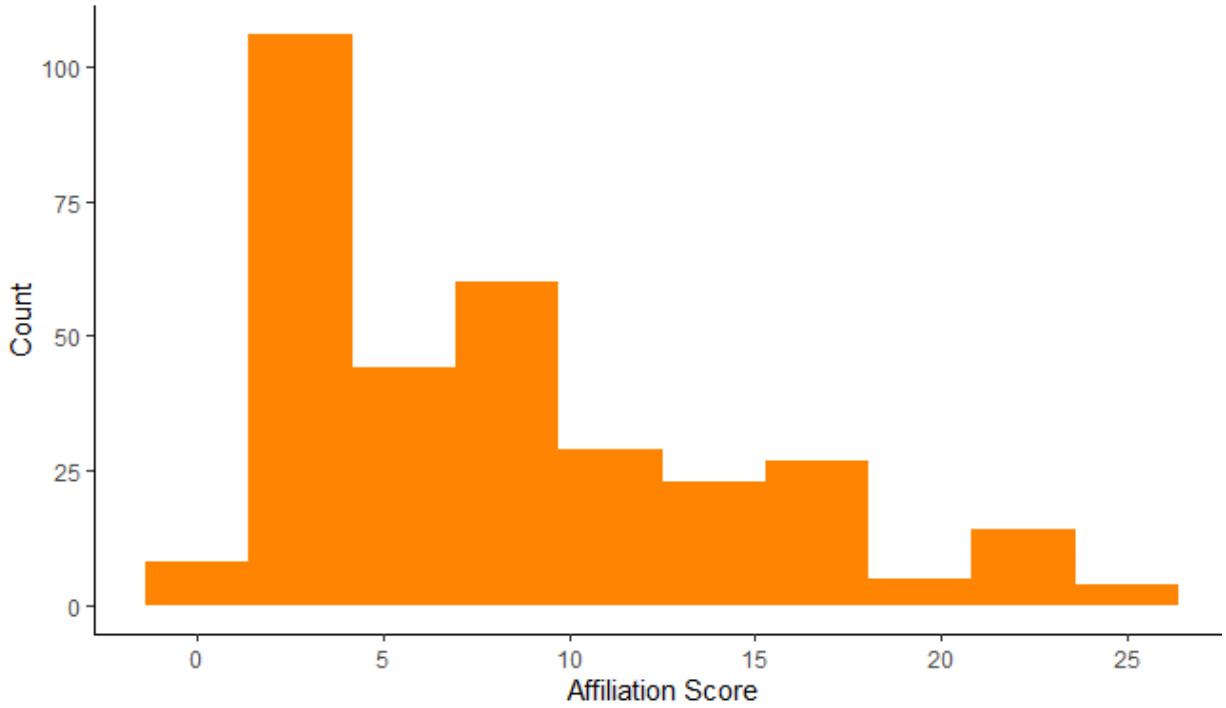
Using this method, we calculated an affiliation score for each offender in DTOLD. Critically, these scores are most informative when used in comparison with one another (i.e., they are not objective measures of affiliation but rather relative measures that leverage variables in the dataset and allow for comparison within DTOLD). In addition, affiliation is not a direct stand-in for social isolation. For example, the individual who opened fire and shot five Republican

politicians at a charity baseball practice in 2017 had a score of four. Although he radicalized independently and had no extremist or criminal group affiliations, he was married and for a time ran a successful contracting business. Thus, he was not socially isolated but rather less affiliated with extremist actors and groups than other offenders in DTOLD were.

Few offenders had an affiliation score of zero, and those individuals likely come the closest to the idea of a "lone actor" terrorist as understood by the public, policy-makers, and even academics. An example often cited in the literature as a "prototypical lone wolf" is Ted Kaczynski (Schuurman et al., 2018). More recently, scholars have begun recognizing that he was "exceptional in terms of his social isolation," living in the Montana wilderness and shunning most contact with the outside world (Bakker & de Graaf, 2010; Spaaij, 2012; Schuurman et al., 2018). Of note, Kaczynski is not in DTOLD because his last attack predates the earliest case in the dataset. At the other end of the spectrum, no individual in DTOLD scored higher than 25. These extremes, however, are relatively rare. Figure 3 shows the distribution of affiliation scores for offenders in DTOLD.

Borum et al. (2012) suggest that loneness is typically construed or framed as a false dichotomy between being a lone terrorist and being a group terrorist. In our analysis, we find supporting evidence that this dichotomy is false. If it were accurate, we might expect to see a U-shaped graph, with peaks at very low scores (the lone terrorists) and very high scores (the group terrorists). Instead, we see in Figure 3 that most individuals fall somewhere in the middle, rather than at either extreme.

Figure 3. Frequency of affiliation scores in the DTOLD database



Source: CNA.

Affiliation and lethality

Scholars have long found that lone actors are more lethal than group terrorists are. Hewitt's (2002) analysis of 30 cases of lone wolf terrorism in the US found that although these cases represented 2 percent of all arrests, they were responsible for 15 percent of all terrorist fatalities. Moreover, the lethality of lone actors has increased over time. Between 1955 and 1977, 7 percent of victims of terrorist attacks were killed by unaffiliated (lone) individuals, but this number rose to 26 percent between 1978 and 1999 (Hewitt, 2002). More recently, Phillips (2017) found that lone actors are more lethal than group offenders; in the US, for example, an attack by a lone wolf is estimated to result in 124 percent more deaths than an attack by an unknown group offender. And in a 2023 study, Turner et al. found that when all actors are intending to kill, terrorists acting alone perpetrate "more severe attacks" in the US and are associated with "significantly more casualties in attacks" than others (their analysis considers terrorists acting alone, those acting with others, those who are part of informal groups, and those who are part of formal groups).

Two notable exceptions to this consensus are Spaaij (2012) and Schuurman et al. (2018), who found that casualties from lone actor terrorism have been relatively limited. Spaaij (2012) analyzed 74 cases of lone actor terrorism and found no substantial evidence that the lethality of lone wolf terrorism was increasing. This point is emphasized in Spaaij and Hamm's (2015) US-focused study, in which they wrote that "strictly in terms of lethality, *lone wolf terrorism in America is not on the rise* [emphasis theirs]." Schuurman et al. (2018) found that lone actors have a lethality rate of 0.62 deaths per incident compared to a rate of 1.60 for group terrorists.

To test the relationship between affiliation and lethality in DTOLD, we used affiliation scores to divide the data into four quartiles, ranging from least affiliated (lowest affiliation) to most affiliated (highest affiliation) (see Table 3). Doing so allowed us to compare domestic terrorists in groups, making comparisons of lethality between the different levels of affiliation easier. Our analysis indicates that attackers with the least affiliation conducted attacks that resulted in more deaths and injuries compared to more affiliated terrorists. For both deaths and casualties, we found statistically significant differences between the least affiliated group and all other levels of affiliation (although for casualties, we did not find a significant difference with every level).

Table 3. Affiliation quartile table

Affiliation Quartile	Count	Average Affiliation	Average Killed	Average Killed and Injured
Lowest affiliation	80	2.8	1.7	15.4
Lower affiliation	80	4.9	0.75	2.3
Higher affiliation	80	8.6	0.39	1.3
Highest affiliation	80	17	0.35	0.74

Source: CNA.

We re-ran this analysis on only the 114 attacks that resulted in at least one casualty to see whether the less affiliated terrorists killed or injured more victims. We found no significant differences in the number of *deaths* across the quartile of affiliation in lethal attacks. However, the test revealed that the lowest affiliation group within the subset of lethal attacks *killed and injured* at a significantly higher rate than both the higher and highest affiliation groups.

Affiliation and target type

Scholars have argued that lone actors are more likely to attack "softer targets," including retail establishments, restaurants, and other low-security locations, as compared to "high-value targets," such as a courthouse or other government building. For example, Gill and Corner (2016) found that the general public is the most commonly selected target by lone actor terrorists. Horgan et al. (2016) also argue that lone actor terrorists are significantly more likely to target ordinary citizens than a political or government target. An explanation often given for this trend is that lone actors lack some of the skills, training, and resources of groups, so they choose easier targets. Schuurman et al. (2018) argue there is a "general tendency" among lone actors to execute "simple, straightforward operations," and Becker (2014) describes lone actors' relative "weakness" as compared to groups.

We used a regression model to look at the affiliation of attackers compared to the location targeted in their attack; our findings support the hypothesis in the literature that more affiliated attackers tend to target more hardened and complex locations. As can be seen in Figure 4, attackers who targeted government property (affiliation score = 10.9) and industrial facilities (affiliation score = 15.6) were the most affiliated. In contrast, attackers who targeted locations with low security where one might encounter members of the public (e.g., public transit facilities, streets, retail) had lower affiliation scores. Although it may seem significant that those who targeted K-12 schools were by far the most isolated (affiliation score = 2), note that the sample size for this kind of attacker was one.

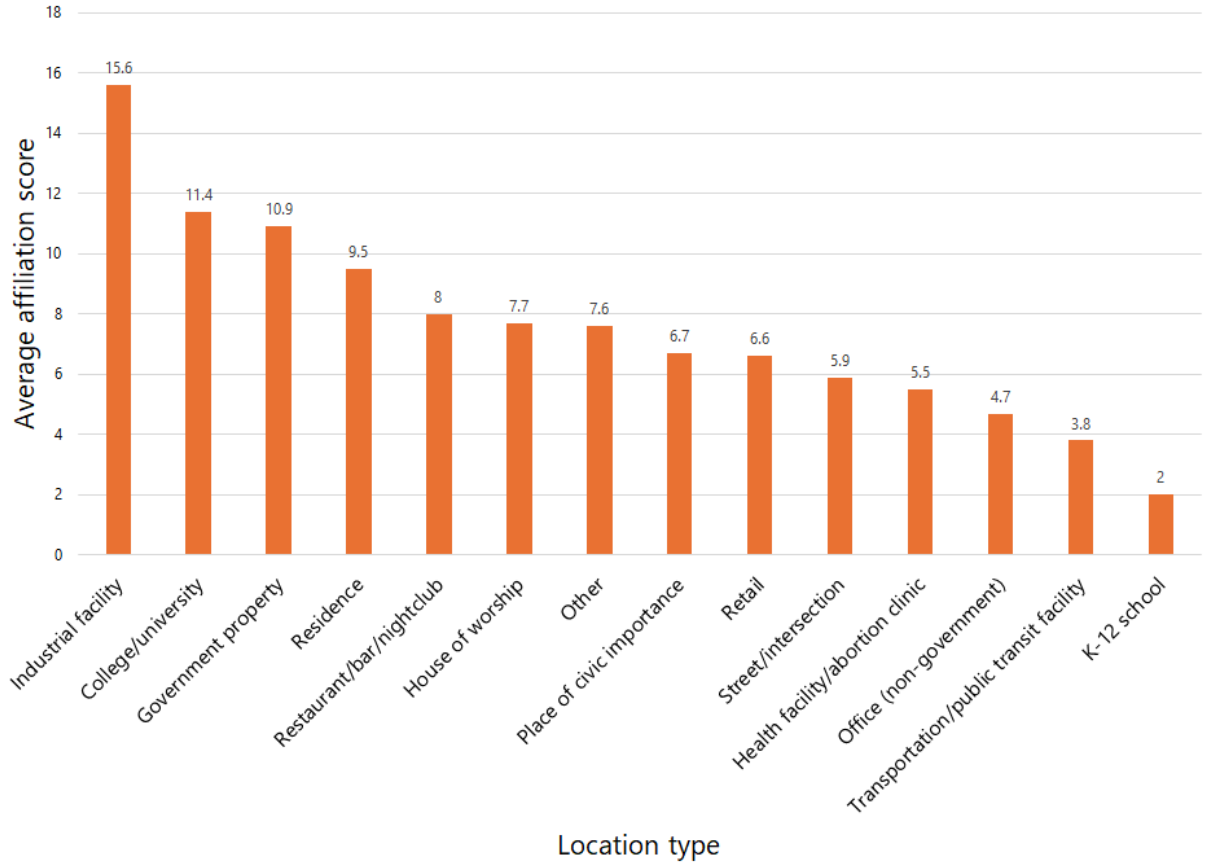
An exception seems to be colleges and universities. Although they might have more security than an average street or restaurant, most universities are open to the public and easily accessible, so attacks on these locations seem to contradict the argument that more affiliated actors attack hardened targets. Upon further analysis, we identified 16 attacks in which the target was a college or university. Half of these attacks (8 of 16) were carried out by environmental extremists, either members of the Earth Liberation Front (ELF) or Animal Liberation Front. The average affiliation score of these offenders—who were members of extremist groups, carried out attacks together, and in some cases were in romantic relationships with other individuals in ELF—was 13.5. However, these actors did not perpetrate attacks in public and easily accessible areas such as the college green or the university cafeteria. Instead, the attacks occurred in parts of the university that are less public, such as labs where animal husbandry experiments and GMO testing were being conducted.[11] This analysis, therefore, supports the hypothesis that government facilities and other hardened locations are more often targeted by violent extremists with higher levels of affiliation.

Affiliation and mental health

Although scholars disagree on the exact percentage, there is growing consensus that between 20 to 40 percent of lone terrorists in the US seem to have some sort of mental health issue or disorder (Gill et al., 2013; Gill et al., 2021; Turner et al., 2023). At the higher end of this range, a 2019 report by the FBI on lone offender terrorism reported that 38 percent of offenders were diagnosed with a psychiatric disorder,

[11] The average affiliation score of nonenvironmental attackers whose attacks occurred at colleges and universities was 8.5.

Figure 4. Average affiliation and location of attack



Source: CNA.
Note: The sample size for those who targeted K-12 schools was one, so this finding is not statistically significant.

while in another 35 percent of cases, offenders were suspected of having an "undiagnosed mental disorder" (FBI, 2019a). An important data point for comparison is that the National Institute of Mental Health estimates that nearly 20 percent of US adult men live with some kind of mental illness ("Mental Illness," 2023). Thus, the estimated prevalence of mental illness among lone actors ranges from the same as the general population to more than double. What is more instructive, particularly given this comparison, is the rate of mental illness among lone offenders as compared to group- or movement-affiliated terrorists.

Notably, the literature comparing lone actors to members of terrorist groups has found that lone actors have *significantly higher rates of mental illness* than group offenders. Spaaij (2012) and Spaaij and Hamm (2015) found that the rates of "psychological disturbance" and "mental health disorder" were considerably higher among lone wolves. Other scholars have quantified this difference, including Hewitt (2002), who found that 22 percent of lone actors in his database displayed symptoms of mental illness compared with 8.1 percent of group-affiliated terrorists. Gruenewald et al. (2013) also found that lone offenders had a significantly higher rate of mental illness than group offenders—40 percent versus 7.6 percent—although their sample was limited to exclusively far-right extremists. Corner and Gill's analysis (2015) found that 31.9 of offenders in their lone actor sample had a mental illness, but that

only 3.4 percent of their group actor sample did. Put simply, the odds of a lone-actor terrorist having a mental illness are 13.49 times higher than the odds of a group actor having one (Corner & Gill, 2015).

In one of the most nuanced analyses of this issue, Corner et al. (2016) disaggregated both the actor types (into lone mass murderers, lone actor terrorists, solo actor terrorists, lone dyads, and terrorist group members) and mental health disorders (into categories used by the Composite International Diagnostic Interview classifications). They found only three disorders that are more prevalent among lone actors compared to group actors: schizophrenia, delusions, and autism spectrum disorder (Corner et al., 2016). They also found a negative association between mental disorder and what they described as "the degree to which the individual co-offends" (Corner et al., 2016). Finally, they found that group actors demonstrate not just lower levels of mental disorders than lone actors but also lower levels than would be expected within a *general population* (Corner et al., 2016).

To examine the link between affiliation and mental health, we calculated a new analytic variable: composite mental health. We coded this binary variable as 1 (yes) if any of the conditions in Table 4 were met or 0 (no) if they were not. This variable is far more inclusive than measures used in other studies (e.g., diagnosed mental illness). We chose to take this approach in response to critiques made of the use of dichotomous mental health variables (Corner & Gill, 2016). Specifically, we recognized that a person might not have a formal diagnosis for a wide range of reasons, including lack of access to affordable behavioral health care, the geographic inaccessibility of behavioral health care, and stigma around help-seeking behaviors. We consequently constructed a more inclusive variable to allow for a broader range of inputs.

Table 4. Mental health composite variable

Variable	Positive Codes
Anticipated outcome	3 = Suicide 4 = Killed
Actual outcome	1 = Suicide attack 2 = Suicide during or shortly after attack
Mental health issue	1 = Self-diagnosed 2 = Professionally diagnosed 3 = Speculated by friends and family
Substance abuse issue	1 = Yes
History of suicidality	1 = Yes, within six months before attack 2 = Yes, greater than six months before attack 3 = Yes, timeline unknown
Psychosis at time of attack	1 = Yes, auditory hallucinations 2 = Yes, visual hallucinations 3 = Yes, delusions 4 = Yes, unspecified

Source: CNA.

Table 5 contains this variable as compared to affiliation scores. Using the Kruskal-Wallis test, along with a post hoc Dunn Test, we found that those with a mental health issue were *more lone* than those without ($p < 0.001$). Our finding supports the literature suggesting that offenders with lower affiliation scores have greater incidences of mental health issues than group-based actors.

Table 5. Mental health and affiliation

Mental Health Issue	Count	Average Affiliation
No	165	9.6
Yes	155	6.9

Source: CNA.

Discussion

Our analysis of affiliation and lethality contributes to the literature in two ways. First, it adds another data point to the arguments made by Hewitt (2002), Phillips (2017), and Turner et al. (2023) that lone attackers—in our case, less-affiliated actors—are more lethal than group-affiliated offenders. Importantly, it also reveals that the trend between affiliation and lethality seems linear—when split into quartiles, the number of lethalities declined as affiliation increased.[12]

Second, our analysis of affiliation and mental health issues supports the general consensus in the literature that lone actors are more likely to have mental health issues than affiliated offenders are. We are aware of two dominant explanations in the literature. The first focuses on the recruiting practices of terrorist or extremist groups. Various scholars argue that terrorist groups can be both rational and strategic and may therefore be selective in who they recruit because they have an interest in the survival of the group, the achievement of their cause, and the approval of the constituency they claim to represent (Crenshaw, 1998; Borum, 2004; Corner et al., 2016). Individuals displaying obvious or serious mental health or behavioral issues may not be selected by groups for membership if these concerns are seen as conflicting with the group's best interests (Corner & Gill, 2015). The second explanation is that these individuals may be socially isolated and may not have the interpersonal skills needed to contact an extremist group (Corner & Gill, 2015). Other researchers concur with this argument—De Roy van Zuijdewijn and Bakker (2016) and Schuurman and Carthy (2023) both found that lone actors are more socially isolated.

We do not disagree with these two explanations, but we note a few shortcomings. To begin, the former explanation assumes a degree of psychological dysfunction far more significant than our data suggest. Our composite mental health variable is inclusive of individuals who might be struggling with a range of issues that would not necessarily be obvious to others in a group. In addition, both explanations are predicated on conceptualizations of group membership that may be slightly outdated given the current communications environment. The very idea of membership, or selection for membership, suggests a narrow understanding of the concept that overlooks a range of affiliative behaviors possible in online spaces (e.g., lurking, liking, posting, moderating). Given this, we think that the second explanation, particularly the focus on impaired social skills (which notably does not preclude behaviors such as lurking and liking) likely has more explanatory power in the context of today's online environment.

[12] Importantly, this does *not* mean there is a linear relationship.

Question 2: Lethality

Research question: What variables are strongly correlated with lethality?

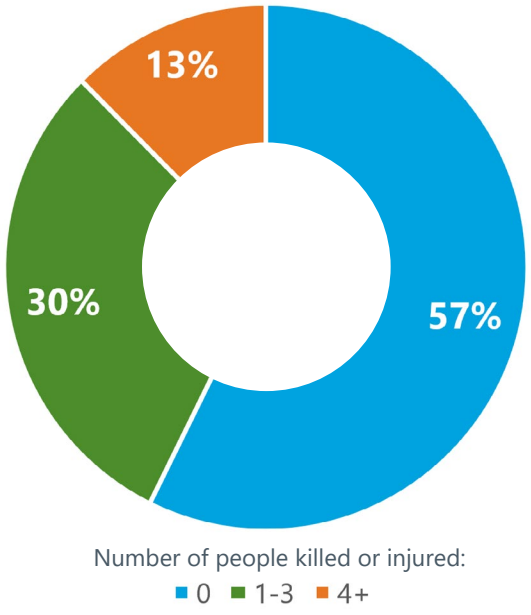
The lethality of domestic terrorist attacks in the United States is a subject of increasing scrutiny as academics and practitioners seek to understand and prevent ideologically motivated violence against the public. We found that most domestic terrorists do not kill or injure anyone and that just 20 percent of offenders in DTOLD committed lethal attacks. More specifically, as Figure 5 illustrates, 57 percent neither killed nor injured anyone, 30 percent killed or injured between one and three people, and 13 percent killed or injured four or more people.[13]

Although the data include significant outliers (see Table 6), most offenders are less lethal than the mean.

Lethality and ideology

Although Islamist violent extremism continues to be the most lethal ideology internationally, research and intelligence assessments indicate that in recent years, far-right extremists—including White identity extremists—were and will continue to be the most lethal terrorist threat in the US (Miller, 2017; Jones et al., 2020a). Jasko et al. (2022) supported the conclusion that Islamist violent extremists are the most lethal at the global level but found no difference in the level of violence perpetrated by right-wing and Islamist extremists[14] in the US. However, Jasko

Figure 5. Deaths and casualties by offenders in DTOLD



Source: CNA.

[13] DTOLD does not include perpetrator deaths or injuries in fatality or casualty counts.

[14] Jasko et al. (2022) use the term *Islamist extremism* to refer to the ideology of groups such as al-Qaeda, ISIS, Boko Haram, and al-Shabaab.

Table 6. Summary statistics of lethality

Lethality	Minimum	25th Percentile	Median	Mean	75th Percentile	Maximum
Total killed	0	0	0	0.8	0	60
Total killed + injured	0	0	0	4.9	1	927

Source: CNA.

et al. (2022) also found that both in the US and at the global level, right-wing and Islamist extremists are more likely to commit violent acts than left-wing extremists are. Moreover, Doxsee et al. (2024) affirmed earlier findings with data showing that violent far-right extremists were responsible for more than 80 percent of fatalities caused by terrorist attacks in the US between 2019 and 2024.

In our analysis of ideology and lethality, we sought to determine whether domestic terrorists' lethality levels were correlated with their ideological commitments (see Table 7). The results of our Kruskal-Wallis test and post hoc Dunn Test indicated that incel/male supremacist and NPA ideology are associated with more fatalities (4.4 average fatalities), although we note that incel/male supremacists have a relatively low count in the dataset (14) and that the NPA category was skewed by the inclusion of the 2017 Las Vegas shooting—the most lethal attack in the dataset.[15] Overall, given the low count of offenders in the incel/male supremacist ideological category, we found no significant statistical evidence that lethality differs among ideologies.

To further analyze the relationship between ideology and lethality, we condensed the 21 ideological categories into three: far left (e.g., environmental/animal rights, anti-authoritarian/fascism), far right (e.g., White identity, anti-government, Second Amendment, abortion), and other (e.g., other, no ideology, NPA). We sorted offenders with conflicting ideological elements into the group that aligned with their most prominent belief. We also parsed the dataset into three categories related to lethality: offenders who killed or injured no one, offenders who killed or injured one to three people, and offenders who killed or injured four or more people. Through a Pearson's Chi-squared test, we found indications of a statistically significant association between these two categorical variables (type of extremist and lethality) ($p = 0.018$), suggesting that the distribution of lethality differs across ideologies. To explore this relationship further, we ran a log-linear regression (Poisson regression). The model shows that far-right offenders are significantly overrepresented in the group of perpetrators that killed or injured one to three people ($p = 0.002$). Offenders with "other" ideologies were also more likely to be involved in attacks that killed or injured one to three people ($p = 0.015$). In contrast, far-left extremists were less involved in violence resulting in injury or death. There were no clear group differences among offenders who killed or injured four or more people, most likely due to the small number of offenders in this group ($n = 44$). Overall, these findings suggest that most extremists did not kill or injure anyone, but

[15] Of note, there is continuing doubt as to whether the perpetrator's crime meets the definition of *terrorism* because investigators were unable to determine what motivated him to commit mass murder (FBI, 2019b). Despite this doubt, we opted to include Paddock in the database for three reasons: (1) the attack does meet the criteria for inclusion in GTD (Miller, 2018), (2) witness statements suggest that anti-government sentiments might have motivated the attack (Miller, 2018), and (3) the potential impact of an outlier case on the data has no bearing on consideration for inclusion.

Table 7. Average fatalities and casualties by ideology

Ideology	Number of Offenders	Average Fatalities	Average Casualties
Anti-government extremism	104	0.8	2.1
White identity extremism	85	1.4	3.6
Specific ethnic/religious hate	52	1.0	3.2
Xenophobic/anti-immigrant extremism	50	1.7	4.4
Conspiracy theory	47	0.8	2.0
NPA	44	1.5	22.8
Environmental/animal rights extremism	39	0.6	1.2
Other	38	0.9	2.8
No ideology	24	0.5	1.7
Christian extremism	18	1.2	3.0
Anti-LGBTQ+ extremism	17	3.6	9.9
Sovereign Citizen extremism	17	0.4	1.6
Black identity extremism	15	1.2	4.4
Abortion extremism	14	0.5	1.2
Incel/male supremacist extremism	14	4.4	11.0
Anti-authoritarian/fascism extremism	13	0.8	3.0
Anti-capitalist extremism	11	0.0	0.5
Other religious extremism	10	2.1	5.3
Second Amendment extremism	9	0.3	0.9
Anti-imperialism extremism	7	1.7	4.0

Source: CNA.

the likelihood of physical harm varies by ideological affiliation, with far-right and "other" extremists more likely to be involved in such incidents than are left-wing extremists.

In some cases, offenders expressed beliefs that aligned with more than one ideology in personal writings, social media posts, or manifestos, but they committed an attack that aligned with only one ideology. For example, the El Paso shooter expressed White supremacist, anti-immigrant, anti-government, anti-LGBTQ+, and environmental extremist views, but his attack targeted only Hispanic immigrants. To capture this nuance, DTOLD codes for both ideology and ideology of attack. *Ideology of attack* refers to the elements of the individual's ideological alignment that were evident in the attack as determined by a range of variables, including the targets chosen for the attack, comments during the attack itself, or comments to the police or court about why they carried out the attack.

In our analysis of the ideology of attack and lethality, we sought to determine whether domestic terrorist attacks linked to certain ideologies had levels of lethality that were statistically distinct

from one another. Because many offenders had multiple ideologies of attack, they may be counted in more than one category; therefore, the number of offenders in Table 8 add up to greater than the number in the dataset. In conducting the same statistical test that we used for ideology, we found no significant differences between the rates of fatalities and casualties among attacks linked to different ideologies. Although offenders with no publicly available ideology on average caused more casualties, we found that this difference is not significant.

Type of attack by ideology

Although violent extremists are united by their strategic use of violence, variances in their targets and tactics reflect the diverse motivations of each extremist ideology, and might have explanatory power regarding the relationship between lethality and ideology (i.e., if there is a relationship between attack type and ideology, and certain attack types are known to be more lethal, this may partly explain the lethality finding). Recent data suggest that between January and August 2020, far-left extremists primarily targeted demonstrators and the

Table 8. Average fatalities and casualties by ideology of attack

Ideology	Number of Offenders	Average Fatalities	Average Casualties
Anti-government extremism	84	0.3	1.0
White identity extremism	63	1.3	3.4
Specific ethnic/religious hate	44	1.0	3.3
NPA	40	2.1	26.4
Environmental/animal rights extremism	37	0.0	0.0
Conspiracy theory	31	0.6	1.8
Xenophobic/anti-immigrant extremism	28	1.8	3.5
Other	25	0.3	2.6
No ideology	23	0.2	1.4
Black identity extremism	14	1.2	4.2
Sovereign Citizen extremism	14	0.4	1.6
Abortion extremism	12	0.3	1.1
Anti-authoritarian/fascism extremism	11	0.1	0.6
Christian extremism	11	1.6	3.5
Anti-capitalist extremism	8	0.0	0.6
Other religious extremism	8	2.0	5.3
Incel/male supremacist extremism	6	3.3	10.2
Anti-LGBTQ+ extremism	5	0.4	2.4
Anti-imperialism extremism	3	3.0	5.7
Second Amendment extremism	1	1.0	2.0

Source: CNA.

government, military, and police (Jones et al., 2020b). Although far-right extremists also primarily targeted these groups, they targeted private individuals as well. The data show that by 2022, far-right extremists were overwhelmingly targeting private individuals, while far-left extremists were still primarily targeting government and law enforcement (Doxsee et al., 2024).

Various researchers have documented the weapons used by different types of violent extremists. Jones (2021) found that explosives and incendiaries were the primary weapon in 50 percent of all far-right attacks from 1994 to 2020 and that firearms were used in 27 percent of attacks. Explosives and incendiaries were the most common weapons used by the far left—they were involved in 81 percent of far-left attacks between 1994 and 2020 (Jones et al., 2020b). Melee weapons were the second most common weapon among the far left and were used in 7 percent of attacks in the same time frame (Jones et al., 2020b). On the far right, 27 percent of attacks and plots in 2020 involved a vehicle as a weapon, 25 percent involved explosives and incendiaries, and 24 percent involved firearms (Jones et al., 2020b).

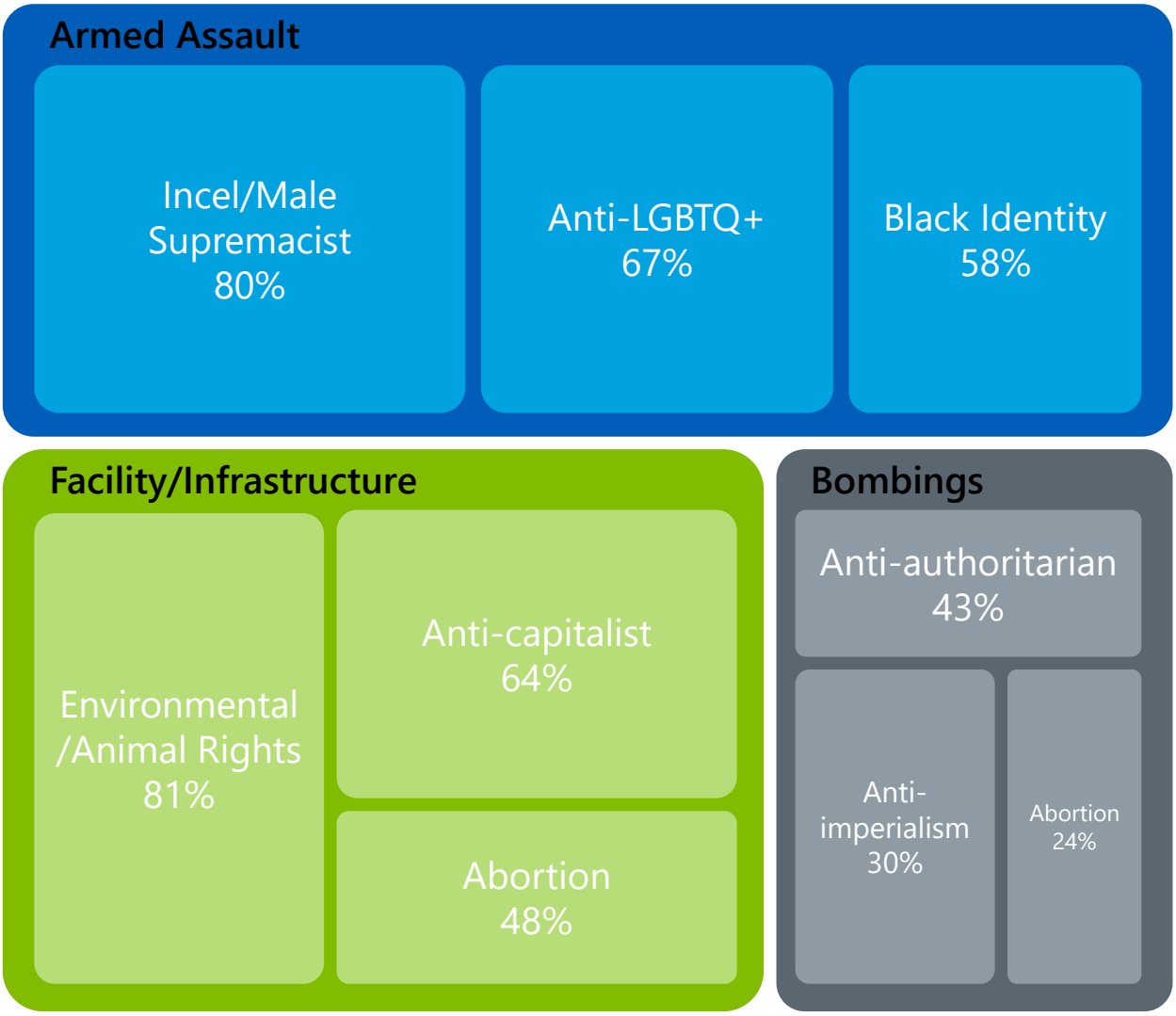
We sought to determine whether domestic terrorists of specific ideologies commit certain types of attacks more often than offenders of other ideologies. Using Fisher's exact test, we determined there are significant differences in the types of attacks committed by offenders of each ideology. As shown in Figure 6, incel/male supremacist offenders were the most likely to commit armed assault attacks, with 80 percent of offenders of this ideology in the dataset committing this type of attack. Environmental/animal rights extremists were the most likely to commit facility/infrastructure attacks, and anti-authoritarian extremists were the most likely to commit bombings. In contrast, anti-capitalist and environmental/animal rights extremists were the least likely to commit armed assault attacks, with just 7 percent of both groups of offenders committing this type of attack. Black identity extremists were the least likely to commit both facility/infrastructure and bombing attacks, making up 4 percent of extremists committing facility/infrastructure attacks and 0 percent of those who committed a bombing attack.

Critically, the relationship between attack type and ideology provides a partial explanation for the relationship between lethality and ideology, as far-left actors execute a disproportionate number of low-casualty facility/infrastructure attacks, while far-right actors execute a disproportionate number of armed assaults. To some degree, this is a chicken and egg question as we do not know if the offenders are choosing their attack type *because* it is more or less likely to result in death and injury (or if death and injury are a secondary concern and the focus is on attack type itself). That said, in at least some cases, the former is likely true. For example, both anti-abortion terrorists and environmental terrorists embrace ideologies that place a premium on life, which likely explains why they more frequently attack infrastructure rather than persons. However, where ideological elements are not instructive, further research is needed to determine why those with specific ideologies are more or less likely to commit specific types of attacks and to what degree anticipated deaths and injuries drive this selection.

Lethality and mental health

As noted above, although recent studies indicate an increased prevalence of mental health issues among lone actors relative to other terrorists and the general population, the research does not support the same conclusion for the broader terrorist population (Hewitt, 2003; Corner et al., 2016; De Roy van Zuijdewijn & Bakker, 2016; Grimbergen & Fassaert, 2022). Sarma et al.'s (2022) systematic literature review and meta-analysis did not support the assertion that terrorists in general have more mental health issues than would be expected in the general population, finding that the lifetime prevalence of a diagnosed mental disorder is 29 percent in the general population and 17.4 percent

Figure 6. Ideology and type of attack



Source: CNA.

among terrorists (28.5 percent in studies broadly reporting any psychological problems) (Sarma et al., 2022).

However, the literature does indicate that a history of mental illness is one of many risk factors for radicalization and participation in terrorism (Gill & Corner, 2017; Gill et al., 2021). LaFree et al. (2018) found that individuals with radicalized friends or family members, a criminal history, or a history of mental illness were more likely to be engaged in violent extremism, and Smith (2018) found that various National Institute of Justice–sponsored studies have also identified psychological issues as risk factors associated with radicalization.

That said, the literature on the relationship between mental health issues and lethality is extremely limited. Corner and Gill (2015) found that lone actors with diagnosed mental illnesses kill and injure at higher rates than lone actors without diagnoses. In addition, Gill et al. (2014) found that lone actors who

successfully carry out an attack are more likely to have a mental illness. However, to our knowledge, no research has explored the link between mental health issues and lethality in the broader terrorist population.

To test whether there is a relationship between lethality and the presence of mental health issues, we used the composite mental health variable described in the previous section. This binary variable, which we coded as 1 (yes) if any of the conditions in Table 4 were met, is more inclusive than measures used in other studies (e.g., diagnosed mental illness). As shown in Table 9, our sample sizes for this analysis were relatively even.

To begin, we found that 26 percent of offenders in DTOLD had a known history of a mental health issue (56 percent NPA) within one year of their attack, compared with National Institute of Mental Health estimates that 23.1 percent of the general population and nearly 20 percent of US adult men live with some kind of mental illness ("Mental Illness," 2023). This is likely an understatement given the large quantity of missing data for this variable, as we were able to definitively rule out a history of mental health issues for only 10 percent of the offenders in the database (32 of 319).

Looking at the distribution, offenders with a mental health issue show a lower density of nonlethal attacks. Similarly, when we compared the means using the Wilcoxon rank sum test and the Kruskal-Willis rank sum test, we found that the means of these populations are significantly different. The regression also shows that there is a statistically significant linear relationship between composite mental health and lethality. That is, offenders with a mental health issue are slightly more lethal on average than offenders with no mental health issue. However, in this analysis, we assumed that missing data were negative, which means that our results will be influenced by media coverage bias. Lethal offenders are more likely to garner significant media attention than nonlethal offenders, which means we often have more data about lethal offenders' mental health history than we do for nonlethal offenders. And after controlling for NPA data, we found that there is no statistically significant relationship between lethality and the mental health composite variable, although offenders with mental health history show more and higher lethality outliers.

Lethality and trauma

Terrorism researchers have long posited a relationship between traumatic experiences (such as adverse childhood experiences (ACEs)) and radicalization to violent extremism (Post et al., 2003; Borum, 2004; Ellis et al., 2015; Windisch et al., 2022). Researchers have noted that the rates of childhood trauma in violent extremists are higher than in the general population, with 45 percent of their interviewees reporting being the victim of childhood physical abuse compared to 28.3 percent of American adults (Simi et al., 2015). Logan et al. (2024) found that 60 percent of left-wing extremists and 50 percent of right-wing extremists experienced emotional

Table 9. Mental health issue and lethality

	Nonlethal	Lethal
No mental health issue	107	57
Mental health issue	77	80

Source: CNA.

neglect or abuse, 20 percent of left-wing extremists and 10 percent of right-wing extremists experienced sexual abuse, and 10 percent of left-wing extremists and 20 percent of right-wing extremists experienced physical neglect or abuse. Several studies have documented the relationship between ACEs and violent extremism. Grimbergen and Fassaert (2022), Carthy and Schuurman (2024), and Logan et al. (2024) all found that ACEs are associated with radicalization trajectories. Importantly, none of these studies implied that experiencing ACEs is predictive of radicalization. Instead, as Simi et al. argued (2016), the experience of childhood trauma can result in maladaptive coping mechanisms, which can in some instances create a vulnerability to radicalization.

Despite the notable presence of trauma in terrorist life histories, to our knowledge, no research has examined whether trauma plays a role in explaining the variance of attack lethality. The closest research would be work by Carthy and Schuurman (2024), in which they specifically linked ACEs to ideological violence, finding that individuals who radicalize and participate in terrorist violence are more likely to have experienced ACEs than individuals who radicalized but did not engage in violence.

Unfortunately, there was too much missing data in the childhood life history section of DTOLD to sustain analysis of the relationship between ACEs and lethality. However, more data were available in the adult trauma variables, so we calculated a new analytic variable—composite adult trauma—based on nine variables in the adulthood life history variables section of the dataset: adult socioeconomic status (SES), significant relationship issue, significant employment issue, significant legal issue, significant interpersonal conflict, physical abuse as an adult, sexual abuse as an adult, emotional abuse as an adult, and crisis greater than six months before attack. Each variable was worth one point, so we added one point to the total score for each variable coded as yes. The maximum possible score was nine.[16] For the purposes of this analysis, we counted missing data (cells coded as NPA) as zeroes.

A cursory look at the data suggested that offenders with lower adulthood trauma composite scores might have a higher density of nonlethal attacks and that offenders with slightly higher composite scores might have slightly higher rates of lethal attacks. However, comparing the means, we found no statistically significant difference between the mean lethality of populations with different composite adulthood trauma scores. Ultimately, the sample sizes for offenders with composite scores of three and four were extremely small compared to the sample sizes for offenders with composite scores of zero, one, and two. As a result, there appears to be insufficient data to determine a relationship between either adult or childhood trauma and lethality.

Discussion

Our findings broadly confirm what others have already found: domestic terrorists with far-right ideological commitments are significantly overrepresented in the group of perpetrators who killed or injured one to three people. However, when we parsed out ideological commitments with more nuance, we found that these statistically significant differences no longer existed (i.e., no single far-right ideology is driving this relationship). Nor did they exist when we focused exclusively on the ideologies salient in the attacks. Perhaps the more compelling finding is that although our data do not suggest a statistically significant relationship between lethality and mental health issues, those with mental health issues both (a) commit more very-lethal attacks, and (b) commit attacks that are comparatively more lethal than the very-lethal attacks by offenders with no mental health issues. In addition, of the 164 offenders without a known mental health issue,

[16] For socioeconomic status, the offender received a point only if their adulthood SES was coded as 1 (poverty).

107 (65 percent) perpetrated nonlethal attacks; in comparison, 77 of the 156 attacks by offenders with a mental health issue (49 percent) perpetrated nonlethal attacks.

Question 3: Leakage

Research question: Do domestic terrorists of different ideologies or types share information about their plans or "leak" differently?

Within the public violence literature (i.e., the literature on domestic terrorism, mass shootings, school shootings, and so on), leakage has been identified as a core warning behavior (Meloy et al., 2014). Leakage means the would-be assailant communicates an "intent to do harm to a target" prior to committing an attack (Meloy & O'Toole, 2011). Leakage occurs across the spectrum of public violence typologies, including political and public figure assassinations (Fein & Vossekuil, 1999), adolescent-perpetrated mass murders (Hempel et al., 1999), and lone actor terrorism (Gill et al., 2013). Relatedly, there is a relatively robust literature examining the determinants, rates of occurrence, and consequences of leakage. In their 2021 study of factors associated with a mass shooting perpetrator's decision to communicate their intent to do harm, Peterson et al. identified a relationship between leakage and both suicidality and a history of counseling. In fact, perpetrators with a history of attending counseling were seven times more likely to leak their plans than perpetrators who never attended counseling (Peterson et al., 2021). In their exploration of predictors of leakage, Silver et al. (2018) found that offenders with grievances against a specific person or entity were more likely to leak their plans. Relatedly, Horgan et al. (2016) found that lone actors are more likely to exhibit leaking behaviors, and Capellan & Lewandowski (2019) found that compared to individuals motivated by psychosis (Peterson et al., 2021), those motivated by a specific ideology are more likely to "leak." However, no published studies thus far have compared rates of leakage among various ideologies.

Building on Meloy & O'Toole's (2011) conceptualization of leakage, we used various data points in the database to construct two composite binary variables for leakage: narrow and broad. Table 10 contains the elemental variables in each definition of leakage. These variables capture the presence or absence of leakage behaviors but notably do not characterize the *extent* to which the individual engaged in leakage behaviors.

For 27 cases in the dataset, data were not available for both variables in the narrow definition of leakage. In these 27 cases, we coded the composite "narrow" leakage variable as NPA (see Table 11). There were no cases in which data were missing for all the contributing variables for the broad definition of the leakage composite variable.

Leakage and ideology

Using the narrow definition, 31.6 percent (101 of 320) of offenders in the dataset leaked some information prior to their attack. To analyze whether DVEs leaked at different rates based on ideology, we compared leakage rates across ideological groups (see Table 12). Importantly, many offenders articulated multiple ideologies, meaning that most cases were counted more than once. Second Amendment, anti-LGBTQ+, and incel/male supremacist extremists leaked the most often with rates of 89 percent (8 of 9), 82 percent (14 of 17), and 79 percent (11 of 14), respectively. Inversely, by the narrow definition, extremists with no identifiable ideology, environmental/animal rights extremists, and abortion extremists leaked the least often with rates of 27 percent (6 of 22), 22 percent (8 of 36), and 23 percent (3 of 13), respectively.

When the definition is broadened to include behaviors that are generally considered warning or concerning behaviors (e.g., obsessive interest in firearms or mass violence), the overall rate of leakage nearly doubles,

Table 10. Leakage composite variables

Definition	Variable	Positive Codes
Narrow, Broad	Warning, threat, or announcement	1 = Yes, deliberate 2 = Yes, unintentional
Narrow, Broad	Social media use related to attack	1 = Yes, prior 2 = Yes, during (live)
Broad	Evidence of extremist symbols	1 = Yes
Broad	Notable or obsessive interest in firearms	1 = Yes, as juvenile 2 = Yes, as adult 3 = Yes, as both
Broad	Notable or obsessive interest in mass violence	1 = Yes
Broad	Notable or obsessive interest in vigilante organizations	1 = Yes
Broad	Notable or obsessive interest in another extremist individual	1 = Yes

Source: CNA.

Table 11. Presence of leakage by definition

Presence of Leakage	Narrow Definition	Broad Definition
Leakage	101	191
No leakage	192	129
NPA	27	0

Source: CNA.

Table 12. Leakage rates

Ideology	N (# of NPA cases)	Narrow Leakage	Broad Leakage
Second Amendment extremism	9 (0)	89%	100%
Abortion extremism	14 (1)	23%	43%
Anti-authoritarian/fascism extremism	13	69%	92%
Anti-capitalist extremism	11 (1)	50%	73%
Anti-imperialism extremism	7 (1)	67%	71%
Anti-LGBTQ+ extremism	17 (0)	82%	100%
Anti-government extremism	104 (5)	54%	71%
Black identity extremism	15 (1)	43%	87%
Christian extremism	18 (2)	63%	89%
Conspiracy theory	47 (3)	64%	89%
Environmental/animal rights extremism	39 (3)	22%	64%
Incel/male supremacist extremism	14 (0)	79%	100%
No ideology	24 (2)	27%	46%
NPA	45 (9)	8%	27%
Other	38 (2)	42%	61%
Other religious extremism	10 (1)	44%	100%
Sovereign Citizen extremism	17 (2)	67%	88%
Specific ethnic/religious hate	52 (1)	49%	73%
White identity extremism	86 (7)	41%	80%
Xenophobic/anti-immigrant extremism	50 (5)	49%	82%

Source: CNA.

Note: In 7 percent of cases, data were not available for either variable in the narrow definition of leakage. When this occurred, we removed the case before calculating the percentage of cases with narrow leakage. The number of such cases is captured parenthetically in the N column in the chart.

increasing to 59.7 percent (191 of 320). Similar to the findings using the narrow definition, we found that under the broad definition, anti-LGBTQ+, incel/male supremacist, other religious extremists (e.g., not Christian or Islamist), and Second Amendment extremists leaked the most frequently. One hundred percent of extremists in the dataset ascribing to these ideologies leaked in methods fitting the broad definition. Abortion extremists, extremists with no identifiable ideology, and environmental/animal rights activists again leaked the least often.

Leakage and suicidality

To analyze the relationship between leakage and suicidality, we created a binary composite suicidality variable based on five suicide-related variables in the database (Table 13). If the offender had a positive code for any of these seven variables, they were coded as positive (1) for the binary composite suicidality variable.

We found a positive relationship between narrow leakage and suicidality such that the odds are higher that suicidal offenders will leak details related to their plans ($p = 0.018$). The same is true for the broad definition ($p = 0.007$). However, in both cases, suicidality accounts for less than 2 percent of the variation in leakage. Essentially, the data suggest that there are likely other variables with more explanatory power for understanding variations in leakage between offenders.

Leakage and affiliation

Very little previous scholarship has examined the intersection of a terrorist's leakage behaviors and the degree of affiliation to groups. Schuurman et al. (2017) found that lone actors infrequently take measures to maintain plot secrecy, with 86 percent of lone actors in their dataset communicating their extremist beliefs to others, 58 percent indicating to others they were involved in violent activities, and 26 percent sharing specific details of their plans with others. Furthermore, almost half (49 percent) of the lone offenders in Schuurman et al.'s (2017) dataset interacted with the authorities while planning and preparing for their attack. Rose and Morrison (2023) similarly found that 83.9 percent of the individuals in their lone-actor sample exhibited

Table 13. Binary suicidality composite variable

Variable	Positive Codes
History of suicidality	1 = Yes, within six months before attack 2 = Yes, greater than six months before attack 3 = Yes, timeline unknown
Nature of suicidality	1 = Attempt, voluntary hospitalization 2 = Attempt, involuntary hospitalization 3 = Attempt, hospitalization 4 = Attempt, outcome unknown 5 = Ideation
Expected outcome of attack	3 = Suicide 4 = Killed
Attack outcome	1 = Suicide attack 2 = Suicide during or shortly after attack
Legacy artifact	4 = Suicide note 5 = Last will and testament

Source: CNA.

leakage behaviors. However, their study consisted primarily of jihadist terrorists who leaked details to other jihadist extremists. Furthermore, none of these studies examined differences in leakage behaviors between lone and group actors. We found a positive relationship between affiliation quartile and leakage such that when an offender is more affiliated, the odds of leakage occurring increase ($p = 0.013$). However, the data suggest that this relationship accounts for only about 3 percent of the variation in leakage. As with suicidality, other factors may be more influential in explaining variations in offender leakage.

Discussion

Relatively little domestic violent extremism research has explored leakage by ideology. Therefore, most of the findings outlined in the preceding paragraphs stand alone in recent literature. However, the lack of leakage behaviors for those DVEs who do not ascribe to an ideology is especially interesting. Leaking provides unique opportunities for intervention prior to further radicalization or the commission of an attack. Thus, this gap has implications for system stakeholders and practitioners working on prevention efforts.

Our findings on leakage and suicidality are consistent with research that found associations between suicidality and leaking in mass shooters, framing the behavior as a cry for help (Peterson et al., 2021). This finding is relevant to the work of both mental health and risk assessment professionals, who must respond to leaking behaviors appropriately to address both actions and underlying causes.

Finally, our findings on affiliation and leakage varied from literature on the behavior of mass murderers and Islamist terrorists, which found higher rates of leakage among lone actors (Horgan et al., 2016; Rose & Morrison, 2023). This kind of finding highlights a broader issue. Although individuals engaged in public violence sometimes display similar behaviors, further research is needed to delineate groups and, possibly, to develop distinct approaches to domestic violent extremism prevention and intervention within each group.

Question 4: Terrorist profiles

Research question: What constellation of psychosocial, trauma-related, and life history variables are the most strongly correlated with domestic terrorists of different ideologies?

Terrorism scholars have long rejected the notion that it is possible to develop a single profile of the terrorist actor (O'Brien et al., 2013; Atran, 2010; Bjørgo & Horgan, 2008; Horgan, 2008; Horgan, 2003). VPPRC's first report on mass shooters acknowledged this reality and called for a de-emphasis on identifying *the* mass shooter profile in part by presenting *multiple* profiles (e.g., K–12 school shooter, workplace shooter) (Peterson & Densley, 2019). Many of the variables included in these profiles—referred to by VPPRC as "individual-level psycho-social life history variables"—have at other times been described as risk factors (e.g., violent history, criminal record, mental illness) and may directly apply to DVEs.

That said, typologies (i.e., organized systems of types) have come to be seen as somewhat unsophisticated and unsuited to quantitative measurement. Collier, LaPorte, and Seawright, however, argued that conceptual typologies (and the categorical variables on which they depend) are "valuable analytical tools" that can refine concepts and provide new insights (Collier et al., 2012). Moreover, although extensive attention has been paid to risk factors correlated with radicalization (Wolfowicz et al., 2020; Smith, 2018; McCauley & Moskalenko, 2017), less research has examined "behavioral variation between and across individuals who have committed terrorist crimes" (Horgan et al., 2018). Some recent work has attempted to fill this gap by taking up the concept of offender profiling and disaggregating the "terrorist"

population by exploring differences in ideology and group affiliation (Horgan et al., 2018).

Our goal with this line of effort was to contribute to the discussion about terrorist profiles using a novel methodology that would either add to the evidence that profiles do not exist or reveal profiles that were undiscoverable via other forms of analysis.

Results

Researchers have multiple options for measuring how different offenders may relate to each other and for measuring relationships within data. We approached the issue of typologies by asking a set of questions that we thought would have the most utility for practitioners engaged in prevention work: Are there unique life history profiles among offenders? If so, are they related to offender ideology? Through this approach, we could group offenders with similar life history variables into clusters and then test the relationships between clusters and offender ideology.

We grouped offenders into 10 clusters based on life history variables (mental health, childhood life history, and adult life history) using a partitioning around medoids clustering algorithm.[17] Through this approach, we could quantify variations in offender life history variables and group similar offenders into clusters (see Table 14). Notably, the clusters are of such a wide range that they are analytically unremarkable taken alone. They suggest co-occurrence of issues that have long been recognized to co-occur (e.g., economic and parental stability), and in more than one case, a cluster exists at both the high and low ends of a single spectrum (e.g., adult crises). In short, the DTOLD data suggest that there is no single profile of today's domestic terrorist and also that there is no clear constellation of profiles oriented around mental health history, childhood life history, and adult life history variables.

The clusters that we identified captured the full range of human experiences, meaning there were both high issue/crisis clusters and low issue/crisis clusters. To some degree, this finding affirms analysis suggesting that there is no profile of a domestic terrorist. That said, even though the clusters alone were relatively unremarkable, they could have practical value if they were correlated with other relevant variables. In other words, even if there is no clear life history profile for domestic terrorists, perhaps certain clusters would be more likely to correlate with certain ideologies. Thus, we tested relationships between the clusters and all ideologies that included more than 30 cases.[18] In most cases, we found no practically or statistically significant relationships with any clusters. However, environmental/animal rights extremism and conspiracy theory extremism did have relationships with specific clusters.

Environmental/animal rights extremists (Cluster two, see Figure 7) were statistically more likely to be sorted into the "economic and parental stability" cluster. Compared with the other clusters, this cluster showed higher socioeconomic status (slightly higher as adults, notably higher as children), fewer legal issues, lower rates of parental disappearance, and lower rates of parental divorce (67 percent reported no divorce versus an average of 22 percent among the other clusters). It also includes a high proportion of offenders raised by both parents (90 percent versus an average of 27 percent among the other clusters). The relationship between environmental/animal rights extremism and being sorted into this cluster is significant at the $p < 0.01$ level, suggesting these extremists are more likely to fit this profile.

[17] We selected 10 clusters to optimize silhouette width without compromising the interpretability of the data.

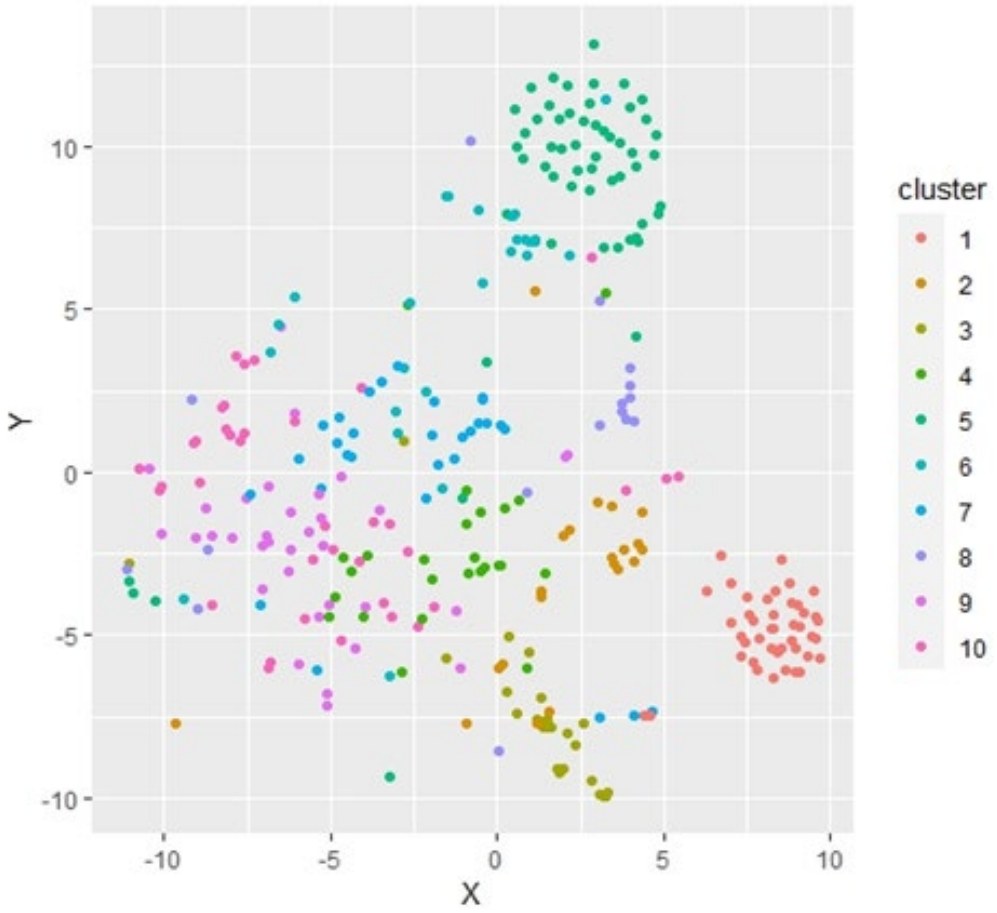
[18] The minimum n of 30 is standard because n = 30 is the minimum sample required for the Central Limit Theorem to apply. The ideologies with n ≥ 30 in DTOLD are White identity extremism, xenophobic/anti-immigrant extremism, anti-government extremism, environmental/animal rights extremism, conspiracy theory extremism, other extremism, no ideology discernible, and specific ethno-religious hate extremism.

Table 14. Clusters

Cluster Number	Cluster Name	Distinguishing Life History Variables
1	Missingness cluster	Extremely high rates of missing data in relevant life history variables.
2	Economic and parental stability cluster	Higher recorded childhood and adulthood socioeconomic status, fewer legal issues, less parental disappearance, less parental divorce, and higher rate of being raised by both parents.
3	Low issues and crises cluster	Lower rates of crisis in adulthood, lower rates of interpersonal issues, lower rates of employment issues, lower rates of relationship issues, lower rates of medical issues, and fewer reported mental health issues.
4	No distinguishing characteristics	Cluster four has no distinguishing variables.
5	Anti-government extremist cluster	Consisted largely of anti-government extremists but showed no practically significant relationships. Rather, it showed high NPA counts across all life history variables. Although statistically significant, this finding does not provide practical insight into potential anti-government offender profiles.
6–8	No distinguishing characteristics	Clusters six to eight have no distinguishing variables.
9	High issues and crises cluster	High rates of adulthood employment issues, interpersonal conflict issues, legal issues, higher rates of crises in adulthood, high rate of professionally diagnosed mental health issues, high rate of medical issues, and high rate of reported delusional disorders.
10	Diagnosed mental health issues cluster	High rates of adulthood mental health crises, high rates of professionally diagnosed mental health issues (including higher rates of autism spectrum disorders, delusional disorders, and mood disorders), and higher rates of suicidal ideation and history of suicidality.

Source: CNA.

Figure 7. Clusters in DTOLD



Source: CNA.
Note: The X and Y axes reflect scaled Gower distance measures.

That said, the "economic and parental stability" cluster also offers more complete data than other clusters. For example, childhood socioeconomic status shows 24 percent missing values in this cluster versus 73 percent missing on average among the other clusters.

As a result, it is possible that environmental/animal rights extremists are not necessarily more likely to be raised by two parents of higher socioeconomic status; rather, these traits may simply be more likely to be reported. Further, this cluster includes offenders from other ideologies, including anti-government extremism, White identity extremism, conspiracy extremism, and other extremism. And environmental/animal rights offenders are spread across all 10 clusters, with only 8 out of the 38 (21 percent) environmental/animal rights extremists in the dataset appearing in this cluster.

Conspiracy theory extremists (e.g., COVID-19, 5G) were more likely to be sorted into the "low issues and crises" ($p < 0.02$), "high issues and crises" ($p < 0.02$), and "diagnosed mental health issues" ($p < 0.01$) clusters (clusters 3, 9, and 10, respectively; see Figure 7). The "low issues and crises" cluster included

6 out of 47 conspiracy extremists (about 13 percent). This cluster shows better mental health and life stability compared to other clusters. More offenders in this cluster were reported to have no employment issues, relationship issues, or legal issues; they also showed no adulthood crisis or interpersonal conflict (40 percent reported to have no crisis versus an average of 7 percent among other clusters; 60 percent reported to have no interpersonal conflict versus an average of 16 percent among other clusters). Offenders in this cluster also demonstrated better mental health overall; 88 percent were reported as having no mental health issues overall (versus 5 percent on average among other clusters), and no offenders in this cluster were coded as having a formal diagnosis from a licensed mental health practitioner. This cluster also included more offenders with no reported history of substance abuse or suicidality (48 percent with no reported history of suicidality versus 7 percent on average among the other clusters).

By contrast, the "diagnosed mental health issues" cluster included slightly more offenders raised by two parents (56 percent versus an average of 31 percent among the other clusters), but was overwhelmingly distinguished by high rates across mental health variables. More offenders in the cluster experienced mental health crises in adulthood (44 percent versus 5 percent on average among the other clusters), were professionally diagnosed with mental health issues (62 percent versus 14 percent on average among the other clusters), or were speculated to have mental health issues by friends and family. A high proportion, relative to the other clusters, reported autism spectrum disorder (18 percent versus an average of 1 percent among the other clusters), delusional disorders (26 percent versus an average of 8 percent among the other clusters), mood disorders (74 percent versus an average of 12 percent among the other clusters), a history of suicidal ideation (56 percent versus an average of 4 percent among the other clusters), or a history of suicidality with unknown timeline (26 percent versus an average of 1 percent among other clusters). The cluster also showed higher levels of compliance with psychotherapy and family support for prescribed psychiatric treatment (41 percent versus an average of 4 percent among other clusters), and it had more complete mental health data overall. That said, only 8 of the 34 offenders in this cluster were conspiracy offenders (slightly less than 25 percent).

Finally, 12 of the 47 conspiracy extremists in the dataset were sorted into the "high issues and crises" cluster. This cluster showed some of the same mental health trends seen in the "diagnosed mental health issues" cluster, including high rates of crises in adulthood as well as adulthood interpersonal conflict issues, employment issues, and legal issues. This cluster also showed high rates of professionally diagnosed mental health issues (65 percent), mental health issues speculated by friends and family (41 percent), and reported delusional disorders (49 percent versus 6 percent on average among other clusters). The rates of medical issues were also higher, with approximately half of the offenders in this cluster reporting some history of medical problems (versus 15 percent on average among other clusters). Conspiracy theory extremists made up about 30 percent of the offenders in this cluster (12 of 37).

Overall, the data suggested three possible clusters of variables, or profiles, for conspiracy theory extremists: "low issues and crises," "diagnosed mental health issues," or "high issues and crises" clusters. But, like environmental/animal rights extremists, conspiracy extremists were spread across all 10 clusters, and no one cluster was composed entirely (or even mostly) of these offenders.

A lengthier description of our data collection and quality control processes can be found in Appendix: Cluster Methodology.

Discussion

Not only did no clear life history profiles emerge from the analysis, but more than half (five of eight) of the ideologies included in this analysis also showed no meaningful relationships with a life history cluster. Of the three ideologies that did show statistically significant relationships with a cluster, none produced a unique ideological profile. Moreover, no ideology fit neatly into a single cluster, and no cluster was ideologically homogenous. Thus, although these clusters may offer possible profiles of conspiracy and environmental/animal rights extremists, they do not represent all possible profiles of these extremists. Furthermore, these results are not causal. An environmental/animal rights extremist is more likely to be sorted into the "economic and parental stability" cluster, and thus more likely to be raised by two married parents of higher socioeconomic status. But having these characteristics does not make an offender more likely to be an environmental extremist; plenty of offenders who were not environmental/animal rights extremists were raised in the middle class by two married parents. The fact that each cluster contained offenders from multiple ideologies underlines this point.

Overall, the data and analysis support—via a new dataset and methodology—the conclusion that there are no profiles or typologies associated with domestic terrorist life histories or ideologies. Groups of offenders in each ideology may share some characteristics (as is the case with environmental/animal rights extremists), but offenders in other ideologies will likely fit those profiles as well. Given the broad skepticism with which DVE typologies and profiles have been approached in recent years, this finding is not particularly surprising. It does raise the question, however, of whether the field has placed a problematic—and perhaps even unjustified—amount of emphasis on both ideology (making the presence of ideology a litmus test for inclusion in DVE databases) and ideological content (consistently classifying and categorizing DVE offenders and attacks by ideology). Other variables (e.g., attack lethality, target type, weapon choice) might have clearer implications for practitioners if they were analyzed against the clusters and if relationships were revealed.

Question 5: Offender typologies

Research question: Are lethal lone actor domestic terrorists more like (a) mass shooters or (b) lethal non-lone domestic terrorists in terms of psychosocial, trauma-related, or life history variables?

This question seeks to determine whether there are meaningful psychosocial, trauma-related, or life history distinctions between lethal lone actor domestic terrorists (i.e., those without co-offenders), mass shooters (from VPPRC's MSD), and lethal non-lone domestic terrorists (i.e., those with co-offenders).

To conduct this analysis, we completed a crosswalk of DTOLD with VPPRC's MSD. For variables coded in both DTOLD and MSD, we made no changes. For example, both databases have a variable for whether the attack included multiple locations (0 = no and 1 = yes). In cases in which the data collected were the same but the numbering was slightly different (e.g., DTOLD's numbering started with 1 and MSD's started with 0), we changed the coding in MSD to match DTOLD. In other cases, a complete recode was necessary. For example, DTOLD had 16 options for coding occupation at the time of attack, and MSD had 3. As these coding schemas were incompatible, we recoded both to reflect either that the offender was working at the time of the attack (1), that the offender was not working (0), or that the data point was not publicly available for that offender (NPA). The combined DTOLD+MSD dataset contained 399

offenders—321 from DTOLD and 78 from MSD. We did not include MSD cases that were outside the date range that was part of DTOLD's inclusion criteria. We also removed duplicates so that offenders in both MSD and DTOLD were not counted twice.

To mitigate some of the challenges associated with decreased media coverage of nonlethal offenders (and because *all* offenders in MSD killed or injured at least four people), we focused our data analysis on the lethal subset of DTOLD+MSD. Doing so reduced the sample to 203 individuals: 125 from DTOLD (78 of whom had co-offenders, and 47 of whom acted alone) and 78 from MSD. In the following paragraphs, we differentiate between lethal lone actors and lethal non-lone actors.

Demographics

Age

There is no statistically significant difference between the average age of mass shooter and lethal lone domestic terrorist populations ($p = 0.158$). In contrast, there is a statistically significant difference between the mean ages of lethal non-lone domestic terrorists and mass shooters. A statistically significant difference also exists between the mean ages of lethal lone and non-lone domestic terrorists ($p < 0.001$). This finding suggests that the age distribution of lethal lone actors is closer to the age distribution of mass shooters than non-lone domestic terrorists.

Sex

We found no significant difference in the sex composition of lethal lone actor, lethal non-lone domestic terrorists, and mass shooters. This finding is unsurprising given that 89 percent of DTOLD offenders and 96 percent of MSD offenders were men.

Mental health

In our analysis, we compared rates of offenders who were coded affirmatively using the mental health composite variable described above. Rates of mental health issues among all lone domestic terrorists were statistically different from both non-lone domestic terrorists and mass shooters ($p < 0.001$). However, *lethal* lone actors had rates of mental health issues that fell between the rates for lethal non-lone domestic terrorists and mass shooters.

Suicidality

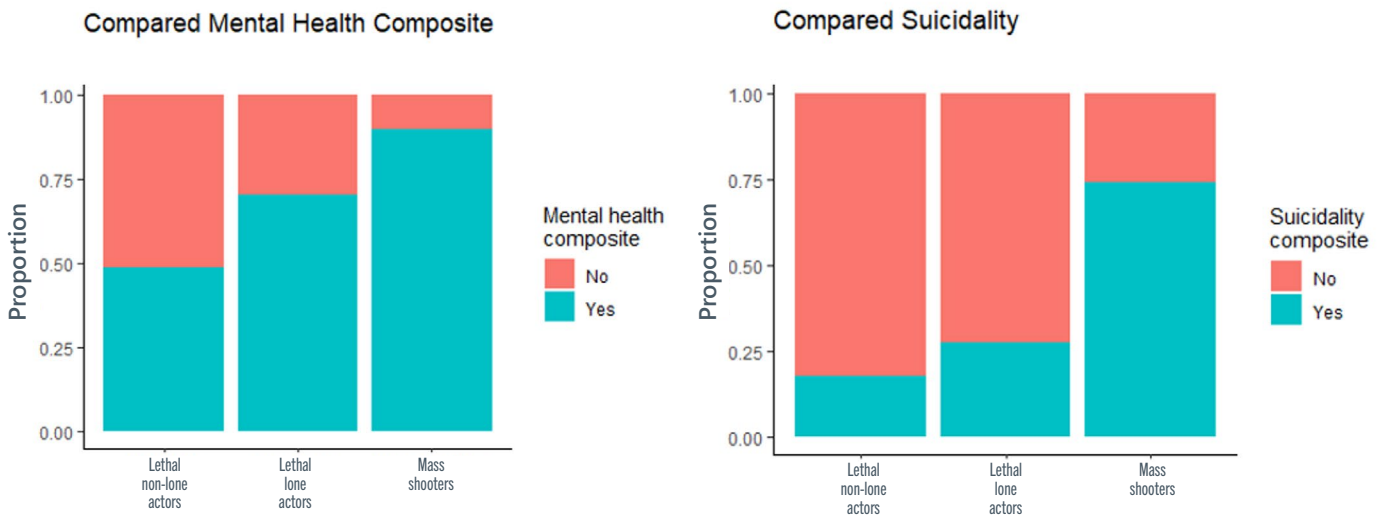
We also compared rates of the suicidality composite among offenders. We found a significant difference between the proportion of suicidal mass shooters versus lethal lone domestic terrorists ($p < 0.001$), but we did not find a significant difference between lethal lone domestic terrorists and lethal non-lone domestic terrorists ($p = 0.262$). This finding suggests that rates of suicidality among lethal lone domestic terrorists are more similar to rates among lethal non-lone domestic terrorists than mass shooters (who show very high rates of suicidality). However, missing data and differences in media coverage may play a role in this result. This is the same conclusion drawn from the analysis that included nonlethal offenders. See Figure 8.

Trauma

Childhood

Approximately 19 percent (15 out of 78) of the affiliated lethal offenders in DTOLD showed one or more reported childhood trauma markers: childhood socioeconomic poverty, mental illness in a member of the household, suicide of a close friend or family member, or childhood abuse or trauma. Comparatively, approximately 35 percent of offenders in MSD (27 out of 78) and 21 percent of lone lethal offenders in DTOLD (10 out of 47) showed one or more of these reported metrics. However, the results overall showed no statistically significant difference between mass shooters, lethal lone domestic terrorists, and lethal non-lone domestic terrorists in terms of childhood trauma. However, the high rate of missing data in the childhood trauma variables in both datasets likely influences these results.

Figure 8. Mental health and suicidality



Source: CNA.

Adult

We compared offenders based on a binary adult trauma variable, which was coded as positive for trauma if the offender had one or more of the following markers: significant relationship, employment, or legal issue(s); interpersonal conflict; adult abuse or trauma; or a crisis more than six months before the attack. We also compared offenders based on the adult trauma composite variable described above (see p. 24). Approximately 45 percent (35 out of 78) of the lethal non-lone offenders in DTOLD showed one or more reported adult trauma markers. Comparatively, approximately 90 percent of offenders in the MSD and 60 percent of lone domestic terrorist offenders in DTOLD (28 out of 47) showed one or more of these reported metrics. In both analyses, lethal lone domestic terrorists were more like lethal non-lone domestic terrorists, but the high rate of missing data remains a concern.

Leakage

Narrow

In terms of leakage narrowly defined—that is, when offenders made some type of warning, threat, announcement, or social media post related to the attack—lethal lone domestic terrorists appear more similar to lethal non-lone domestic terrorists. There is no statistically significant difference between the leakage proportions of lethal non-lone domestic terrorists and mass shooters.

Broad

We compared offender leakage using the broad definition as applied to DTOLD+MSD: some type of warning, threat, announcement, or social media post related to the attack; a notable interest in firearms; or a notable interest in mass violence. Approximately 54 percent of the lethal non-lone offenders in DTOLD (42 of 78) "leaked" under the broad definition, compared with 71 percent (55 of 78) of the mass shooters in MSD. In addition, 43 percent of lethal lone domestic terrorists (20 of 47) leaked under this definition. In this case, again with the caveat of missing data, lethal lone domestic terrorist offenders showed lower rates of leakage than either mass shooters or lethal non-lone domestic terrorist offenders. Interestingly, this finding suggests there is no statistically significant difference between leakage rates between mass shooters and lethal non-lone offenders ($p = 0.047$). See Figure 9.

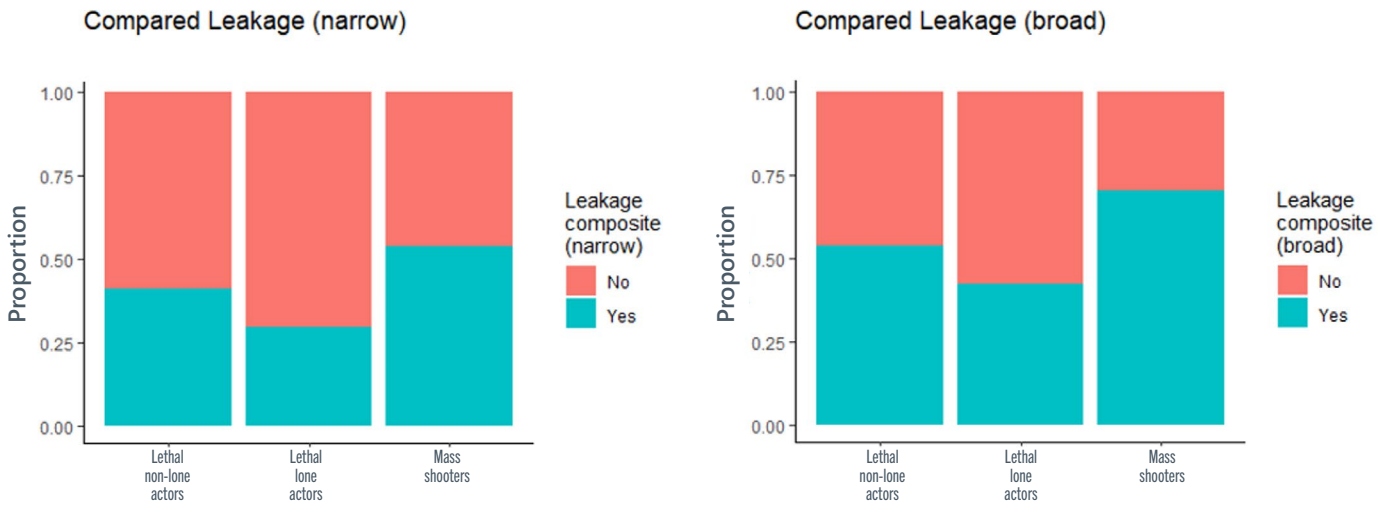
Discussion

The picture that emerges from this analysis is messy. Lethal lone domestic terrorists are more like mass shooters in terms of age, but they are more like lethal non-lone domestic terrorists in terms of suicidality, adult trauma, and narrow leakage. They fall between the two in terms of having mental health issues, and they are distinct from the two insofar as they leak broadly at lower rates than either lethal non-lone domestic terrorists or mass shooters. In addition, the three groups are indistinct from one another in terms of rates of sexual or childhood trauma. See Figure 10.

That said, it is important to note that mass shooters are on average more lethal than domestic terrorists given that, by definition, they have killed at least four people. By contrast, the average lethality for a lone and group offender in DTOLD was 0.79 and 0.17 respectively. Because only 13 domestic terrorists in DTOLD killed four or more people, analysis of this cohort is impossible.

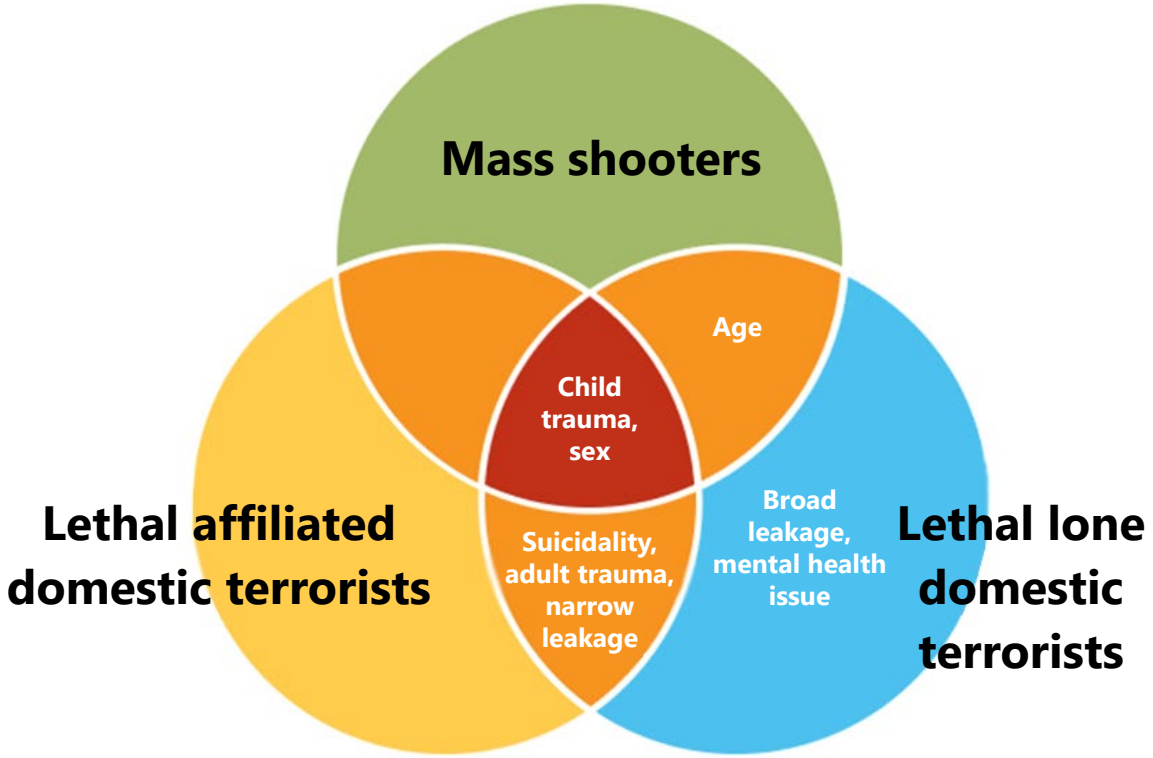
The boundaries between these categories of violent offenders have grown increasingly porous in recent years, as an increasing number of attackers are motivated by a blend of ideological elements and personal grievances that blur the distinction between domestic terrorists and mass shooters. In particular, the notion of nihilistic violent extremism appears to at least partially collapse the traditional distinctions between these cohorts. As a result, the question of whether and how these populations differ is taking on increased urgency. In this preliminary work, we found no simple answer to this question: the three groups are neither fully the same nor fully distinct from one another.

Figure 9. Leakage (narrow and broad) by offender type



Source: CNA.

Figure 10. Lethal lone actors, lethal affiliated actors, and mass shooters



Source: CNA.

Implications and applicability of research

This project was designed to fill a gap in existing knowledge of domestic terrorist offenders. The need for such a database is particularly acute because scholars are increasingly seeking to apply criminological theories to the study of domestic terrorism (Pyrooz et al., 2017; Becker et al., 2020). Criminologists have long endeavored to bring together the rigor of variable-based research and the qualitative insights derived from the study of individual criminal pathways (Corner, Bouhana, & Gill, 2019). While acknowledging the heterogeneity of both routine and terroristic violent offenders, a criminological perspective allows researchers to place terrorism within a wider realm of criminal behavior through such approaches as life-course criminality (Simi et al., 2016). These approaches address the field's concern about the "weak" nature of analysis by exploring the "links between terrorism studies and other fields of violence studies…despite the fact that they share certain common characteristics" (Schmid & Forest, 2018).

DTOLD seeks to facilitate empirical analysis of offender-level life history variables, making it possible to engage in the type of criminological research that has relevance for the domestic terrorist population and to analyze the relationship between life trajectories (psychosocial, trauma-related, and

life history variables), terrorist ideologies, and event outcomes such as attack lethality. To this end, DTOLD was constructed to facilitate analysis across datasets. Accordingly, it includes GTD and VPPRC's MSD IDs when applicable and uses a coding schema similar to those in PIRUS and VPPRC's MSD when possible. In addition, DTOLD includes several new composite variables that attempt to operationalize theories (e.g., continuum of loneness, narrow versus broad leakage) and capture the nuances of lived experience (e.g., mental health issue).

Beyond the creation of the dataset, this project was designed to use aggregated life history data to weigh in on several critical issues within terrorism studies. In several instances, we were able to confirm—via a different dataset or a different methodology—a finding that already existed:

- A significant relationship exists between affiliation and lethality,
- a significant relationship exists between affiliation and mental health issue,
- far-right domestic terrorists are the most lethal cohort active in the US today,
- there are no unique life history profiles,
- a significant relationship exists between affiliation and target type, and
- evidence shows that there are no profiles at the intersection of life histories and ideologies.

In other cases, we produced results that were messy and raised more questions than they answered:

- There is no significant relationship between specific ideologies and lethality, but there is a significant relationship between attack type and specific ideologies, and
- lethal lone actor domestic terrorists, lethal non-lone domestic terrorists, and mass shooters are similar to and different from one another in distinct ways.

Finally, in a few instances, we have contributed something new to the field:

- Validation that Borum et al.'s concept of a continuum of loneness is consistent with the data,
- evidence that offenders with mental health issues commit more very-lethal attacks and attacks that are comparatively more lethal than those without mental health issues,
- data showing that domestic terrorists in general may be more suicidal than the general population, but that they are less suicidal than mass shooters when domestic terrorists kill four or more people (the fatality requirement to qualify as a mass shooter),
- a finding that over 60 percent of the domestic terrorists included in the dataset had contact with a system stakeholder (e.g., law enforcement officials, mental health providers, education professionals) before committing an act of domestic terrorism,
- evidence of a positive correlation between affiliation and leakage,
- data suggesting statistically significant differences in both narrow and broad leakage rates across ideological groups, and
- a positive relationship between both narrow and broad leakage and suicidality, such that the odds are higher that suicidal offenders will leak details related to their plans.

These findings have clear implications for both researchers and practitioners. For researchers, our findings suggest the binary distinction between lone and group actors often employed in the literature may have limited utility. However, the approach adopted in this paper is imperfect in that it leveraged data collected to answer other loosely related research questions, so future work is necessary to confirm these findings and add further nuance to this issue.

Our findings also lead us to question the persistence of ideologically based taxonomies. In particular, the data suggest these distinctions are not particularly meaningful regarding offender life histories and attack outcomes. Moreover, as the lines between ideologies and offender types are increasingly blurry, researchers should carefully consider what type of categorization is best to ensure quality data and actionable findings.

Finally, the existence of a cohort within the dataset (and thus within the GTD) that has no clear ideological agenda, and the finding of similarity between mass shooters and different types of domestic terrorists, suggest that the boundaries between different types of violent extremist actors—domestic terrorists, mass shooters, school shooters, etc.—may be quite porous. Additional research is needed, however, to identify the implications of collapsing or combining some of these cohorts.

For practitioners, our findings highlight opportunities for law enforcement, mental health, and education professionals to improve efforts to identify at-risk individuals and intervene before violence occurs. Improving training for and communication between professionals who may encounter at-risk individuals may help improve detection of these individuals. In addition, the finding of a correlation between suicidality and lethality merits further analysis but has immediate implications for both threat assessment and risk assessment efforts. Finally, given that there are some similarities between the life histories of domestic terrorists and mass shooters, it is worth examining which interventions could be effective at preventing violence by both types of offenders.

Artifacts

Dataset

DTOLD is divided into the following sections:

1. **Record identifiers.** This section is primarily administrative; these variables identify the individual and connect them internally in DTOLD and in other databases. The variables include the offender's MSD and GTD ID numbers, DTOLD offender ID, and any co-offenders' DTOLD IDs.

2. **Relevant dates.** This section captures details pertaining to the dates of the attack(s). The recorded variables are the full date of attack and full date of arrest.

3. **Type of attack.** This section contains details pertaining to the acts and targets of the attack, along with the intentions of the individual who carried out the attack. It records the type of attack(s) perpetrated (e.g., hijacking, bombing or explosion, armed assault), the primary target, the number of individuals killed and injured, the estimated property damage, and the perpetrator's expected outcome of the attack (e.g., arrest, escape).

4. **Location of attack.** This section includes information on the location(s) of the attack. These details include the area category (e.g., urban, suburban, or rural), region, state, city, and type. This section also contains information about the attacker's relationship with the location(s).

5. **Weapons and methods.** This section captures details pertaining to the planning, weapons, and consequences related to the attack. These details include whether the perpetrator planned the attack (rather than committed a spontaneous act of violence), the primary and secondary weapons used to commit the attack, the source of firearms (if firearms were used), and the outcome of the attack for the perpetrator (e.g., if they were arrested or killed).

6. **Offender demographics at time of attack.** This section contains demographic information on the individual who carried out the attack, including age, occupation, cultural background, and family status. It captures basic census-style variables, including age at the time of attack, race, residency status, native country, immigration generation, education, relationship status, parental status, and occupation. This section also captures details about the offender's religious practice and work history. Finally, it includes variables related to the offender's law enforcement and military background (if applicable).

7. **Life history variables, childhood.** This section captures details about the offender's childhood life history variables. These variables relate to their childhood socioeconomic status, their parents' marital status, who raised them (e.g., two parents, single parent), whether there was domestic violence or alcoholism/substance abuse in their home growing up, and whether they experienced physical, sexual, or emotional abuse (or neglect) as a child. Most variables in this section are intended to capture whether the offender experienced ACEs, such as experiencing violence, abuse, or neglect; having a family member attempt or die by suicide; or growing up in a household with instability due to parental separation.

8. **Life history variables, adulthood**. This section contains information about the offender's adulthood life history variables. These are similar to, but differ slightly from, the variables collected in the childhood life history variables section. The data points in this section are the offender's adult socioeconomic status; a significant relationship, employment, or legal issue; significant interpersonal conflict; physical, sexual, or emotional abuse as an adult; and a crisis more than six months before the attack.

9. **Health and mental health.** This section records data pertaining to the individual's physical and mental health, psychological state, mental health treatment, and drug and alcohol abuse leading up to and during the attack. It documents whether the offender was offered psychotherapy or prescribed psychiatric medication within a year of the attack, whether their family was supportive of the prescribed treatment, and whether they exhibited any destructive behaviors. It also contains variables related to suicidality and whether they exhibited signs of psychosis at the time of the attack.

10. **Previous crime and violence.** This section includes information on the offender's history of criminal and violent behavior and past time incarcerated. Variables related to criminal behavior include whether the offender had a criminal record or history of police contact, a conviction leading to imprisonment, or a gang or militia affiliation. Information on violent behavior in this section includes previous homicide(s), a history of violence unrelated to the individual's criminal record, perpetration of bullying or domestic violence, perpetration of sexual abuse, or abuse of animals. This section also includes data on past solitary confinement or known affiliation with a prison gang.

11. **Pathway toward radicalization.** The variables in this section capture details about how an individual was radicalized, came to support extremist and radical views, and began to view violence as a desirable and legitimate means of action. These details include the individual's age at initial interest in the extremist ideology, whether the individual had family or friends with radical beliefs or criminal histories, their sources of initial and ongoing exposure to extremist content, and any connection to fiction or popular culture (e.g., the attack was inspired by *The Turner Diaries*). It also includes details about their potential recruitment by and interaction with members of violent extremist groups such as any direct communication with a member of such a group, training by an extremist group, or known role in an extremist group.

12. **Grievance and motivation.** This section contains information about the individual's ideology as well as the ideology and specific grievances or motivations behind the attack (e.g., fame-seeking, afterlife reward-seeking). It differentiates between the individual's professed ideology and the ideological elements present in the attack.

13. **Social contagion and warning signs.** The variables in this section capture details about warning signs ahead of the attack, including explicit warnings or threats and other implicit behavioral indicators (e.g., slipping grades, a crisis within six months of the attack, and social media use related to the attack). Specifically, this section documents the individual's use of extremist symbols, whether the individual's weapons were confiscated, whether they had been reported for concerning behavior, whether they issued a warning or threat before the attack, and whether they were active on social media. Other data in this section pertain to the individual's notable

or obsessive interest (if applicable) in firearms, mass violence, vigilante organizations, or other extremist individuals.

Dissemination activities

The results for this project have been disseminated to academics via an (under review) academic article and a conference presentation:

- McBride, M., Strayer, M., Hagy, L., Haney, K., Jenkins, M., Plapinger, S., Xu, A., & Stern, J. *Introducing the domestic terrorism offender-level database (DTOLD): Psychosocial and life history data on US domestic terrorists, 2001–2020*. Under review.
- McBride, M., & Jenkins, M. (2024, November 13–16). *DTOLD: Leveraging data on domestic terrorist actor life histories to improve P/CVE efforts* [Conference presentation]. 2024 ASC Annual Meeting, San Francisco, CA, United States.

In addition, CNA shared findings with stakeholders via a conference presentation and a series of short practitioner-focused papers. The short paper series (which was an addition to the project) radically closed the gap between research and practice by delivering findings to practitioners on a timeline far shorter than that of the academic publication cycle. The series packaged our findings in three- to four-page papers written specifically for practitioners.

- McBride, M., & Strayer, M. (2024, July 23–25). *DTOLD: Leveraging data on domestic terrorist actor life histories to improve P/CVE efforts* [Conference presentation]. 2024 Homeland Security Conference, Miami Beach, FL, United States.
- McBride, M., Haney, K., Strayer, M., & Stern, J. (2024). *Suicidality among domestic terrorists*. CNA. https://www.cna.org/reports/2024/05/suicidality-among-domestic-terrorists
- McBride, M., & Jenkins, M. (2024). *Domestic terrorists' contact with system stakeholders before attacks*. CNA. https://www.cna.org/reports/2024/08/domestic-terrorists-contact-with-system-stakeholders-before-attacks
- McBride, M., & Hagy, L. (2024). *The challenge of detecting ideologically unattached terrorists*. CNA. https://www.cna.org/quick-looks/2024/10/The-Challenge-of-Detecting-Ideologically-Unattached-Terrorists.pdf

Appendix: Cluster Methodology

Data analysis

Through this cluster analysis, we explored which life history variables (e.g., mental health history, childhood life history, adult life history) tend to occur together and then tested the relationship between these clusters and offender ideology. We used Gower distance and silhouette width to cluster mixed data types. The Gower method calculates how similar two offenders are to each other by noting the places their answers match and diverge. Gower calculates this similarity as a distance, measured between 0 and 1. These distances are then plotted on a graph and used to sort offenders into groups, called similarity clusters, using a clustering method called partitioning around medoids (Ahsanul Islam, 2023a).

Silhouette width is used to determine how many clusters the data should be sorted into. Average silhouette width (ASW) is used to select the optimal number of clusters for the dataset (Ahsanul Islam, 2023b). ASW measures the distance between a data point and the other points in its cluster and compares it with the distance to points in other clusters. In this case, 10 clusters provided the best silhouette width without overfitting.

We compared clusters against the eight ideologies with more than 30 offenders in the DTOLD dataset ($n > 30$). To examine the relationship between clusters and ideology, we used a series of multinomial logistic regressions. These regressions asked the question, were offenders with specific ideologies more likely to be sorted into certain clusters? Very high or very low likelihoods suggest potential relationships. Unremarkable (i.e., statistically insignificant) likelihoods suggest no relationship. For example, if no cluster is more or less likely to include Second Amendment offenders than any other cluster, the data would not support the existence of a Second Amendment extremist "profile" within the life history variables.

Limitations

Of course, this analytic approach has limitations. We chose 10 clusters to minimize outliers without overfitting, but selecting a different number of clusters would yield variations in profiles. Similarly, clustering algorithms become more complex, difficult to run, and difficult to interpret as more dimensions are added. In our analysis, we focused on the variables that make DTOLD unique: childhood life histories, adult life histories, and mental health. The same method could be used with other variables (such as criminal history, demographics, or pathway to radicalization) to explore potential profiles across different areas.

Our analysis also hinged on the number of variables in DTOLD, the complexity of the data, the method of data collection, and the amount of missing data. Missing data influenced the distance calculations and the clustering algorithm. This is a feature, not a bug—our analysis was designed to account for whether two offenders had missing data in the same places or in different places. However, the cluster analysis would therefore be subject to the same media and coverage biases present in the overall dataset.

Data complexity was an important challenge in this analysis. DTOLD is built to be easily readable. As a result, some columns contain overlapping values, which can prove challenging for certain kinds of analysis. For example, offenders in DTOLD are coded

for every relevant ideology (e.g., a White identity offender with xenophobic and anti-LGBTQ+ views is coded as White identity, xenophobic/anti-immigrant, and anti-LGBTQ+), which causes significant overlap. This overlap complicates any ideology-based analysis performed on the DTOLD dataset. Our analysis used one hot encoding and asymmetric variable coding to navigate this issue and make results more representative. This method translated ideology into a series of binary columns (e.g., conspiracy theory extremist [Y/N], anti-government extremist [Y/N]), and weighted yes answers as more important than no answers. The Gower method is flexible enough to handle this level of data complexity.

However, the Gower method also has drawbacks. Gower distance is sensitive to outliers and requires a thorough understanding of the data and all variables. It performs best with clean, straightforward data (Szeppannek et al., 2024). Our team invested significant time and expertise into weighting, cleaning, and parsing the data to produce clear and representative clusters.

Figures

Tables

Abbreviations

ACE	adverse childhood experience
DHS	Department of Homeland Security
DTOLD	Domestic Terrorism Offender-Level Database
DVE	domestic violent extremist
ELF	Earth Liberation Front
FBI	Federal Bureau of Investigation
FY	fiscal year
GTD	Global Terrorism Database
LH-A	Adulthood Life History Variables
MSD	Mass Shooter Database
N/A	not applicable
NDAA	National Defense Authorization Act
NPA	not publicly available
PIRUS	Profiles of Individual Radicalization in the United States
SES	socioeconomic status
START	National Consortium for the Study of Terrorism and Responses to Terrorism
UCR	Uniform Crime Report
VPPRC	Violence Prevention Project Research Center

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