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# Warning Behaviors of Explicit Threateners: Exploring Patterns of Co-Occurrence and Their Comparative Ability to Predict Violence

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Proximal warning behaviors have been proposed as critical signals of rapidly escalating risk of targeted violence in threat assessment. Research has shown this collection of eight behaviors to be associated with targeted violence and, in certain samples, for individuals to more frequently exhibit certain clusters of these behaviors. The present study aimed to replicate and extend previous findings by examining how the eight warning behaviors co-occurred in a sample ($N = 257$) of community-based individuals who made an explicit threat of violence and if any of the warning behaviors demonstrated incremental predictive validity over the other behaviors regarding their ability to predict physical violence. Multidimensional scaling revealed that six of the eight behaviors—pathway behavior, fixation, identification, novel aggression, energy burst, and leakage—all co-occurred more frequently when plotted in two-dimensional space, with significantly tighter "clustering" for participants who had committed an act of violence. When compared via stepwise logistic regression, pathway, energy burst, and novel aggression behaviors emerged as the strongest predictors of physical violence, all increasing the odds of violence approximately three times. These results align with previous literature, in which most warning behaviors co-occurred, and suggest that the presence of a greater number of warning behaviors should evoke more stringent threat management strategies, although it should be noted that nonviolent participants displayed a not insignificant number of warning behaviors as well.

***Public Significance Statement***

Individuals who committed violent acts of terrorism have been discovered to demonstrate multiple warning behaviors (e.g., research and planning, fixation) more frequently. This study sought to replicate and extend this finding in a sample of individuals from the general public who made an explicit threat of violence. Certain warning behaviors—pathway behavior, fixation, identification, novel aggression, energy burst, and leakage—co-occurred frequently for all participants, but more so for participants who committed physical violence after their threat. Pathway behavior, energy burst, and novel aggression were all associated with higher risk of violence occurring after an explicit threat.

*Keywords:* warning behaviors, explicit threats, threat assessment, violence, multidimensional scaling

Threat assessment has been defined as the systematic process of gathering information to recognize a threat posed by a specific person, group, or organization (Meloy, Hoffman, Deisinger, & Hart, 2021). Threat assessment is naturally followed by threat management, which is comprised of the creation and execution of subsequent strategies to

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mitigate or neutralize the aforementioned threat, although some literature has considered both processes to fall under the broader heading of threat assessment (Calhoun & Weston, 2003; Meloy, 2000; Turner & Gelles, 2003). Within this definition, a "threat" is conceptualized as any risk or potential danger as opposed to solely an explicit statement or utterance of an intention to harm (Meloy, Hoffman, Deisinger, & Hart, 2021), although threat assessment is frequently employed in the evaluation of the latter.

There has been much discourse on the overlap of threat assessment and the associated domain of violence risk assessment. Although previous literature has proposed some differences between the disciplines (see Meloy, Hoffman, Deisinger, & Hart, 2021), they share the key objective of evaluating and managing the risk of violent behavior, often through the use of empirically supported assessment models and tools. In addition to well-established risk factors for general violent offending, found on instruments such as the Historical-Clinical-Risk Management 20 Version 3 (Douglas et al., 2013), assessors have endeavored to identify additional factors that may be particularly important in the rapidly evolving operational settings in which acute threats must often be assessed (Meloy, Hoffman, Deisinger, & Hart, 2021) and impending violence is often intentional or targeted. Meloy et al. (2012) proposed a collection of eight warning behaviors that threat assessors should attend to, yet only a small body of research exists on the link between these behaviors and violence. The present study aimed to increase knowledge of this nexus by exploring how warning behaviors may co-occur in discernable patterns and which discrete behaviors may be more indicative of potential future violence.

## Targeted Violence and Threat Assessment

Targeted violence is a form of violence that is characterized as being purposeful and premeditated and aimed at achieving a particular objective (Meloy et al., 2013; Schouten & Brennan, 2016). Threat assessment was initially developed as a substitute for violence risk assessment in cases of extreme targeted violence, such as targeted attacks on public figures, and grew out of the descriptive research and operational techniques of the U.S. Secret Service that were developed to refine the evaluation of threats such as these (Borum et al., 1999; Fein & Vossekuil, 1999). However, threat assessment was substantially less structured than violence risk assessment at its inception (Meloy, Hoffman, Deisinger, & Hart, 2021).

The success of the threat assessment process relies on the assessor's ability to identify key indicators such as attack behaviors (Borum et al., 1999), preattack signals (Dietz & Martell, 2010), or warning behaviors (Meloy et al., 2012). These behaviors are purported as unique to targeted violence due to its premeditated nature and can serve as predictive signals of an individual's likelihood to engage in it, which subsequently enables the implementation of tailored threat management strategies aligned with the person's risk level (Cornell & Maeng, 2018; Maeng et al., 2020). It is crucial to note that if an individual shows no discernable signals of violent intent before the act itself, threat assessment is ineffective (Unsgaard & Meloy, 2011), which is why the practice is only applicable to planned violence. These are considered active behavioral patterns that the individual is currently engaged in (Meloy et al., 2012), similar to dynamic factors frequently evaluated in violence risk assessments (Douglas et al., 2013). Therefore, it is paramount to highlight the pivotal role of these signals or behaviors, as understanding their significance within threat assessment not only refines our evaluation process but also provides essential insights imperative for effective threat mitigation (Meloy et al., 2012).

## Warning Behaviors in Threat Assessment

Over the last two decades, studies have begun to explore whether specific discernible factors can predict imminent violence and/or increase the risk of violence (Meloy, Hoffmann, Bibeau, & Guldimann, 2014). A specific set of behaviors has been shown to occur proximally to the enactment of targeted violence and has begun to receive greater attention within threat assessment research (Meloy et al., 2012). This collection of eight warning behaviors has been proposed to be an indication that an individual's risk of targeted violence is rapidly and dynamically escalating (see Table 1 for a list of the eight behaviors).

These behaviors have been found to be displayed frequently by perpetrators of targeted violence across diverse contexts (Allwinn et al., 2019; Burnette et al., 2018; Meloy et al., 2019; Silver et al., 2018), including samples of public figure attackers and assassins, terrorists, school shooters, and mass murderers. For instance, at

**Table 1**
*Definitions of the Eight Warning Behaviors (Meloy et al., 2012)*

| Behavior | Description |
|---|---|
| Pathway behavior | Research, planning, or preparation for an attack |
| Fixation | Intense preoccupation with a specific person or cause |
| Identification | Identification with law enforcement/military, previous attackers, or other perpetrators of violence; a “warrior mentality” |
| Novel aggression | Violent behavior that is committed for the first time and is unrelated to other pathway behaviors; a test of ability for violence |
| Energy burst | Acceleration in frequency or variety of behaviors/activities related to the intended target of the violence |
| Leakage | Communication of intent to be violent to a third party |
| Last resort behavior | Increasing distress or desperation that leaves no alternative to violence |
| Direct communication of threat | Communication of a threat of violence directly to the target |

least 45% of both psychotic and nonpsychotic mass murderers exhibited all eight warning behaviors, except for direct communication of threat (Allwinn et al., 2019), and all school shooters displayed at least four of eight warning behaviors in another study (Meloy, Hoffmann, Roshdi, & Guldimann, 2014). Additionally, almost all participants (92%) in a sample of severely mentally ill targeted violence perpetrators exhibited at least a single warning behavior before committing their offences (M. F. E. Almond et al., 2023).

Researchers have also conducted comparative analyses between violent and nonviolent groups, where the findings demonstrated the differences between the two in terms of warning behaviors. Specifically, pathway behavior, fixation, identification, novel aggression, energy burst, and last resort behavior were shown more often by perpetrators of school shootings and/or terrorist acts, but no differences in leakage were observed, and directly communicated threats were made less frequently by perpetrators of terrorism (Meloy et al., 2019; Meloy, Hoffmann, Roshdi, & Guldimann, 2014). The total number of warning behaviors that participants displayed significantly predicted violence in research on community individuals who threatened violence (M. F. E. Almond & Douglas, 2025) as well as within school-aged adolescents (Burnette et al., 2018). In another study examining the manifestos of mass shooters, the analysis revealed the presence of six warning behaviors across the 27 examined documents. Among these, fixation, identification, novel aggression, last resort behaviors, energy burst, and direct communication were found to be the most frequent warning behaviors identified (Slemaker, 2023).

Moreover, several studies have used the Terrorist Radicalization Assessment Protocol–18 (TRAP-18; Meloy, 2017) to analyze the warning behaviors displayed by terrorists compared with other individuals of concern. The TRAP-18 is a specialized threat assessment tool that is comprised of 18 indicators tailored to identify potential involvement in terrorism or radicalization; eight of these indicators are the proximal warning behaviors in Table 1. Unlike the eight warning behaviors proposed to associate with general targeted violence, the TRAP-18 also includes 10 distal (distant in time; evolving) characteristics that typically require time for the perpetrator to exhibit (e.g., personal grievance, mental disorder) and is specialized for use within the context of threats of terrorism (Meloy, 2017).

In Meloy et al.’s (2019) seminal study, half of the proximal warning behaviors within the TRAP-18 were displayed more frequently by perpetrators of terrorist acts versus nonviolent persons of concern: pathway behavior, identification, energy burst, and last resort behavior. However, direct threats were made less frequently by terrorist attackers. In two other studies of German Islamic terrorists and American sovereign citizen actors, pathway behavior, identification, leakage, and last resort behavior were associated with targeted terrorist violence (Böckler et al., 2020; Challacombe & Lucas, 2019). Results were equivocal concerning novel aggression and energy burst behaviors, as they were positively linked with violence in one study and negatively associated in the other. As such, although the TRAP-18 in its entirety appears to effectively distinguish individuals who have engaged in terrorism-related targeted violence from those who have not (Allely & Wicks, 2022), only a few proximal warning behaviors have consistently been shown to predict targeted violence in the context of terrorism.

Notably, Goodwill and Meloy (2019) moved beyond simple examination of the association between proximal warning behaviors, other TRAP-18 indicators, and targeted violence by exploring how these variables may cluster or co-occur, using multidimensional scaling (MDS). This multivariate technique estimates the proximity between variables by quantifying similarities between the variables within a matrix and subsequently plotting the distance between them in *n*-dimensional Euclidian space (Borg & Groenen, 2005). Shorter distances between the variables are indicative of greater propensity for the variables to cluster together—in Goodwill and Meloy's study—for the TRAP-18 indicators to co-occur. Results of MDS are typically interpreted visually with the aid of previously specified theories, hypotheses, or behavioral themes.

Goodwill and Meloy (2019) discovered a pronounced clustering of six proximal warning behaviors: pathway behavior, fixation, identification, leakage, energy burst behavior, and last resort behavior. By contrast, novel aggression and directly communicated threats were plotted substantially farther away from the other TRAP-18 indicators, indicating statistical dissimilarity. It is noted that these behaviors occurred substantially less frequently than the others (i.e., 20%–21% vs. at least 67%). Furthermore, when individual participants (split into terrorist attackers and nonattackers) were plotted on the same dimension as the behaviors, attackers were clustered more closely to the six warning behaviors specified previously relative to nonattackers. Goodwill and Meloy concluded that there was a prominent co-occurrence among most of the proximal warning behaviors (in comparison to the TRAP-18 distal characteristics), particularly for the attackers within their sample.

This study was a critical first step in the investigation of how warning behaviors may co-occur, which carries practical implications for threat assessment. It suggests that warning behaviors do not typically occur in isolation and that they appear to differentiate attackers from nonattackers more effectively than distal characteristics (Goodwill & Meloy, 2019). Given their frequent co-occurrence, it is possible that the behaviors may interact in various ways: As Kraemer et al. (2001) proposed with traditional risk factors, they could be proxies, mediators, or moderators of other behaviors or risk factors or combine synergistically to increase risk level (see also Douglas & Skeem, 2005, regarding dynamic risk factors).

Despite its novelty and importance, Goodwill and Meloy's (2019) research focused on a single sample of individuals engaged in terrorism, and hence it remains unknown whether this pattern of clustering is robust across different types of targeted violence perpetrators. The relatively small sample size and focus on a single method of statistical analysis to examine co-occurrence were further limitations of this study. Additionally, although a small body of literature on the prevalence of each warning behavior exists, little research has been conducted regarding the comparative predictive ability of each behavior to ascertain if particular behaviors are more indicative of targeted violence than others.

## The Present Study

The present study aimed to replicate and extend the findings of Goodwill and Meloy (2019) by exploring the co-occurrence of warning behaviors in a larger and more representative sample comprised of individuals from the general population who have made a threat of violence. The present study further extended knowledge of the predictive ability of warning behaviors by investigating which behaviors contributed most substantially to the prediction of violence following a threat. Specifically, the three main objectives of the study were

- to determine whether warning behaviors co-occur within specific groups or clusters in a community sample,
- to determine which warning behaviors are most predictive of future violent behavior in the presence of co-occurring behaviors, and
- to determine which clusters of specific warning behaviors are most predictive of future violent behaviors.

# Method

## Participants

Participants were the same as those used in M. F. E. Almond and Douglas's (2025) study. Three hundred forty-five participants were recruited via Amazon's Mechanical Turk (MTurk). MTurk is an online crowdsourcing platform on which human intelligence tasks are advertised to individuals seeking work, who are usually compensated for their completion. Although not its sole purpose, MTurk is commonly used for the recruitment of human research participants from the general population for certain study methodologies (i.e., online surveys; Buhrmester et al., 2011; Paolacci et al., 2010) as brief task postings can easily direct qualified participants to external sites or software. To qualify for this study, participants were required to be at least 18 years of age, be able to speak and read English, and currently reside in Canada or the United States. Participants were required to have made an explicit threat of violence, either verbally or by writing (i.e., internet forums or by letter), against another individual, identifiable group, or organization between 2015 and 2020. We defined an explicit threat as "at least one instance of communication that implicitly or explicitly states a wish or intent to damage, injure or kill a specific person, identifiable group of people, or organization." Participants were excluded if they indicated that their threat was made within the same situation as a violent act or immediately before a violent act, for example, making a threat to a robbery victim moments before the robbery is committed. Participants self-identified as perpetrators of explicit threats, as official criminal records have been shown to underestimate true crime rates (Blumstein & Larson, 1971). Self-reported crime rates have additionally been found to be akin to other standard measures of crimes (Hindelang et al., 1981; Huizinga & Elliott, 1986). All participants received monetary compensation ($7.50, the minimum wage at the time of the study) within 24 hr of completing the survey.

The study implemented an attention/validation check to identify and screen out invalid responses from potential bots and inattentive participants, a recommendation made by previous studies that utilized MTurk (Aruguete et al., 2019; Hanniball et al., 2020; Monjazeb & Douglas, 2024; Rouse, 2015). This entailed querying participants at the beginning and at the end of the survey on their relationship with the victim to which they made a threat and assessing the similarity of their responses; participants' responses needed to be identical to be included within the statistical analyses. Three hundred forty-five participants met the inclusion criteria and consented to the survey. Eighty-eight responses were excluded from all study analyses, as their responses did not match in the validation check, resulting in a total sample size of 257 participants.[1] All participants who passed the attention/validation check completed the survey. There were little missing data. Only two participants did not indicate their status on one warning behavior (energy burst), whereas one participant did not for identification and novel aggression, respectively. These cases were excluded from analyses involving the missing items, but not from the entire study.

The sample was predominantly male (64.6%; $n$ = 166) and included individuals from various ethnic backgrounds, with the majority identifying as White/Caucasian (75.9%; $n$ = 195). One participant indicated that their ethnicity did not fall in the above categories, and another participant did not provide an ethnicity. Most participants reported being in a romantic relationship (84%; $n$ = 216) and possessing at least some college- or university-level education (95.3%; $n$ = 245). See Table 2 for detailed participant demographics. Detailed demographics are not always reported in studies of adults who make explicit threats (e.g., Mitchell et al., 2019; Warren et al., 2008). The current sample shows higher educational achievement and prevalence of intimate relationships when compared with one sample of forensic inpatients (Warren et al., 2011), which is to be expected given its nature.

## Procedure

Participants were recruited via an Amazon MTurk advertisement. This post provided participants with a brief overview of the study and a link that directed them to the start of the survey, which was hosted on Qualtrics. Prior to accessing the survey, participants were required to confirm their eligibility by confirming the applicability of each inclusion criterion. If participants did not confirm all criteria, they were directed away from the survey. If a participant indicated that they made an explicit threat of violence, they were

[1] Amazon's MTurk unfortunately does not provide more nuanced statistics for its human intelligence tasks, such as the number of workers who viewed the advertisement or clicked on the survey link provided. A total of 601 participants answered at least one inclusion criterion, but 256 of these either did not meet all criteria or did not indicate their consent and were therefore redirected away from the survey.

**Table 2**
*Participant Demographics*

| Variable | Violent, *N* (%) | Nonviolent, *N* (%) | Total, *N* (%) |
|---|---|---|---|
| Gender | | | |
| Male | 86 (64.7) | 80 (64.5) | 166 (64.6) |
| Female | 47 (35.3) | 43 (34.7) | 90 (35.0) |
| Nonbinary | 0 (0) | 1 (0.8) | 1 (0.4) |
| Ethnicity | | | |
| White | 94 (70.7) | 101 (81.5) | 195 (76.2) |
| Black/African American | 33 (24.8) | 9 (7.3) | 42 (16.4) |
| Asian/Pacific Islander | 3 (2.3) | 9 (7.3) | 12 (4.7) |
| Hispanic/Latinx | 3 (2.3) | 3 (2.4) | 6 (2.3) |
| Other | 0 (0) | 1 (0.8) | 1 (0.4) |
| Country of residence | | | |
| United States | 128 (96.2) | 123 (99.2) | 251 (97.7) |
| Canada | 5 (3.8) | 1 (0.8) | 6 (2.3) |
| Relationship status | | | |
| Married | 120 (90.2) | 79 (63.7) | 199 (77.4) |
| In a relationship | 4 (3.0) | 13 (10.5) | 17 (22.6) |
| Single | 9 (6.8) | 32 (25.8) | 41 (16.0) |
| Highest education | | | |
| Completed high school | 3 (2.3) | 9 (7.3) | 12 (4.7) |
| Some college/university | 4 (3.0) | 10 (8.1) | 14 (5.4) |
| Completed college diploma | 2 (1.5) | 7 (5.6) | 9 (3.5) |
| Completed 4-year university degree | 66 (49.6) | 75 (60.5) | 141 (54.9) |
| Some graduate education | 7 (5.3) | 3 (2.4) | 10 (3.9) |
| Completed graduate degree | 51 (38.3) | 20 (16.1) | 71 (27.6) |
| Income bracket | | | |
| Under $20,000 | 15 (11.3) | 14 (11.2) | 29 (11.3) |
| $20,000–$34,999 | 18 (13.5) | 27 (21.8) | 45 (17.5) |
| $35,000–$49,999 | 32 (24.1) | 25 (20.2) | 57 (22.2) |
| $50,000–$74,999 | 38 (28.6) | 34 (27.4) | 72 (28.0) |
| $75,000–$99,999 | 22 (16.6) | 20 (16.1) | 42 (16.3) |
| Over $100,000 | 6 (4.5) | 4 (3.2) | 10 (3.9) |

subsequently asked if the threat had been made within the same situation as an act of physical violence (i.e., a verbal threat is elicited and is followed by an act of violence within minutes or seconds). If participants endorsed this follow-up question, they were excluded. This was to ensure that the threat occurred sufficiently in advance of any violent behavior and therefore allowed for other factors predictive of the latter (i.e., warning behaviors) to emerge.

Participants who met the inclusion criteria were then presented with an online consent form. If they wished to consent, they were required to deliberately select an option indicating this before being shown the survey. All participating individuals therefore provided their explicit informed consent before proceeding with the study. Given the potential hazards of collecting data via Amazon MTurk, as described above, an attention/validation check required participants' answers to a question about their threat to be identical; the two questions that comprised the check were the first and last of the survey. These questions had 16 different categorical response options; it is highly unlikely that bots answering randomly or inattentive participants would select the same response. The survey was anticipated to take approximately 30–60 min to complete; however, it was theoretically possible for participants to take as few as ten. All participants who took shorter than that time were excluded from the analyses. Participants who provided valid responses took an average of 31.10 min ($SD$ = 19.70), with a minimum of 10.40 min and a maximum of 111.92 min. Participants were subsequently presented with a debriefing form that outlined the purpose of the study and received $7.50 (minimum wage in the United States at the time of the study) within 24 hr of participating. Requisite ethics approval from Simon Fraser University's Institutional Review Board (Study

Number: 30000473) was obtained prior to the collection of data.

## Measures

### *Warning Behaviors*

The eight warning behaviors proposed by Meloy et al. (2012; see Table 1) were examined in this study: (a) pathway behavior; (b) fixation, (c) identification, (d) novel acts of aggression, (e) energy burst behavior, (f) leakage, (g) last resort behavior, and (h) threats of violence made directly to the victim. The presence of each warning behavior was queried via a single item of the online self-report questionnaire. Participants were asked if they had displayed each warning behavior prior to their threat and violent acts, with descriptions of the behaviors adapted from Meloy et al.'s definitions; presented in plain, nonincendiary language; and amended where needed to facilitate comprehension. For example, fixation was assessed by prompting participants to consider if they were "strongly interested in the victim (target) of [their] threat and found [themselves] often occupied with thoughts of them and/or talking about them frequently." See Appendix for the exact wording in which each warning behavior was queried. A full version of the larger study's survey (M. F. E. Almond & Douglas, 2025) is available upon request. The combined warning behaviors' internal consistency was excellent ($\alpha = .90$).

### *Violent Behavior*

Survey participants were queried about their engagement in either the commission or attempted execution of a violent act subsequent to issuing a threat, with the outcome variable coded in a dichotomous (yes/no) manner. Frequency and severity of the violence were not assessed. For the purposes of this study, an act of violence was defined as "the actual or attempted infliction of bodily harm upon another individual," aligning with the definition found in the Historical-Clinical-Risk Management 20 Version 3 framework (Douglas et al., 2013). The Historical-Clinical-Risk Management 20 is the most commonly utilized structured professional judgment risk assessment tool for evaluating the risk of general violent behavior worldwide (Singh et al., 2014). However, threatened violence was excluded from the definition of violence within the present study, as it was already a criterion of participant inclusion. Examples of violent acts were provided to participants: "Violent physical contact, such as pushing, shoving, slapping, punching, throwing objects, or using weapons; other unwanted physical contact, such as touching of a sexual or nonsexual nature, spitting, or throwing bodily fluids." Half the sample (51.8%; $n = 133$) engaged in physical violence after issuing a threat. Physical assault, committed by 55.6% ($n = 50$) of the sample who were violent, was the most prevalent, while acts such as attempted or actual homicide (18.0%; $n = 24$), sexual assault (14.3%; $n = 19$), robbery (12.8%; $n = 17$), kidnapping or hijacking (6.8%; $n = 9$), weapons offences (4.5%; $n = 6$), arson (3.0%; $n = 4$), and human trafficking (3.0%; $n = 4$) were also perpetrated.

## Data Analyses

All analyses were performed using Statistical Package for the Social Sciences Version 29 unless otherwise noted. Descriptive statistics (i.e., percentages and frequencies) were first calculated to assess the prevalence of each warning behavior displayed by participants who did and did not perpetrate violence following their threat. Simple independent-samples $t$ tests and chi-square tests were employed to assess differences in warning behaviors across groups. Second, to engage in a preliminary examination of the association between warning behaviors, Pearson correlations were calculated for all possible pairwise combinations of the eight warning behaviors for violent and nonviolent participants. Due to the large number of pairwise combinations (i.e., 28 for each subgroup of participants), a Bonferroni correction was applied to the typical $\alpha$ value of .05. This resulted in a $\alpha$ value of .0018 for each pairwise combination. After the generation of separate correlation matrixes for violent and nonviolent participants, statistically significant differences between correlation values were explored using the web-based application MML-WBCORR (Fouladi & Serafini, 2018; accessed at https://github.com/measurement-and-modelling-lab/MML-WBCORR). This application tests significant differences between correlation values simultaneously (i.e., within a single statistical test).

Next, the predictive ability of each warning behavior in comparison to the other behaviors was examined via forward stepwise multivariate logistic regression, which begins with a null model and subsequently adds a predictor variable in a stepwise manner until the predictive ability of the model can no longer be improved. Model statistical significance and goodness of fit were assessed via Wald chi-square ($\chi^2$) statistics and pseudo-$R^2$ values; effect size was determined through odds ratios. As all predictor variables were dichotomous, the assumptions of no influential observations and linearity of independent variables and log odds were not applicable to this model. To investigate multicollinearity, Pearson correlations between all pairwise combinations of warning behaviors for the entire sample of participants were calculated. The highest observed correlation between warning behaviors was $r$ = .55, which is relatively high but far from an unacceptable value (i.e., >.85; Schroeder, 1990).

Last, MDS analysis was employed to explore how warning behaviors may cluster together or co-occur, and if differences in clusters could be observed for violent and nonviolent participants. This technique has extensive precedent for use in research concerning various kinds of violent behavior (e.g., homicide; Salfati & Bateman, 2005; Trojan & Salfati, 2010; adolescent and adult sexual offending; L. Almond et al., 2006; Häkkänen et al., 2004; Santtila et al., 2005; robbery and burglary; Goodwill et al., 2012; Kocsis et al., 2002) and was employed by Goodwill and Meloy (2019) in the first investigation of the clustering of warning behaviors. The PROXSCAL function of Statistical Package for the Social Sciences was initially utilized to generate a similarity matrix for the eight warning behaviors across all participants, thereby creating measures of proximity for all data. An ordinal PROXSCAL analysis was subsequently performed upon the similarity matrix. Stress statistics (goodness-of-fit measures that measure the discrepancies between the input and predicted output distances) were then examined; lower stress values are generally accepted as indicators of better fit of the MDS plot regarding the original associations between the data, quantified by the similarity matrix (Goodwill & Meloy, 2019). Specifically, Kruskal's stress measure (Stress 1) that is generated by the PROXSCAL analysis has been proposed as poor if the value is greater than .20, fair if it is between .10 and .20, good if it falls between .05 and .10, and excellent if the value is under .05 (Kruskal & Wish, 1978). Additionally, goodness of fit can be assessed by scaled-stress (S-stress) values, which quantify the difference between the estimated and observed similarity matrices based on the dimensions generated by the MDS test and are stated to be indicative of strong plot fit if under 2.5% (Hair et al., 1998), and by dispersion accounted for and Tucker's coefficient of congruence scores, which should fall close to 1 (Dugard et al., 2010).

Proximities in the data across all participants were visualized via a two-dimensional scatterplot, in which associations were quantified by final coordinate (centroid) values. Next, drawing on methodology used by Goodwill and Meloy (2019) to elucidate differences in behavior proximity for violent and nonviolent participants, each participant's $x$ and $y$ mean centroid values were calculated by averaging the final ($x$, $y$) coordinates of each warning behavior that was present for each participant. If a warning behavior was not recorded as present for a participant, no final coordinates for that behavior were included when calculating that participant's mean centroid values. An additional two scatterplots were generated to show the location of each participant by their mean centroid values within the same dimensions as the MDS variable plot. The differences in $x$ and $y$ centroid means between violent and nonviolent participants were further investigated statistically using independent-samples $t$ tests.

## Results

Participants who committed an act of violence after an explicit threat displayed an average of 5.31 warning behaviors ($SD$ = 2.56). Percentages of violent participants who displayed each behavior ranged from 31.5% (both leakage and last resort behavior) to 83.5% (direct threat of violence to target). A lower average number of warning behaviors were displayed by nonviolent participants ($M$ = 2.05; $SD$ = 2.00). The warning behavior displayed least frequently by nonviolent participants was leakage (6.6%); direct threats of violence were displayed most frequently (73.4%). Violent participants displayed a significantly greater number of warning behaviors overall, $t(243.46) = 11.31$; $p < .001$, and all behaviors except direct threats were displayed more frequently by violent participants ($\chi^2$ = 33.17–64.67; all $p < .001$). Percentages of all warning behaviors displayed by violent and nonviolent participants are shown in Table 3.

**Table 3**
*Differences in Prevalence of Warning Behaviors Between Violent and Nonviolent Participants*

| Behavior | Violent ($n$ = 133): $N$ (%)/$M$ | Nonviolent ($n$ = 124): $N$ (%)/$M$ | Total ($n$ = 257): $N$ (%) | Test statistic | Effect size |
|---|---|---|---|---|---|
| Pathway | 91 (35.4) | 23 (8.9) | 114 (44.4) | 64.67** | 0.50 |
| Fixation | 89 (34.8) | 38 (14.8) | 127 (49.6) | 33.17** | 0.36 |
| Identification | 82 (32.0) | 20 (7.8) | 102 (39.8) | 56.43** | 0.47 |
| Novel aggression | 83 (32.4) | 19 (7.4) | 102 (39.8) | 58.79** | 0.48 |
| Energy burst | 86 (33.7) | 21 (8.2) | 107 (42.0) | 60.43** | 0.49 |
| Leakage | 81 (31.5) | 17 (6.6) | 98 (38.1) | 60.58** | 0.49 |
| Last resort | 81 (31.5) | 23 (8.9) | 104 (40.5) | 47.78** | 0.43 |
| Direct threats | 111 (83.5) | 91 (73.4) | 202 (78.6) | 3.87* | 0.12 |
| Total (*SD*) | 5.31 (2.56) | 2.05 (2.00) | 3.75 (2.83) | 11.31** | 2.31 |

*Note.* Test statistic was either a chi-square value or $t$ value, depending on whether the variable was dichotomous or continuous. The effect size was either a φ coefficient or Cohen's $d$.
* $p < .05$. ** $p < .01$.



## Research Question 1: Correlations Between Warning Behaviors for Violent and Nonviolent Participants

Across all participants, all warning behaviors were significantly correlated with one another ($r$ = .48–.66; all $p < .001$; see Table 4) except for direct threat of violence, which was not correlated with any other behavior ($r$ = .02–.12; $p$ = .056–.698). For participants who perpetrated physical violence, all warning behaviors were also significantly correlated ($r$ = .40–.62; all $p < .001$; see Table 5) aside from direct threat of violence ($r$ = −.11–.07; $p$ = .216–.874). Within the subgroup of nonviolent participants, most pairs of warning behaviors were also significantly correlated ($r$ = .29–.55; all $p <$ .001). However, last resort behavior was not correlated with pathway, fixation, and energy burst behaviors, and direct threat of violence was not correlated with any other behavior ($r$ = .05–.27; $p$ = .003–.562; see Table 6). When all correlations between warning behaviors were compared across groups using MML-WBCORR, a significant difference was revealed ($\chi^2 = 280.15$; $p < .001$). However, when post hoc comparison analyses between pairs of correlations were performed to determine the location of the difference, only the difference in correlations between pathway and last resort behavior was significant ($r$ = .48 [violent] vs. $r$ = .15 [nonviolent]; $p < .001$). As 28 comparisons were required, a Bonferroni correction set the α value at .0018 for these tests.

## Research Question 2: Comparative Predictive Ability of Warning Behaviors

Forward stepwise multivariate logistic regression produced three separate steps, with each step displaying statistical significance in terms of

**Table 4**
*Correlations Between Warning Behaviors Across All Participants*

| Warning behavior | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. Pathway | — | | | | | | | |
| 2. Fixation | .62* | — | | | | | | |
| 3. Identification | .66* | .59* | — | | | | | |
| 4. Novel aggression | .64* | .60* | .62* | — | | | | |
| 5. Energy burst | .58* | .58* | .55* | .60* | — | | | |
| 6. Leakage | .57* | .57* | .60* | .66* | .57* | — | | |
| 7. Last resort | .49* | .48* | .52* | .53* | .52* | .53* | — | |
| 8. Direct threat | .10 | .12 | .10 | .06 | .09 | .12 | .02 | — |

*Note.* $n$ = 257. All numbers are Pearson correlation ($r$) values.
* $p < .0018$.

**Table 5**
*Correlations Between Warning Behaviors for Violent Participants*

| Warning behavior | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. Pathway | — | | | | | | | |
| 2. Fixation | .62* | — | | | | | | |
| 3. Identification | .61* | .57* | — | | | | | |
| 4. Novel aggression | .51* | .54* | .55* | — | | | | |
| 5. Energy burst | .51* | .48* | .44* | .46* | — | | | |
| 6. Leakage | .52* | .55* | .49* | .56* | .40* | — | | |
| 7. Last resort | .48* | .49* | .43* | .46* | .50* | .46* | — | |
| 8. Direct threat | .05 | .07 | −.01 | −.10 | −.06 | .06 | −.11 | — |

*Note.* $n = 133$. All numbers are Pearson correlation ($r$) values.
* $p < .0018$.

predicting future violence. In the first step ($\chi^2 = 73.09$; $p < .001$; Nagelkerke $R^2 = .34$), pathway behavior emerged as the strongest contributor within the model; pathway behavior as a predictor demonstrated statistical significance ($p < .001$) and resulted in a participants' odds of violence increasing by over 11 times (95% CI [6.13, 21.07]; see Table 7 for statistical output). In the second step ($\chi^2 = 92.30$; $p < .001$; Nagelkerke $R^2 = .42$), energy burst was included alongside pathway behavior, and both warning behaviors were statistically significant predictors of violence (both $p < .001$). Their presence increased the odds of violence over four (95% CI [2.34, 9.42]) and over five (95% CI [2.94, 11.51]) times. The third step of the model ($\chi^2 = 99.20$; $p < .001$; Nagelkerke $R^2 = .45$) consisted of pathway behavior ($p < .001$), energy burst ($p = .001$), and novel aggression ($p = .008$). The odds ratios of these behaviors were 3.95 (95% CI [1.88, 8.26]), 3.49 (95% CI [1.67, 7.28]), and 2.91 (95% CI [1.32, 6.41]). No other warning behaviors were subsequently found to make significant contributions to the predictive ability of the model.

## Research Question 3: Clustering of Warning Behaviors for Violent and Nonviolent Participants

Goodness of fit of the ordinal PROXSCAL analysis was determined to be sufficient, as the Stress 1 score was .02 (excellent; Kruskal & Wish, 1978), and the S-Stress percentage was .001% (Hair et al., 1998). The dispersion accounted for and Tucker's coefficient of congruence values were also extremely close to 1 (both .999; Dugard et al., 2010). See Figure 1 for the visualized results of the MDS analysis, showing the placement of the warning behaviors and all individual violent and nonviolent participants. Visual inspection revealed that six of the eight behaviors were clustered closely together in the bottom left corner of the scatterplot (between

**Table 6**
*Correlations Between Warning Behaviors for Nonviolent Participants*

| Warning behavior | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| 1. Pathway | — | | | | | | | |
| 2. Fixation | .45* | — | | | | | | |
| 3. Identification | .47* | .42* | — | | | | | |
| 4. Novel aggression | .55* | .50* | .42* | — | | | | |
| 5. Energy burst | .34* | .54* | .39* | .52* | — | | | |
| 6. Leakage | .29* | .40* | .46* | .55* | .51* | — | | |
| 7. Last resort | .15 | .27 | .36* | .31* | .23 | .29* | — | |
| 8. Direct threat | .05 | .09 | .12 | .11 | .13 | .08 | .05 | — |

*Note.* $n = 124$. All numbers are Pearson correlation ($r$) values.
* $p < .0018$.

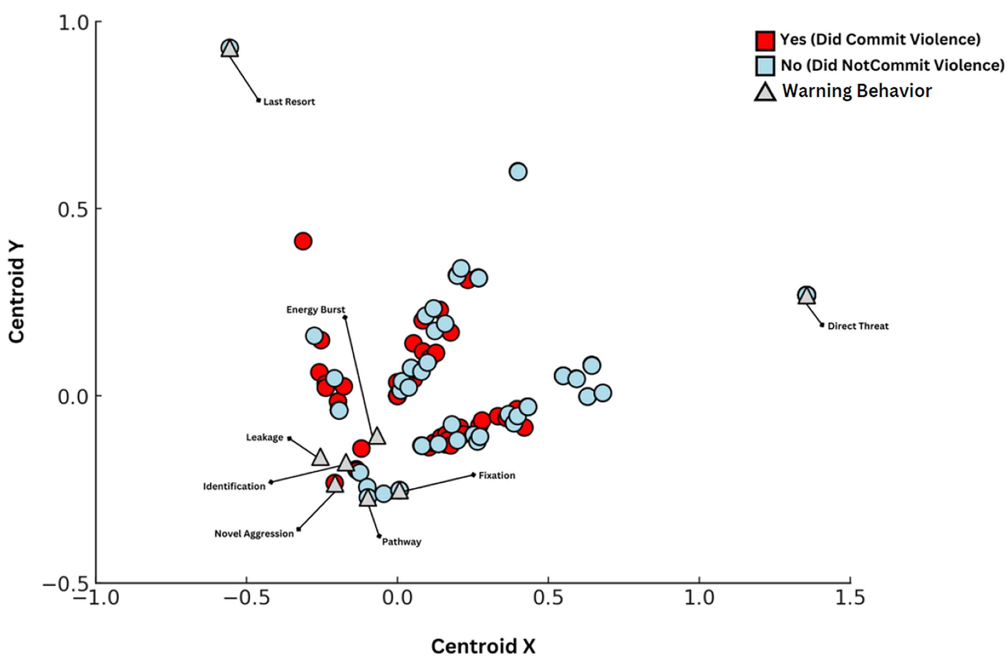
**Table 7**
*Comparing the Predictive Ability of Warning Behaviors via Forward Stepwise Logistic Regression*

| Predictor variable | $B$ | $SE$ | Wald $\chi^2$ statistic | $p$ | Odds ratio | 95% CI $LL$ | 95% CI $UL$ |
|---|---|---|---|---|---|---|---|
| Model 1 | | | | | | | |
| Pathway behavior | 2.43 | .32 | 59.59 | .000 | 11.37 | 6.13 | 21.07 |
| Model 2 | | | | | | | |
| Pathway behavior | 1.76 | .35 | 25.56 | .000 | 5.82 | 2.94 | 11.51 |
| Energy burst | 1.55 | .36 | 18.99 | .000 | 4.70 | 2.34 | 9.42 |
| Model 3 | | | | | | | |
| Pathway behavior | 1.37 | .38 | 13.25 | .000 | 3.95 | 1.88 | 8.26 |
| Energy burst | 1.07 | .40 | 7.04 | .008 | 3.49 | 1.67 | 7.28 |
| Novel aggression | 1.25 | .38 | 11.05 | .001 | 2.91 | 1.32 | 6.41 |

*Note*. Models 1–3 were significant overall. Model 1: $\chi^2 = 73.09$; $R^2 = .34$; $p < .001$. Model 2: $\chi^2 = 92.30$; $R^2 = .42$; $p < .001$. Model 3: $\chi^2 = 99.20$; $R^2 = .45$; $p < .001$. Five predictors were excluded from Model 3: fixation ($\chi^2 = .48$; $p = .49$), identification ($\chi^2 = 2.28$; $p = .13$), leakage ($\chi^2 = 2.37$; $p = .12$), last resort behavior ($\chi^2 = 3.37$; $p = .07$), and direct threat ($\chi^2 = 2.87$; $p = .09$). $SE$ = standard error; CI = confidence interval; $LL$ = lower limit; $UL$ = upper limit.

centroid $x$ coordinates of −.257 and .005 and $y$ coordinates of −.271 and −.105, respectively), while last resort behavior and direct threats of violence were plotted substantially farther away. This can be interpreted to mean that the six former behaviors were reported by the same participants (across the entire sample) more frequently and the others were not.

**Figure 1**
*Plotted Centroid Coordinates of Violent Participants, Nonviolent Participants, and the Eight Warning Behaviors*




*Note*. Gray triangles are the plotted coordinates of the eight warning behaviors averaged across all participants. Red circles are the plotted coordinates of each individual violent participant, whereas blue circles are the plotted coordinates of each individual nonviolent participant. See the online article for the color version of this figure.

Independent-samples *t* tests revealed significant differences in both *x* and *y* centroid means between the two groups of participants. Participants who had been violent following their threat were more likely to have lower *x* centroid values, that is, spanning toward the negative dimension on the left side of the plot, $t(172.74) = 7.31$; $p < .001$, and lower *y* centroid values, that is, reaching toward the bottom of the plot, $t(162.64) = 4.68$; $p < .001$. Large ($d = 1.01$) and moderate ($d = .65$) effect sizes were observed for these differences (Cohen, 2013). This suggests that significant differences exist between violent and nonviolent participants in terms of behavior clustering; specifically, that the behaviors cluster more tightly for the violent group and therefore co-occur more frequently. See Figure 2 for a visual representation of the differences in centroid values between participant groups.

## Discussion

The present study aimed to replicate and extend the findings of Goodwill and Meloy (2019) with respect to the co-occurrence of the eight proximal warning behaviors and their association with subsequent violence within a larger and more generalizable sample. Our study serves to build further confidence within the fields of violence risk and threat assessment by fostering a more reliable understanding of the potential co-occurrence of warning behaviors prior to acts of targeted violence, thereby safeguarding against the acceptance of false positives, and/or anomalous results. Similar to prior research, via a correlation matrix and MDS, we discovered a pronounced correlation and clustering of the majority of the behaviors yet observed this pattern to be present for both violent and nonviolent participants. Additionally, through regression analyses, we observed pathway, novel aggression, and energy burst behaviors to be the most predictive of future violence. By systematically identifying and evaluating the relative importance of individual warning behaviors in predicting violence, this not only allows for a more nuanced examination of the factors contributing to violence risk but also identifies key predictors that may inform targeted interventions and risk management strategies.

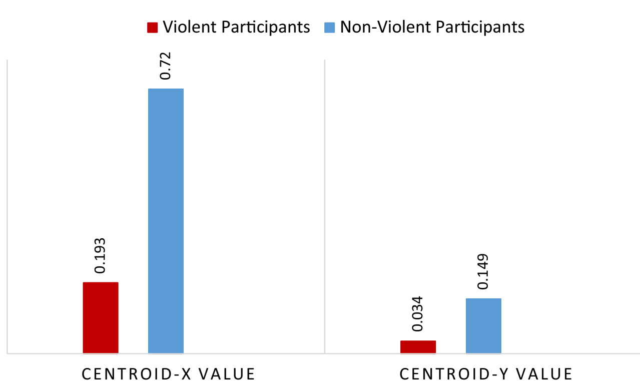
### Conclusions and Implications

#### *Co-Occurrence of Warning Behaviors*

The study first examined correlations between eight warning behaviors within both violent and nonviolent threateners. It was found that almost all warning behaviors were significantly correlated with one another, except for last resort behavior in nonviolent participants and direct threats in both groups; similarly, visual inspection of the scatterplot produced by MDS analysis showed that all warning behaviors except direct threats of violence and last resort behavior clustered together. These findings echo the results of Goodwill and Meloy's (2019) previous MDS analysis within a sample of

**Figure 2**

*Mean Centroid Differences of Warning Behaviors Between Violent and Nonviolent Threateners*




*Note.* See the online article for the color version of this figure.

individuals who committed acts of terrorism, as they also discovered a distinct clustering of six warning behaviors (although instead of last resort behavior, their outlier was novel aggression). Notably, the singular warning behavior that was not correlated with the others across analyses and participant groupings was direct threats of violence to the target. This could reflect the theorizing of Warren et al. (2021), who suggest that direct threats may not reliably predict violent behavior and may actually be counterproductive to violent behavior because they serve as a warning of the threatener's intent beforehand. However, this could also be attributed to the high base rate of direct threats across threateners who were and were not physically violent within this sample. Direct threats were still significantly correlated with violence and may be another important warning signal that simply does not co-occur with the others. It may also be the case that in another sample of individuals who did not all threaten, direct threats would show an even more prominent association with violence.

Both correlation and MDS analyses revealed clustering of behaviors that was remarkably similar across both violent and nonviolent participants. However, the pattern displayed by the violent (red) cases in Figure 1 and the statistical significance of the independent-samples *t* tests suggest that clustering of warning behaviors is more *frequent* in individuals who are physically violent. This reflects previous risk and threat assessment literature in that at-risk (i.e., behaviorally concerning) individuals still present with risk factors and/or warning behaviors, but persons who go on to violence frequently display a greater number of them (Nijdam-Jones et al., 2021; Williams et al., 2025). Therefore, there appears to be no silver bullet combination of warning behaviors that signal violence, but threat assessors should evaluate the number of behaviors a person of concern displays and regard greater numbers as indicative of a higher risk of targeted violence and perhaps a higher priority in triage. However, if resources permit, it is recommended that individuals presenting with any of the behaviors be assessed, as each has been individually linked to violence (M. F. E. Almond & Douglas, 2025) and the presence of even one has been likened to a "storm in one's backyard" rather than merely on the horizon (Goodwill & Meloy, 2019).

The similarity of behaviors shown by both violent and nonviolent participants complicates the accurate identification of individuals at risk, leading to potential misclassification and ineffective interventions. To address this, a multifaceted approach is necessary, focusing on other individualized aspects beyond just warning behaviors. It is essential to gather comprehensive information through thorough assessment strategies, including structured interviews, open-source investigations, and records from various sources (e.g., police incident reports). By broadening the scope of assessment, we can better capture the full range of potential risk factors, ensuring a more accurate and nuanced understanding of the individual (Calhoun & Weston, 2013; National Center for the Analysis of Violent Crime, 2019). For instance, structured interviews with the individual of interest, if possible, are crucial as they allow for direct assessment of their behavior, attitudes, and potential risks. In addition to this, interviews with individuals who frequently interact with the person of interest can provide detailed insights into the individual's behavior, attitudes, and patterns that may indicate potential risks, by offering valuable context about daily interactions, emotional states, triggers, and recent behavioral changes (Meloy, Hoffman, Deisinger, & Hart, 2021; National Center for the Analysis of Violent Crime, 2019). This comprehensive approach, as is recommended in many structured professional judgment tool manuals, enables a more precise risk assessment, fosters an informed and thorough risk formulation, and helps tailor intervention strategies effectively (e.g., Douglas et al., 2013).

Because our results suggest that the mere presence of certain combinations of warning behaviors may not always differentiate individuals at risk of violence, it is crucial to consider how these behaviors interact with empirically supported factors beyond these behaviors, such as dynamic risk factors like active mental health symptoms and substance use. Using flexible yet evidence-based structured professional judgment threat assessment tools (e.g., the Workplace Assessment of Violence Risk–21, White & Meloy, 2010; Guidelines for Stalking Assessment and Management–V2, Kropp et al., 2024) allows professionals to more accurately evaluate these interactions. By considering both warning behaviors alongside the historical and dynamic risk factors included within these tools, it is assumed that professionals can better distinguish between violent and nonviolent individuals. Research consistently supports the effectiveness of such structured decision-making aids in enhancing risk and threat assessment accuracy (Cornell & Crowley, 2021; Douglas & Otto, 2021; Viljoen et al., 2021; Wertz et al., 2023). Furthermore, rather than focusing solely on the presence or absence of warning behaviors, further investigation into the intensity, temporal patterns, and progression of these behaviors in tandem should be prioritized. While examining the simple co-occurrence of these behaviors may offer some insights, it may not be enough to capture nuances in the strength and sequence in which they are displayed, nor if certain behaviors may dominate others in a predictive sense. By delving deeper into these concepts, as recommended for risk factors by Kraemer et al. (2001), we can enhance our understanding of their development. This approach would also provide crucial information for designing early and targeted intervention strategies.

### *Comparison of the Predictive Ability of Warning Behaviors*

Among all the behaviors analyzed in our sample, pathway, energy burst, and novel aggression were found to be the most predictive of violence, when compared with all other behaviors. This aligns with the sparse prior research on the association between specific warnings behaviors and violence (Meloy et al., 2019; Meloy, Hoffmann, Roshdi, & Guldimann, 2014) and provides more detail regarding potential imminent precursors to violence. It is recommended that professionals not only recognize these particular behaviors but remain vigilant and prepared to intervene swiftly upon their detection. By doing so, they can better assess the complexity of an individual's risk profile and tailor interventions accordingly to address the specific needs of the individual to further mitigate the risk of violence. Implementing bystander reporting systems can be highly effective. Adding these specific behaviors into organizational policies and response protocols can enhance the effectiveness of interventions, fostering a safer environment through proactive risk management (Eisenman et al., 2024). By educating bystander reporting monitors about the potential greater association of these three specific warning behaviors, these systems can adjust their screening procedures to detect and prioritize behaviors within these categories.

Our analysis highlighted the need to explore how different warning behaviors might interact and influence the risk of violence. While we solely examined which behaviors demonstrated greater predictability in the presence of other behaviors, and did not examine how the order in which these behaviors occur might affect predictability, previous behavioral sequencing research within a terrorist sample (Meloy, Goodwill, Clemmow, & Gill, 2021) suggests that these behaviors may frequently occur in a reliable order. However, this study only examined cases which ended in planned or perpetrated violent acts of terrorism and did not compare behavioral sequencing for violent and nonviolent cases. As our study did not find great differences between the simple co-occurrence of warning behaviors across violent and nonviolent participants, it would be beneficial to explore whether these behaviors occurring in a specific temporal order is the key to this differentiation. According to Calhoun and Weston's (2003) proposed pathway to violence, parts of pathway behavior, including research and planning, often precede other warning behaviors. This is also supported by the time sequencing analysis conducted by Meloy, Goodwill, Clemmow, and Gill (2021). This could logically be followed by energy burst behavior, a sudden escalation in emotional arousal or aggression, and then novel aggression, suggesting previously unseen violent tendencies as the progression toward violence continues. By recognizing these distinct patterns, interventions can be timed and targeted more effectively to address specific stages of risk escalation.

## Methodological Considerations and Limitations

Selection bias in the sample, which was predominantly comprised of male, White, and educated individuals, is a notable limitation. Although studies have indicated that MTurk samples are more representative of the North American general population compared with postsecondary samples (Schleider & Weisz, 2015), there remains an overrepresentation of certain demographics. Additionally, the high level of education and relatively high average annual income observed in the current sample (95.3% of the sample reported at least some college/university education, 48.2% reported an annual income of $50,000 or higher) aligns with findings from previous MTurk studies (Monjazeb & Douglas, 2024; Paolacci et al., 2010). This is not representative of typical clinical and/or forensic populations (e.g., Warren et al., 2011, as noted previously), and the results of this study may not generalize to these individuals. Moreover, given that our sample was primarily comprised of male participants, who are more frequent perpetrators of violent behavior, it is plausible that rates of physical violence following threats were overestimated, relative to estimates within the general population (Schleider & Weisz, 2015). However, predominately male samples appear common among previous research on explicit threats (Mitchell et al., 2019; Warren et al., 2008, 2011) and in forensic research more broadly.

The study indicates that although some individuals in the sample did commit serious acts of violence, overall, there is a tendency toward less severe threats and violence than present in other studies of targeted violence. The applicability of the study's conclusions to individuals in environments in which more severe violence is observed, such as correctional and forensic psychiatric settings, may be limited due to this. However, 32.3% of the sample perpetrated actual or attempted homicide or sexual assault, so serious acts of violence were not uncommon. Furthermore, most research on warning behaviors has been conducted with forensic populations who have perpetrated severe violence, such as mass killers and terrorists. Although these studies provide valuable information on warning behaviors that precede targeted violence, studying the role of warning behaviors within a more generalizable sample is advantageous; it offers a broader understanding of how these behaviors manifest prior to more common and less severe acts of violence.

It is possible that quality of data in this study may be impacted by potential untruthfulness in responses and variations in attention levels during completion. Participants' responses could be influenced by recall bias, where their memory of past events affects their answers. There is also the concern that participants may not provide truthful responses, possibly motivated by the offered compensation or social desirability bias, yet these same concerns are present in clinical work with forensic clients and in most self-report psychological research. The latter issue is somewhat mitigated by the anonymous nature of the survey, although we acknowledge that online surveys are not immune to social desirability (Dodou & de Winter, 2014). Untruthfulness was mitigated by a validity check question at the beginning and end of the survey that identified and excluded participants who did not consistently report the same victim of their threat. As mentioned above, this question offered 16 different response options, making it statistically unlikely for a participant to randomly select the same option at both time points; if participants did not provide the identical responses, they were excluded from statistical analyses.

Although this is the first study to assess warning behaviors via self-report, there were several challenges in assessing them reliably in this fashion. First, there is the issue of language interpretation: Participants may interpret and articulate their behaviors differently, leading to discrepancies in reporting. Second, the retrospective design of the present study is another of its limitations, as participants were prompted to recall an instance where they had made a threat and displayed these behaviors previously. Participants were explicitly prompted to consider warning behaviors demonstrated prior to violent acts, but it is acknowledged that they may not have always done so. This suggests that these behaviors are associated with violence and potential predictors of it—not causal factors. It is further possible that the large number of observed relationships between the warning behaviors, and between the behaviors and physical violence, may be inflated by common method variance (Podsakoff et al., 2012), as all data originated from the same survey that was administered at a single time. If so, this could imply that a single person may not show quite as many warning behaviors in practice prior to their violence, although as stressed above, even the presence of a single behavior is cause for concern.

Despite these potential issues in self-reported warning behaviors, it is important to note that our findings align with previous literature, evidencing content validity. Specifically, violent participants demonstrated warning behaviors significantly more frequently than nonviolent participants, and other previously observed patterns were supported as well (e.g., warning behaviors clustering, except for direct threats; Goodwill & Meloy, 2019). Last, a criterion for inclusion was explicit (but not necessarily direct) threats of violence; this likely led to the overrepresentation of direct threats, the eighth warning behavior, as opposed to any explicit threat either directly to the victim or to a third party.

## Considerations for Future Research

Future research should continue to examine the chronological order of warning behaviors to uncover patterns of escalation that reliably precede violence. Investigating the time sequencing of warning behaviors can provide vital insights into the typical chronological order of these behaviors by identifying discernable patterns that may precede targeted violence. Although Meloy, Goodwill, Clemmow, and Gill (2021) have examined this in a terrorist sample using the TRAP-18 indicators, which include the eight warning behaviors, larger and more diverse types of violence (e.g., sexual violence, gratuitous violence) need to be assessed.

Moreover, there is a notable gap in the literature regarding prospective longitudinal studies in threat assessment. Pertinent existing research relies on retrospective data, which can introduce hindsight and confirmation biases. These biases, common in known-outcome studies, can skew interpretations and overlook contradictory evidence, impacting the reliability and generalizability of findings. Therefore, careful consideration of these biases is crucial in mitigating their effects and enhancing the validity of retrospective research. To address this gap, future studies should prioritize prospective or pseudoprospective designs that systematically document warning behaviors over time, starting from the point of threat disclosure, for as long as ethically possible. Partnerships with law enforcement may be one way to do this. Additionally, future studies should strive to use data collected from official sources such as national crime statistics and police incident reports in addition to open-source data, as they provide reliable, comprehensive, and accurate information, which is imperative to producing valid and actionable findings.

Future research should examine diverse types of offenders (e.g., sexual offenders, psychopathic offenders) to investigate potential differences in the clustering of warning behaviors. This understanding can contribute to the development of targeted interventions and prevention efforts, including early intervention strategies. For instance, understanding that certain warning behaviors are frequent among attackers could enable authorities to implement targeted surveillance and community engagement efforts aimed at identifying and supporting at-risk individuals before potential violence occurs. By intervening proactively based on these behavioral patterns, authorities can disrupt threats and enhance public safety more effectively. Finally, future research should investigate the variations in warning behaviors between young people and adults, considering developmental factors such as impulsivity that can affect behavior. Adolescents often display different characteristics and risk factors compared with adults, including increased impulsivity and susceptibility to peer influence (Cauffman & Steinberg, 2000; Romer, 2010). Relatedly, individuals with personality-related concerns like psychopathy, which can also impact impulsivity (Hare & Neumann, 2008), could be more likely to enact violence without preparatory steps. Therefore, it is crucial to examine how warning behaviors manifest across different populations to tailor risk assessment and intervention strategies to each group. By comparing warning behavior profiles across different age cohorts, researchers can identify age-specific risk markers and inform targeted prevention efforts aimed at mitigating youth violence. Moreover, understanding the developmental trajectories of warning behaviors from adolescence to adulthood can provide valuable insights into early identification and management of violence risk across the lifespan.

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(*Appendix follows*)

## Appendix

### Warning Behaviors Questionnaire Items

1. Did you make the threat directly to the victim, or to law enforcement?
2. Prior to making the threat, did you do any research, planning, or other types of preparation for carrying out the threat?
3. Prior to making the threat, were you strongly interested in the victim (target) of your threat and found yourself often occupied with thoughts of them and/or talking about them frequently?
4. Prior to making the threat, did you find yourself identifying with other people who have committed violence, experiencing a "warrior mentality," or identifying with groups like law enforcement, the military, or assassins/hitmen?
5. Prior to making the threat, did you commit any aggressive or violent behaviours unrelated to the threat for the first time (e.g., you have engaged in minimal violence or no violence beforehand)?
6. Prior to making the threat, did you feel more energetic? Did you increase the frequency of violent or non-violent behaviour, or any behaviour that was related to the victim (target) in any way?
7. Prior to making the threat, did you tell anyone about your intent to make the threat or commit violence in any fashion (e.g., in person, via the telephone or the internet) or post your intent to make the threat or commit violence on any public internet forum or other public place?
8. Prior to making the threat, did you feel like nothing mattered anymore and experienced increasing desperation or distress? Did you feel trapped, like there is no alternative other than violence, and that the consequences of violence were justified?

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