Received: 12 April 2019 | Revised: 12 June 2019 | Accepted: 3 July 2019

DOI: 10.1002/bsl.2434

SPECIAL ISSUE ARTICLE

WILEY

Visualizing the relationship among indicators for lone actor terrorist attacks: Multidimensional scaling and the TRAP-18

Alasdair Goodwill[1] | **J. Reid Meloy**[2]

[1]Ryerson University, Toronto, ON, Canada

[2]University of California, San Diego, CA, USA

Correspondence
Reid Meloy, Department of Psychiatry, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093
Email:reidmeloy@gmail.com

This validation study analyses data from a sample of North American terrorist attackers (n = 33) and non-attackers (n = 23) through the lens of the Terrorist Radicalization Assessment Protocol (TRAP-18; Meloy, 2017) utilizing a multivariate statistical approach – multidimensional scaling – to visualize potential clustering (co-occurrence) of risk factors. Rarely done in terrorism research, the results plotted in two-dimensional space show the clustering and co-occurrence of most of the eight proximal warning behaviors among the attackers, but not among the non-attackers, and less of a clustering and association of distal characteristics, but their presence in both attackers and non-attackers. These findings provide further empirical support for the rational-theoretical model of the TRAP-18, a structured professional judgment instrument for threat assessment of lone actor terrorists. It advances the quantitative analysis of operationally relevant and behaviorally observable indicators for use by law enforcement and counterterrorism professionals and their consultants. Findings are discussed in relation to other research on pre-offense behaviors of lone actor terrorists, and recommendations are made for both operational use and further research.

1 | INTRODUCTION

Multiple or mass homicide, the preferred result of most terrorist attackers, is a baffling and frightening phenomenon which is both infrequent and tenaciously present in recorded human history. The movement from extremist beliefs

(Berger, 2018) to violent action on behalf of such beliefs (Meloy, Hempel, Mohandie, & Shiva, 2001) is likewise often nuanced and unpredictable, leaving counterterrorism professionals tasked with preventing such acts awash in false-positives and seeking help from behavioral science. Fortunately, there has been progress in recent years.

Retrospective studies of terrorists, those who commit acts of politically motivated violence against non-combatants, have moved from theoretical attempts to develop a "profile" of a terrorist to the empirical analysis of datasets of such individuals, ranging from those embedded in groups (Sageman, 2004) to lone actors (Gill, 2015). Likewise, uncontrolled descriptive studies of terrorists have yielded to comparative studies, such as ideologically motivated versus non-ideological mass murderers (Horgan, Gill, Bouhana, Silver, & Corner, 2016); individual terrorists versus autonomous cells in Europe (Meloy, Roshdi, et al., 2015); jihadist versus single-issue versus right wing terrorists (Gill, Horgan, & Deckert, 2013); terrorists versus murderers in Iraq (Dhumad, Candilis, Cleary, Dyer, & Khalifa, 2019); and violent versus non-violent extremists in the UK (Knight, Woodward, & Lancaster, 2017). These efforts have all contributed to the disaggregation of the meaning of "terrorist" and "terrorism" (Desmarais, Simons-Rudolph, Brugh, Schilling, & Hoggan, 2017) and the recognition that differences in static (e.g., age, education, history of criminality) and dynamic (e.g., roles, pre-offense behaviors) characteristics yield more operationally relevant data (Borum, 2015) and help to bridge the gap between academia and pragmatic efforts at prevention.

However, a greater specificity in describing mostly static variables, even those gleaned from comparative studies, does not necessarily indicate correlates of risk for committing a terrorist act, and they fall short of predictors of risk of violence (Kraemer et al., 1999) without predictive or postdictive studies (Monahan, 2012, 2016).

Accurately predicting the risk of an individual committing an act of terrorist violence is likely to be impossible due to the low base rate for such acts; however, prevention is attainable if the focus is upon fact-based behaviors, and threat management is employed to mitigate such behaviors of concern (Meloy & Hoffmann, 2014). Borum (2015) noted four elements for the development of an operationally relevant scheme for terrorism-related threat assessment:[2] (a) broadly conceiving risk factors from both an idiographic and nomothetic perspective; (b) emphasizing prevention/management of risk rather than prediction; (c) being open to different pathways and different roles in terrorism (e.g., violent actor or supporter) for a person of concern (Horgan, Shortland, & Abbasciano, 2018); and (d) recognizing that large group factors (such as age and education) may or may not apply to the individual case. The key is to identify those risk factors that co-occur and distinguish those who commit a terrorist act from the many who may be radicalized to a particular cause, and even support or facilitate such a cause (Horgan et al., 2018), but pose no risk of violence.

Advances in the risk or threat assessment of terrorist violence have yielded six recognized instruments for the use of professionals in the field: The Extremism Risk Guide (ERG 22+), Islamic Radicalization (IR-46), Identifying Vulnerable People (IVP), Multi-Level Guidelines (MLG Version 2), Terrorist Radicalization Assessment Protocol (TRAP-18), and the Violent Extremism Risk Assessment (VERA Version 2 Revised) (Lloyd, 2019). All of these instruments are in various stages of testing for their reliability and validity, and will not be reviewed here. This study focuses on the analysis of data on a sample of North American terrorist attackers and non-attackers through the lens of the TRAP-18 (Meloy, 2017), utilizing a multivariate statistical approach – multidimensional scaling (MDS) – to visualize potential clustering (co-occurrence) of TRAP-18 risk factors. This approach was utilized to advance the quantitative analysis of operationally relevant and behaviorally observable indicators for use by law enforcement and counterterrorism professionals and their consultants.

The use of MDS in investigative psychology has had widespread success in various areas of criminal behavioral research, including arson (Canter & Heritage, 1990; Häkkänen, Puolakka, & Santtila, 2004), homicide (Salfati, 2000; Salfati & Bateman, 2005; Trojan & Salfati, 2010), sexual assault (Canter, Bennell, Alison, & Reddy, 2003; Canter & Fritzon, 1998; Canter & Wentink, 2004; Häkkänen, Lindlöf, & Santtila, 2004; Santtila, Junkkila, & Sandnabba, 2005), robbery (Goodwill, Stephens, Oziel, Yapp, & Bowes, 2012), burglary (Kocsis, Cooksey, & Irwin, 2002), and sexual offending among youth (Almond, Canter, & Salfati, 2006). To our knowledge such an analysis has rarely been applied to terrorists and their behaviors (Horgan et al., 2018), and this is the first attempt to use MDS in the threat assessment of terrorism.

Multidimensional scaling is a visually based statistical analysis that represents associations between variables as distance in dimensional space (Schiffman, Reynolds, & Young, 1981). Nonmetric MDS analysis works by first configuring a similarity matrix between the variables based upon a measure of association; the most common in criminal behavioral research utilizing police data is the Jaccard coefficient (Goodwill, Alison, & Humann, 2009; Jaccard, 1908). The Jaccard coefficient has been argued to be the most suitable measure of association to implement when analyzing police (and other third party and observational) databases due to the inherent "messiness" of the data . Specifically, with data derived from interview and observational records, as much police and terrorism-related data are, there is relatively accurate information on what has occurred; however, there is often less reliable information on what has not occurred (and/or has not been recorded, or indeed mentioned, in file material or information provided by witnesses, suspects or third parties). As such, the Jaccard coefficient is appropriate in these cases, as the strength of the relationship between two variables is not increased by mutual non-occurrence of two variables. In other words, when it is evident that the two behaviors have both occurred, the coefficient increases, whereas it decreases if one has occurred and the other has not; and finally the association between the two variables is unaffected in situations where neither has occurred (or been recorded to have occurred).

In MDS, the associations between the variables are represented in *n*-dimensional Euclidian space by the distances between them; a shorter distance signifies a stronger relationship (i.e., high Jaccard coefficients) between the two variables being examined (Borg & Shye, 1995). Of equal significance are the variables that are located furthest apart from each other, as these variables are not likely to co-occur during the offense (i.e., low Jaccard coefficients). Interpretation of the MDS is made by identifying clustering or grouping of variables in the Euclidian space and formulating, typically based on *a priori* hypotheses, latent behavioral themes and/or dimensions.

There have been several methods proposed to interpret MDS plots for underlying latent dimensions (Goodwill et al., 2012, 2013), the most common of which is to use axial or radial "boundaries" to separate and identify localized clusters of behavioral variables in the MDS plot. However, as Shye, Elizur, and Hoffman (1994) point out, MDS boundaries should not be interpreted as distinct and precise in that they beget definitive types, but instead as nominal "fuzzy boundaries" between areas of item relatedness and/or behavioral themes.

Ultimately, the MDS output provides the basis for investigating the underlying latent dimensions of a number of behavioral variables simultaneously. This investigation can lead to a greater understanding of how a set of items are interrelated, and lead investigators to draw further, possibly unique, inferences based on the themes, clusters or groupings of behaviors produced under the MDS analysis. Although this is useful information in itself, the analysis provides information on an aggregate data level, generalizing the behavioral themes across all offenses (cases) under analysis. Investigators interested in utilizing MDS for specific case analysis must further assess how a particular offense fits (or not) under the latent dimension(s) or theme(s) inferred from the aggregate MDS output.

One approach for investigating the case-specific level of MDS results is to use a "centroid" or "pinpoint" average of the behaviors that have occurred in that offense (Goodwill et al., 2012). Variables entered into the MDS analysis will be plotted in *n*-dimensional space (e.g., variables will be plotted on *x* and *y* axes for a two-dimensional solution, across *x*, *y* and *z* for a three-dimensional solution, etc.) by the strength of their co-occurrence (Jaccard association) with one another. The centroid delineates the average (*x*, *y*) coordinate of all the variables' (*x*, *y*) coordinates that are present in a particular offense, for a two-dimensional MDS solution. The location of this single point (i.e., the offense "centroid") within the MDS plot is thus an aggregation of a single offender's offense behaviors, and, as such, it can be used to associate that offense to one theme or another.

2 | METHOD

2.1 | Sample

The sample for this study has been previously analyzed in Meloy et al. (2019) using univariate methods to determine whether or not terrorist attackers were significantly different from persons of national security concern who did not

mount a terrorist attack. The terrorist attack sample was composed of 33 lone actor terrorists – subjects who committed a politically motivated lethal or near-lethal attack against noncombatants in North America between 1993 and 2015. Most subjects within the sample had committed an act of ideologically motivated violence in which at least one person other than the terrorist was killed, and none were under the command and control of an organized terrorist group. There were 16 extreme right wing, eight single-issue (usually anti-abortion), and nine jihadist attackers. In one case, both subjects were members of the same autonomous terrorist cell. In three other cases, the subjects were one member of a two-member cell composed of a younger brother, a girlfriend, and an "adopted" son, respectively. This was a nonrandom sample of convenience, and cases were selected that were within the Global Terrorism Database managed by the University of Maryland National Consortium (National Consortium, 2018) and known to the authors, as well as new cases which occurred during the course of this study (2014–2018). Cases were included if there were sufficient open source data to code the TRAP-18 variables as either present or absent. All cases are listed by name in Meloy et al. (2019). TRAP-18 indicators were coded by those who were trained on the instrument by the second author (JRM), either in person or through online training available at gifrinc.com. In many cases, primary source material was located through Internet searches, and included criminal investigative reports, trial transcripts, psychiatric and psychological reports, and post-conviction published studies of the terrorist attackers. However, it is important to note that due to the retrospective nature of the data collection, the time when an indicator may have presented itself in the attackers' or non-attackers' progression was not available to the coders and hence the sequence of when indicators first came to attention or developed in the individual could not be analyzed.

JRM consulted with the defense, prosecution, or law enforcement in five of the attack cases; and in several other additional cases, the TRAP-18 was coded by the actual investigator on the case, who, post-resolution, provided case data to the research team. JRM worked with Ms. Jacqueline Genzman in the coding of the rest of the terrorist attackers, and any questions were resolved through analysis of each subject's behavioral patterns, and their goodness of fit with the 18 indicator descriptions in the manual (Meloy, 2017) until consensus was reached.

The no-attack sample was a nonrandom sample of convenience comprising 23 subjects selected from the caseloads of two major metropolitan law enforcement and mental health agencies, one in Canada (n = 10, the no-intent cases) and one in the United States (n = 13, the risk-managed cases) between 2012 and 2016. The Canadian sample was coded by Detective Gwyn Amat and Dr. Melinda Morgan, and consensus was reached on each of the indicators through the same procedure noted earlier. The United States sample was coded by JRM and Dr. Maria Martinez, and consensus was reached on each of the indicators. The two metropolitan samples were composed of subjects who came to the attention of law enforcement and/or mental health and were deemed of sufficient concern to be investigated as a terrorist threat. Upon investigation it was determined that there was no intent, or the case needed to be actively risk-managed. All cases were successfully risk-managed for at least a 3-year period[3] or remained closed without incident during this study. Closed meant that there was no further investigation of the subject, and the same subject did not commit a subsequent act of terrorism. Risk management included a range of responses: face-to-face threat assessment; collateral interviews with family members, peers, or school personnel; review of records (employment, military, driving, criminal, residence, police incidents); civil commitment, release, and discharge planning; safety plan development for school, work, home, and the community at large; social media monitoring; obtaining signed consents to communicate with the subject's psychotherapist, psychiatrist, or case manager to monitor progress in treatment; ensuring compliance with interventions or recommendations established during suspension, expulsion, or work termination; and/or maintaining the case as an open file, usually indefinitely. In two of the comparison cases there was arrest and prosecution. In at least three other cases, there had been arrest, prosecution, and time served in custody before return to the community and CVE (countering violent extremism) involvement. In one case the subject committed suicide. In all other cases, the subjects remained in the metropolitan jurisdiction of the investigators. Examples of the behaviors of concern in the comparison sample are detailed in Meloy et al. (2019). Cases were only included if there were sufficient data to code all of the TRAP-18 indicators.

All the attackers were male, and the average age was 39 years old (SD = 15.8, range 15–88). Their weapons of choice were firearms (n = 26), either explosive or incendiary devices (n = 4), automobiles (n = 2), an airplane (n = 1),

and fake anthrax (n = 1).[4] The number of people killed ranged from 0 to 168. Only three cases resulted in no deaths. The attacks occurred across the United States (n = 31) and Canada (n = 2). Fifty-eight per cent targeted individuals with a different ethnicity than their own.

The demographic variables between the attackers and the comparisons showed similarities and some significant differences. The groups were not matched on any dependent variables. Both groups were virtually all males, with only one female across the total sample. The mean age of the groups, however, was significantly different. The average age of the attackers was 39 years and that of non-attackers was 27 years (SD = 11, range 15–58), with a total mean age across the groups of 34 years.

Thirty-six per cent of the attackers were single (36%) versus 64% of the non-attackers, resulting in a significant difference with a large effect size (φ = 0.53). Fifty-three per cent of the attackers were unemployed or underemployed, while 47% of the non-attackers were unemployed. Forty-six per cent of the attackers had no biological children, while 54% of the non-attackers were childless. Half the attackers (47%) had attended some college, a comparable figure to the non-attackers (52%), but overall education was significantly greater among the attackers (φ = 0.54). Further demographic information and comparisons are available in Meloy et al. (2019).

The US sample included 31 (70.5%) attackers and 13 (29.5%) non-attackers, while the Canadian sample included 2 (16.7%) attackers and 10 (83.3%) non-attackers. In terms of the overall combined sample, 31 of the 33 (93.9%) attacks were on US soil, and 13 out of 23 (56.5%) non-attackers were from the US, with the remainder of the sample from Canadian jurisdictions.

2.2 | Measurement instrument

The TRAP-18 is a structured professional judgment instrument composed of eight proximal warning behaviors and 10 distal characteristics (Meloy, 2017), as listed in Box 1. Each indicator is coded as present, absent, or unknown (insufficient data to code).

The TRAP-18 was originally proposed as a rational-theoretical model to help counter-terrorism professionals prioritize cases for investigation. The proximal warning behaviors (Meloy, Hoffmann, Guldimann, & James, 2011) were combined with proposed distal characteristics (Meloy & Yakeley, 2014) to construct the instrument (Meloy, 2017). Since its introduction in Meloy, Roshdi, et al., (2015), its psychometric properties have been studied in a variety of nomothetic and idiographic studies (see Meloy, 2018b for a detailed history of its origins and development).

The instrument has been shown to have excellent interrater reliability (Challacombe & Lucas, 2018; Meloy, Roshdi,, et al., 2015) and criterion validity on samples of individual terrorists and autonomous terrorist cells (Meloy & Gill, 2016; Meloy, Roshdi, et al., 2015). Its growing construct validity has been extended through its operational usefulness in the retrospective analysis of a number of individual cases of lone actor terrorism (Bockler, Hoffmann, & Meloy, 2017; Bockler, Hoffmann, & Zick, 2015; Erlandsson & Meloy, 2018; Meloy & Genzman, 2016; Meloy, Habermeyer, & Guldimann, 2015). The warning behaviors – the first eight indicators in the TRAP-18 – have been shown to have discriminant validity with medium to large effect sizes in separating school attackers from other subjects of concern with no intent to attack (Meloy, Hoffmann, Roshdi, & Guldimann, 2014), and the TRAP-18 *in toto* was successful in postdicting violence with 76% accuracy within a sample of Sovereign Citizens, an extreme right wing group in the US (Challacombe & Lucas, 2018). Further discriminant validity was demonstrated in Meloy et al. (2019), which found that 10 TRAP-18 indicators were significantly different, with medium to large effect sizes, between attackers and the non-attackers. Garcia-Andrade et al. (2019) found high predictive validity when the TRAP-18 was used to predict future violent incidents of an extremist nature in a sample of severely mentally ill patients. The indicators are further discussed in a number of publications (Meloy et al., 2011; Meloy & Gill, 2016; Meloy, Mohandie, et al., 2015; Meloy & Yakeley, 2014) and in the TRAP-18 *User's Manual* (Meloy, 2017).

BOX 1 Proximal warning behaviors and distal characteristics of the Terrorist Radicalization Assessment Protocol (TRAP-18; Meloy, 2017). Definitions are abbreviated and should not be used as the basis for threat assessment without training and use of the manual (gifrinc.com).

Proximal warning behaviors

1 *Pathway* warning behavior is research, planning, preparation or implementation of an attack.
2 *Fixation*[16] warning behavior indicates an increasingly pathological preoccupation with a person or a cause, accompanied by a deterioration in social and occupational life.
3 *Identification* warning behavior indicates a psychological desire to be a pseudo-commando or have a warrior mentality, closely associate with weapons or other military or law enforcement paraphernalia, identify with previous attackers or assassins, or identify oneself as an agent to advance a particular cause or belief system.
4 *Novel aggression* warning behavior is an act of violence that appears unrelated to any targeted violence pathway and is committed for the first time.
5 *Energy burst* warning behavior is an increase in the frequency or variety of any noted activities related to the target, even if the activities themselves appear innocuous, usually in the hours, days or weeks before the attack.
6 *Leakage* warning behavior is the communication to a third party of an intent to do harm to a target through an attack.
7 *Last resort* warning behavior is evidence of a "violent action imperative" and "time imperative"; it is often a signal of desperation or distress.
8 *Directly communicated threat* warning behavior is the communication of a direct threat to the target or law enforcement beforehand.

Distal characteristics

1 *Personal grievance and moral outrage* joins both personal life experience and particular historical, religious, or political events. The personal grievance is often defined by a major loss in love or work, feelings of anger and humiliation, and the blaming of others. Moral outrage is typically a vicarious identification with a group which has suffered.
2 *Framed by an ideology* is the presence of a belief system which justifies the terrorist's intent to act.
3 *Failure to affiliate with an extremist or other group* is defined as rejection of or by an actual extremist or other group.
4 *Dependence on the virtual community* is evidence of the individual's active communication with or learning from others through social media or the Internet concerning terrorist activities or beliefs.
5 *Thwarting of occupational goals* is a major setback or failure in a planned occupational life course.
6 *Changes in thinking and emotion* is indicated when thoughts and their expression become more strident, simplistic and absolute. Argument ceases and preaching begins. Persuasion yields to imposition of one's beliefs on others. There is no critical analysis of theory or opinion, and the mantra "Don't think, just believe" is adopted. Emotions typically move from anger and argument, to contempt and disdain for others' beliefs, to disgust for the outgroup and a willingness to homicidally aggress against them.
7 *Failure of sexual-intimate pair bonding* is coded if the subject has historically failed to form a lasting sexually intimate relationship.
8 *Mental disorder* is coded if there was evidence of a major mental disorder by history or at present.

9 *Greater creativity and innovation* is defined as an act of planned terrorism which is innovative or likely to be imitated by others.

10 *History of criminal violence* is coded if there is evidence of instrumental criminal violence by history.

2.3 | Procedure and statistical analysis

2.3.1 | Step 1: MDS analysis

A similarity matrix using the 18 (eight proximal and 10 distal) TRAP-18 indicators for all subjects (attackers and non-attackers, N = 56) was produced using a Jaccard measure of association. The similarity matrix was entered into an ordinal (non-metric) Proxscal MDS analysis using the SPSS statistics package (IBM Corp. Released, 2016) to produce a two-dimensional scatterplot of variable associations (see Figure 1). Stress statistics indicate the difference between the input proximities and the output distances in the n-dimensional map. Consequently, the lower the stress score, the better the MDS plot "fits" or replicates the original data associations (i.e., the similarity matrix). Although there are no appreciable guidelines for determining an acceptably low level of stress in any given MDS model is

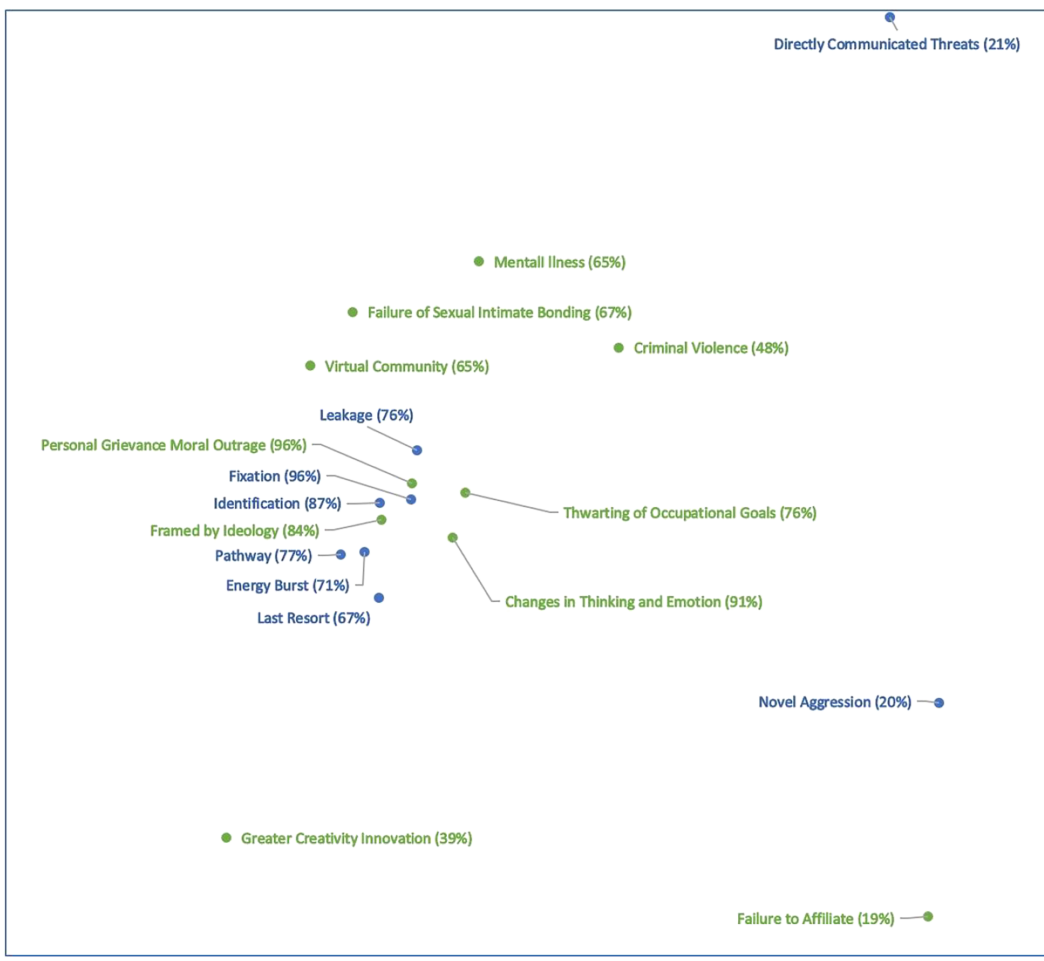

FIGURE 1 Similarity matrix of Terrorist Radicalization Assessment Protocol (TRAP-18) indicators for all subjects (attackers and non-attackers; N = 56) using an ordinal multidimensional scaling analysis [Colour figure can be viewed at wileyonlinelibrary.com]

(e.g., because stress can decrease due to a greater number of variables vs dimensions, larger datasets, greater number of dimensions in solution, non-metric vs metric analysis, etc.), SPSS provides a number of stress indicators that can be used as general "rules of thumb" to evaluate the solution.

Kruskal's stress (i.e., also known as "stress1") function (Kruskal, 1964) is the most commonly used measure in determining a nonmetric model's goodness of fit. Kruskal and Wish (1978) have proposed interpreting stress1 scores using the following criteria: stress1 > 0.20, poor; 0.10 ≤ stress1 ≤ 0.20: fair; 0.05 ≤ stress1 ≤ 0.10, good; 0.025 ≤ stress1 ≤ 0.05, excellent. The current MDS analysis reported a stress1 value of 0.0983, representing a *"good"* fit of the data, and a S-Stress value of 1.69%. Hair, Anderson, Tatham, & Black (1998) proposed interpreting the *S-Stress* (see Young & Harris, 2004, for description) values of < 2.5% as a "near perfect fit". Similarly, Dugard, Todman, and Staines (2010, p. 275) suggest that stress1 values < 0.15 represent a good fit and further suggest that "dispersion accounted for" and "Tucker's coefficient of congruence" should have values "close to 1", which is verified as 0.990 and 0.995, respectively. Frequency of each indicator for all subjects is also noted (Meloy et al., 2019).

FIGURE 2 Centroid analysis of the attackers (orange, *n* = 33) and non-attackers (gray, *n* = 23), and the eight proximal warning behaviors (blue) and 10 distal characteristics (green) of the Terrorist Radicalization Assessment Protocol (TRAP-18) [Colour figure can be viewed at wileyonlinelibrary.com]

2.3.2 | Step 2: centroid analysis

Each subject was then analyzed to ascertain his centroid value based on the (*x*, *y*) coordinates of the TRAP-18 indicators derived from the MDS analysis in Figure 1. The centroid was computed by taking the average (*x*, *y*) coordinate of all TRAP-18 indicators present in that particular subject. Hence, indicators that were not present (or not recorded as occurring) within the subject were not utilized in computing the centroid in any way. Figure 2 illustrates an overlay of the location of each centroid (i.e., subject) on the MDS variable plot, as an orange centroid-dot if the subject attacked or as a gray centroid-dot if the subject did not attack. To aid interpretability and clarity, the 10 distal characteristics are plotted in green and the eight proximal warning behaviors are plotted in blue (note that the position of the 18 TRAP variables are identical to Figure 1). For further clarity and to aid subsequent discussion of variable and centroid groupings, a gray line has been subjectively drawn onto the MDS plot roughly demarcating a division between attacker and non-attacker centroids.

3 | RESULTS

3.1 | Comparative analyses

The total number of TRAP-18 indicators present between attackers [mean ± SE; 11.12 ± 0.41, 95% confidence interval (CI): 10.28–11.96] and non-attackers (9.74 ± 0.82, 95% CI: 8.05–11.43) were not significantly different. However, as Figure 3 illustrates, the number of proximal warning behaviors of attackers (5.21 ± 0.18, 95% CI: 4.85–5.58) were found to be significantly different from and greater than [$t(54) = -2.430$, $p < 0.05$] that of the non-attackers (4.04 ± 0.45, 95% CI: 3.12–4.97). Distal characteristics between attackers (5.91 ± 0.29, 95% CI: 5.33–6.49) and non-attackers (5.70 ± 0.42, 95% CI: 4.83–6.56) were not significantly different.

Figure 4 illustrates the mean centroid differences between attackers and non-attackers, revealing significant differences in the distribution of case profiles (i.e., the *x* and *y* coordinates of a case, based on its behavioral profile) by attacker and non-attacker. Attackers were significantly [$t(54) = 5.96$, $p < 0.001$] more likely to have centroids that were negative in the *x*-dimension (i.e., further left in the MDS plot) than were non-attackers. Further, non-attackers were significantly [$t(54) = 3.38$, $p < 0.01$] more likely to have centroids that were positive in the *y*-dimension (i.e., further to the top of the MDS plot) than were attackers.

4 | DISCUSSION

The TRAP-18 was not designed to specifically predict acts of lone actor terrorism, but to prevent them by efficiently and effectively managing risk. The theoretical model for the TRAP-18 was conceived to help counterterrorism (CT) professionals identify and prioritize cases based upon the presence or absence of proximal warning behaviors and distal characteristics (Meloy, 2017). It was theorized that any one proximal warning behavior would compel active management of the case, while the presence of only a cluster of distal characteristics would suggest continuous monitoring. The premise for this model was that proximal warning behaviors would more readily co-occur with an attack. In this manner, both efficient use of law enforcement funding and personnel could be maximized. The origins of the model were derived from a rational-theoretical approach, utilizing both the experience of the developer and the extant research on lone actor terrorism (Meloy, 2017).

Subsequent research has tested the reliability and validity of the theoretical model with positive results (Challacombe & Lucas, 2018; Garcia-Andrade et al., 2019; Meloy, 2018a; Meloy et al., 2019; Meloy & Gill, 2016; Meloy, Roshdi, et al., 2015). This MDS study further supports the validity of the model by demonstrating that most of the proximal warning behaviors are present and cluster among the attackers, most proximal warning behaviors are

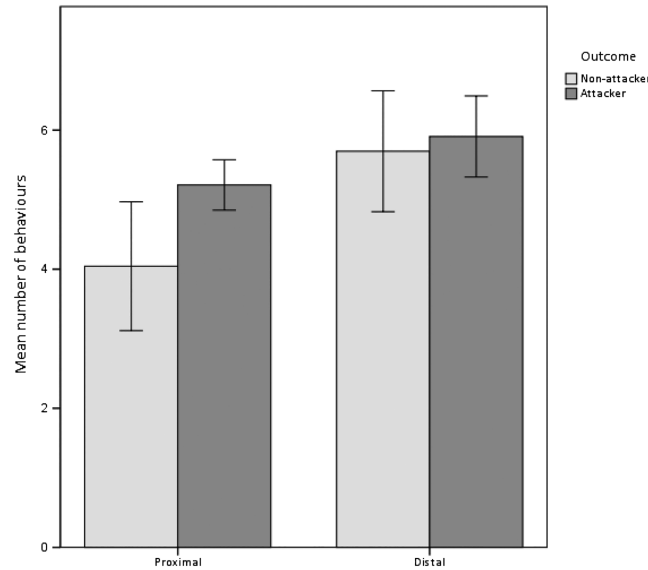

FIGURE 3 Comparison of proximal warning behaviors and distal characteristics of attackers and non-attackers, including 95% confidence intervals

absent among the non-attackers, and there is no significant difference and clustering between most of the distal characteristics, which are present in both the attackers and non-attackers.[6]

Multidimensional scaling allows for visualizing the relationship between the TRAP-18 indicators and the attacking and non-attacking subjects. Figure 1 locates all TRAP-18 indicators in two-dimensional space. Six out of the eight proximal warning behaviors are strongly associated and cluster near the center – indicating they are likely to co-occur – while two warning behaviors (novel aggression and directly communicated threat) are remotely positioned, indicating their low frequency and relatively weak association across all cases. Nonetheless, it is also notable that four distal characteristics – personal grievance and moral outrage, ideological framing, changes in thinking and emotion, and thwarting of occupational goals – also cluster with most of the proximal warning behaviors, suggesting a strong association and co-occurrence among them, while the other six distal characteristics are more weakly associated with the proximal warning behaviors, but have stronger co-occurrence with each other. For example, dependence on the virtual community, failure of sexual pair bonding, and mental disorder are all more likely to co-occur with each other than each one does with leakage, a proximal warning behavior. The visualization of co-occurrence in Figure 1 of all of the TRAP-18 indicators generally supports the theory that proximal warning behaviors will cluster together (co-occur) and are different from most of the distal characteristics, which generally co-occur less readily with each other. The MDS analysis, however, says nothing about the time sequencing of either the proximal warning behaviors or the distal characteristics, an important research approach to studying acts of terrorism (Corner, Bouhana, & Gill, 2019), as it can suggest various causal pathways. However, considering the exhaustive nature of the data collection process (including input from the actual case investigators), the assignment of risk factors to distal or proximal could in itself implicitly connote temporality.

Figure 2 locates the TRAP-18 indicators in two-dimensional space as in Figure 1, but also overlays the attacking and non-attacking subjects, so one can visualize the relationship among the indicators and the cases. The diagonal line is subjectively drawn to separate most of the attackers from the non-attackers to facilitate interpretation.

It appears from the MDS analysis that the attackers cluster, and that they cluster closest to six of the proximal warning behaviors (blue dots), with the exception of novel aggression and directly communicated threat. This suggests that co-occurrence among the attackers and proximal warning behaviors is strong, which is not as evident in the non-attackers. The remote location of novel aggression is probably due to its low frequency (Meloy et al., 2019), and the very remote location of directly communicated threat in the upper right quadrant is due to its negative correlation with attackers and very low frequency (Meloy et al., 2019). The univariate analysis of the proximal warning

behaviors in Meloy et al. (2019) indicated the medium to large effect differences between attackers and non-attackers on various indicators, but did not afford the ability to visualize the clustering and co-occurrence of the proximal warning behaviors among these same individual attackers, as is provided in the MDS analysis.

Turning to the distal characteristics (green dots) and their relationship to attackers and non-attackers, it is evident that three of them – personal grievance and moral outrage, ideological framing, and changes in thinking and emotion – cluster with both the proximal warning behaviors and the attackers. This neither confirms nor disconfirms the theoretical model which posited a more distant time relationship between attack and the distal characteristics, but does suggest a stronger co-occurrence of these three distal characteristics in attackers than in non-attackers. Again, time sequencing is not addressed by MDS, only the likely co-occurrence of the indicators. Such a co-occurrence, however, does indicate that such a clustering of these three distal characteristics should point the threat assessor toward the likely presence of proximal warning behaviors, and perhaps a greater risk of an attack. The presence of these three "strong" distal characteristics suggests a greater likelihood of finding proximal warning behaviors than any of the other seven distal characteristics: mental disorder, history of criminality, failure to affiliate with an extremist or other group, greater creativity and innovation, dependence on the virtual community, failure of sexually intimate bonding, and thwarting of occupational goals.

The association of these strong distal characteristics with the majority of proximal warning behaviors and attacker centroids might suggest that, although the theoretical model of two superordinate domains of indicators (i.e., proximal warning behaviors and distal characteristics) are quantitatively supported by this MDS analysis, these three distal characteristics have special significance: for example, they are all concerned with motivation, and but for their presence, there may be no aggregation of proximal warning behaviors and a subsequent attack. The terrorist attacker joins both his personal grievance, often a loss accompanied by anger, humiliation and blame, with moral outrage, a vicarious identification with a suffering group; this distal characteristic usually precedes, but also may follow, ideological framing wherein he finds a belief system which both rationalizes and justifies his wish to be violent toward the outgroup;[7] these two distal characteristics are accompanied by changes in thinking and emotion, the third distal characteristic in our MDS (Figure 2), co-occurring with the attackers and their proximal warning behaviors. This latter characteristic is a complex variable, but can be broken down into three elements: interpersonal communications, internal fantasies and emotions (Meloy & Yakeley, 2014). The interpersonal communications with others become less argumentative, but more rigid, strident, isolating, humorless, and without critical thought. The mantra "Don't think, just believe" is adopted. Internal life focuses on "narcissistic linking fantasies" (Meloy, 1998) in which the subject believes he has a special and idealized relationship with another. In the case of a terrorist, it could be martyrs who have preceded him, an omniscient or omnipotent god, a movement leader, a religious figure, a political figure, or a relative who has also been radicalized. These fantasies are usually imbued with grandiosity and violence, and serve the goal to cleanse or purify the environment of apostates, infidels, unbelievers or contaminating "others" (Meloy, 2018b). Both religious and secular persecutors can fill the bill. The emotional life that is evident during these changes is a shift from anger, to contempt, to disgust toward the outgroup (Matsumoto, Frank, & Hwang, 2015; Meloy & Yakeley, 2014) which eventually is targeted, and the use of secrecy to advance tactical planning and psychological superiority.

There may also be more research-based reasons for the clustering of these three "strong" distal characteristics with the proximal warning behaviors. Time sequence analysis may determine that such distal characteristics are more temporally proximal to the warning behaviors than are the other distal characteristics (Gill, 2015), and further investigation of the coding of all the indicators is warranted to rule out data-gathering bias and hindsight bias. The hypothesis that these three distal characteristics could actually more pragmatically belong among the proximal warning behaviors also needs to be tested.

Figures 3 and 4 illustrate through comparative analyses that the attackers and non-attackers are different from each other as groups. Figure 3 shows the significantly greater number of proximal warning behaviors in the attackers than in the non-attackers, but no significant difference in distal characteristics, consistent with the model. The 95% CI error bars also demonstrate that there is little overlap when one compares the high and low bars for the proximal

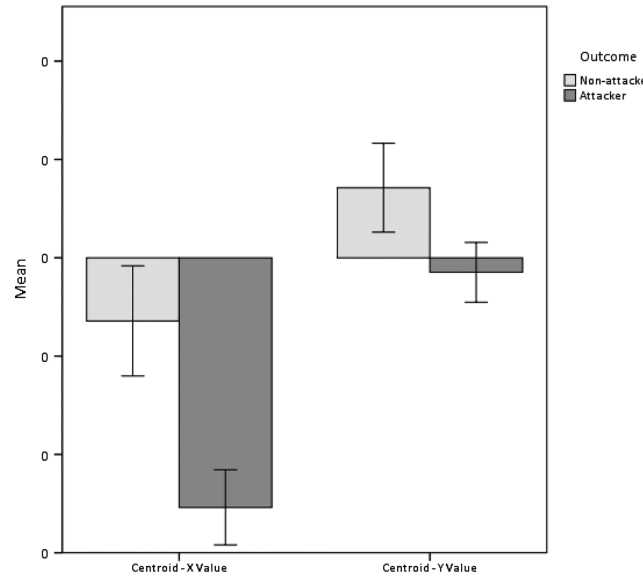

FIGURE 4 Mean centroid differences of Terrorist Radicalization Assessment Protocol (TRAP-18) indicators between attacks and non-attackers, including 95% confidence intervals

warning behaviors for each sample. Figure 4 illustrates the striking and significant differences on both mean centroid *x*-value and *y*-value dimensions for the attackers and non-attackers. Figure 2 helps to understand Figure 4: the non-attackers are mostly above and to the right of the diagonal line, and the attackers are below and to the left of the diagonal line. However, note that the location of the diagonal line was subjectively determined by the authors. There may also be a latent construct for each of the *x* and *y* axes. The *x* (vertical) axis may represent movement from collectivistic failures to more autonomous, isolating successes (from top to bottom). The *y* (horizontal) axis may represent movement from more disparate, expressive, affective hostility and aggression to more focused, predatory aggression (right to left) (Meloy, 2006; Wrangham, 2019). Further testing for these latent constructs is warranted.

4.1 | Operational implications

The findings of this MDS study quantitatively support the theoretical model that there are two superordinate factors – proximal warning behaviors and distal characteristics – in the TRAP-18. They also support a theory of risk for lone actor terrorists: proximal warning behaviors are present among attackers, and largely absent among non-attackers, yet distal characteristics are evident in both attackers and non-attackers; the latter group are persons of concern to the threat assessor who should closely monitor them to see if any proximal warning behaviors appear.

A weather analogy first introduced by Monahan and Steadman (1996) to violence risk assessment still appears to be useful, with some further elaboration. The presence of a cluster of TRAP-18 distal characteristics, along with the absence of all proximal warning behaviors, means there may be storm clouds on the horizon. One does not know if a storm will form and move toward the observer, but a "watch" needs to be initiated. In threat assessment terms, this means that the case should be monitored and reviewed on a regular basis, perhaps indefinitely, but does not warrant a commitment of active management resources. Monitoring should be done contemporaneously in both virtual and terrestrial worlds. The presence of any one proximal warning behavior, however, means the storm may be in one's backyard. A "warning" needs to be initiated. In threat assessment, this means active management: a possible face-to-face threat assessment; collateral interviews with family members, peers or school personnel; review of records (employment, military, driving, criminal, residence, police incidents); civil commitment, release, and discharge planning; safety plan development for school, work, home and the community at large; social media monitoring; obtaining signed consents to communicate with the subject's psychotherapist, psychiatrist or case manager to monitor progress if in mental health treatment (Meloy & Genzman, 2016; Corner & Gill, 2015; Corner et al., 2016); ensure

compliance with interventions or recommendations established during suspension, expulsion or work termination; and consideration of criminal prosecution if there is any evidence of a crime.

The clustering of three strong distal characteristics with the proximal warning behaviors in this MDS study – personal grievance and moral outrage, ideological framing, and changes in thinking and emotion – complicate the weather analogy. A storm is forming, but its arrival may not be imminent. However, active management of the case is likely to be warranted if these three strong distal characteristics are present – even in the absence of known proximal warning behaviors. What is needed to further test this weather analogy is a time sequence analysis of the TRAP-18 indicators to determine if, in fact, co-occurrence of the proximal warning behaviors equates to more imminent risk than the distal characteristics (Corner et al., 2019), and where in a causal pathway the strong distal characteristics appear. The MDS findings, however, do confirm that likelihood of an attack is significantly greater with a clustering of proximal warning behaviors.

4.2 | Further research

Research concerning risk of terrorist attacks in general and lone actor terrorists in particular continues at a productive pace. There are now six risk assessment instruments that warrant further study (Lloyd, 2018), although the TRAP-18 has substantially more peer-reviewed studies testing its reliability and validity, including research independent of its developer (Bockler, Hoffmann & Zick, 2018; Challacombe & Lucas, 2018; Garcia-Andrade et al., 2019). Other studies support in various ways the model of the TRAP-18, highlight its potential weakness, such as an absence of protective factors, and also suggest directions for future research. Corner et al. (2019) demonstrated the usefulness and importance of time sequence analysis in a large sample of lone actor terrorists, as we have noted. Schuurman, Bakker, Gill, and Bouhana (2018) found that lone actor terrorists are generally poor at operational security, leak their intent in various ways over the course of weeks and months – as do most targeted violence attackers (Silver, Simons, & Craun, 2018) – and have broader social contacts than was originally surmised. Silver, Horgan, and Gill (2018) studied the phenomenon of leakage (Meloy & O'Toole, 2011) and confirmed its importance as a significant predictor of a personal grievance against a person or entity, and a continuous operational vulnerability for counterterrorism investigators. Bouhana, et al. (2018) report the striking similarity between extreme right wing terrorists and other ideologically driven lone actor terrorists in their background and preparatory behaviors, confirming an operational premise and finding within the TRAP-18 that it generalizes across ideologies (Meloy & Gill, 2016). Further, Marchment, et al. (2018) studied the geographical hunting patterns of lone actor terrorists and found them to engage in spatial decision-making similar to other criminals. Terrorist violence risk assessment, however, is not necessarily improved by the addition to an instrument of more and more variables arguably associated with such violence (Pressman & Flockton, 2012); a more parsimonious instrument, on the other hand, may be both scientifically reliable and more practically useful for counterterrorism efforts to prevent such acts of targeted violence.

4.3 | Limitations

In the real world, it is abundantly apparent that there are likely to be many more non-attackers than attackers, a limitation to the ecological validity of this study wherein there are more attackers than non-attackers. Also, it is quite conceivable that if risk-managed, some of the attackers would not have attacked; and it is also quite conceivable that our comparison group, if not risk-managed, could have produced an attacker. Given these real-world dynamics for the threat assessor, it cannot be overemphasized that threat assessment and management must focus on behaviors of concern in the present, and not on more distant, static variables, such as age, ethnicity, gender or socioeconomic status.

There are other, unavoidable, limitations in the present analysis. The first, and most obvious, is the quality of the data, given their collection (for the attacker sample at least) is marred by its retrospective nature. TRAP-18 indicators

were assessed and coded based on past events, which may create a hindsight or confirmation bias in the assessment of the case. However, the collection and assessment of attackers in this type of research will inevitably and unconditionally be done in retrospect – an attacker has to attack in order to be deemed an attacker, hence the commission of the terrorist attack has already taken place. As this is a well-known potential limitation to this type of known outcome data collection, mitigation measures were taken, such as double-coding, interrater agreement, case discussions among the researchers and, where possible, having the actual case investigators complete the TRAP-18, as they will probably have the most accurate and detailed information on the subject(s), including the temporal sequencing of some of the TRAP indicators.

Further, as mentioned earlier in relation to data collection, the nature of investigative, security and law enforcement data is not on par with experimental data in the sciences in terms of reliability – in fact, data collected from similar sources as the present study are often described as "messy." Again, as this was a known concern, Jaccard's measure of association was utilized to create variable (i.e., indicators) similarity ratings, rather than a more conventional correlation coefficient. Utilizing correlations would exacerbate problems of "messy" data by increasing or decreasing associations between variables based on mutual non-occurrence, given that we assume less confidence that a behavior has occurred or, more importantly, has not occurred.

An additional limitation of the study stems from the relative frequencies of attackers versus non-attackers in the US versus Canadian samples. Although the non-attackers were relatively equal in frequency across the US (56.5%) and Canadian (44.5%) samples, there was potential limiting bias in the relative frequency of attackers, with the US-based cases making up 93.9% of the attacker sample. It may be that the country (or jurisdiction) from which cases have been sampled has created a confound in the distribution of attacker versus non-attacker centroids visualized in the MDS plot (Figure 2). However, it is unclear, at least in the context of empirical research into the TRAP-18 and more generally in the management and assessment of threat, lone actor and other, whether there are differences in TRAP indicators based on country of origin, sampling or analysis. In light of this, and given the exploratory nature of the current study, the authors chose to combine both samples, particularly because relatively equal amounts of non-attackers (i.e., risk-managed or no-intent cases) were available. Further, the lower frequency of attackers in the Canadian-based sample than in the US-based sample may indeed reflect the base rate (per capita) frequencies of lone-actor terrorism in these countries – an essentially unavoidable confound, but nonetheless a contribution to ecological validity. The collection of more cases in both the US and Canadian samples would be beneficial to future research and provide the ability to further investigate any potential confounds when comparing attackers and non-attackers in the current study.

Multidimensional scaling analysis is an extremely useful tool for interpreting and further understanding the complex association between a set of variables by visualizing the relationships between them. The visualization of the associations can then lead the researcher to make inferences regarding any latent constructs or dimensions, groupings of variables and even division of variables. However, the implicit subjective nature of the interpretation of the MDS plot can often become a significant limitation in MDS studies – and without some *a priori* empirical underpinning for those inferences, it can be akin to "reading tea leaves." In fact, MDS studies can easily manifest a confirmation bias, leading researchers to interpret and provide reasoning for an MDS plots' configuration *post hoc* in order to find favorable or "expected" outcomes in the plot.

In the current study, the authors were careful to limit their interpretation to the more general aspects of the MDS in terms of the overall relative positioning of distal and proximal indicators to each other and their proximity to individual case centroids – without providing extensive interpretation of possible underlying latent constructs in the data. This decision was made precisely to avoid this kind of subjective interpretation, given the study's lower sample size and the current absence of empirical research on the TRAP-18's latent structure. Instead, the authors chose MDS for its robustness as an exploratory data analytic tool, rather than to provide an insight into, or any sort of confirmation of, the indicators underlying latent structure. Therefore, the authors were reticent to make any *a priori* dimensional predictions or indeed any significant *post hoc* dimensional inferences, instead choosing to make interpretations based on the objective coordination between indicators.

Although not necessarily a limitation of the current study, in the sense that the choice of MDS was a deliberate decision to visualize the association between TRAP indicators and potential attack outcomes as an exploratory endeavor, it is important to point out that MDS does not provide similar empirical quantification (i.e., factor loadings) to that provided by other multivariate data reduction tools , such as principal component analysis (PCA) or the confirmatory power of factor analysis. Again, because MDS simply provides a goodness-of-fit "stress" measure, which will decrease, i.e., have a better fit, with increased dimensionality (i.e., a three-dimensional plot will have less stress in fitting indicators than a two-dimensional plot), even the valid determination of how many underlying constructs the indicators may have can prove difficult to confirm, unlike, for example, confirmatory factor analysis. However, a more detailed and nuanced examination of the TRAP-18 indicators under MDS and other multivariate techniques, such as time sequence analysis and PCA, will be a priority and necessity in future research, when such data exist to fulfill their requirements.

ENDNOTES

[2] Threat assessment is a discipline which focuses upon the prevention of intended or targeted violence toward a particular individual or group; risk assessment is the "process of using risk factors to estimate the likelihood of an outcome in a particular population" (Kraemer et al., 1997, p. 340).

[3] This period has been extended 1 year longer than Meloy et al. (2019) after checking to see if there was any terrorist attack by the comparison group cases subsequent to the acceptance of the 2019 study.

[4] One terrorist used both an incendiary device and a firearm.

[5] A fixation warning behavior appears to have one of three cognitive-affective drivers: delusion, obsession or extreme overvalued belief (Rahman, Meloy, & Bauer, 2019)

[6] The significant differences, effect sizes, odds ratios and confidence intervals for each of the proximal warning behaviors and distal characteristics are available in Meloy et al. (2019).

[7] Extremist beliefs require hostility toward an outgroup, usually perceived as an impurity or contaminant of the environment, and may be punishing or persecuting the extremist and his true believers (Berger, 2018). See, for example, the March 2019 manifesto of a New Zealand terrorist, who declared that Whites were being replaced by non-Whites, and a global genocide was occurring to replace them, evidenced in their elevated birth rates; hence a need in his mind to murder 50 Muslims in a mosque in Christchurch.

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How to cite this article: Goodwill A, Meloy JR. Visualizing the relationship among indicators for lone actor terrorist attacks: Multidimensional scaling and the TRAP-18. *Behav Sci Law*. 2019;37:522–539. https://doi.org/10.1002/bsl.2434