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# The Whole Is Greater than the Sum of Its Parts: Risk and Protective Profiles for Vulnerability to Radicalization

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**ABSTRACT**
This study examines how behavioral indicators co-occur as "risk profiles" across different domains relevant to risk assessment as theorized by a Risk Analysis Framework, and how these profiles impact upon vulnerability to radicalization. We unpack both the inter- and intra-domain relationships among profiles, identifying the relative importance of cumulative or interactive effects. We apply latent class analysis, a series of ANOVAs, and moderator analyses to a sample of the UK population (n = 1,500). We examine how the risk profiles relate to scores on the Radicalism Intention Scale, and how profiles relate to, and interact with, one another. Our results suggest that radicalization risk emerges fundamentally from both the interaction and cumulation of processes at different levels of analysis and is therefore highly context dependent. Risk assessment should rely less on quantifying specific indicators and attend to correctly inferring their ***functional relevance*** to the risk being assessed.

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Radicalization; risk factor; protective factor; risk assessment; public health

"Past experience and behavioral research tell us that our most vulnerable individuals are the most susceptible to radicalization to violent extremism" (Department of Homeland Security, 2021: 23). A public health approach to countering violent extremism aims to intervene among the vulnerable, to prevent individuals escalating to criminality or violence. In the present study, we define vulnerability to radicalization as emerging when susceptible people are at risk of being exposed to terrorism-supportive environments. Individuals are "susceptible" if they demonstrate characteristics which make them more likely to adopt a terrorist propensity (Bouhana, 2019).

Identifying and validating risk and protective factors for vulnerability to radicalization leading to involvement in violent extremism is one pillar of the successful implementation of a public health approach. In response, a growing body of pertinent research exists that was synthesized in a meta-analysis (Wolfowicz et al., 2020). Whilst

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an essential step in developing the required evidence base, research demonstrates the multifinality of individual risk factors (Clemmow et al., 2022; Clemmow et al., 2020; Corner et al., 2019). That is, any risk factor can be associated with many potential outcomes. Hence, practice requires knowledge which goes beyond examining the effects of single factors and moves towards understanding how risk factors co-occur and relate to one another to drive or dampen vulnerability.

However, much of the science in this space focusses on the effects of single risk factors on a specified outcome. This is foundational work upon which we base the present study. To now go beyond the study of individual effects, the present study examines a) how risk factors co-occur as risk profiles at different levels of analysis (propensity, situation, exposure), b) how these profiles relate to each other, and c) how these interactions relate to differential vulnerability to radicalization. We employ a previously designed Risk Analysis Framework (RAF; Bouhana et al., 2022) to deduct configurations of risk factors across different domains relevant to risk assessment (propensity, situation, exposure), and further examine how these profiles relate to one another. In doing so, we unpack the nature of both the inter- and intra-domain relationships among risk profiles, identifying when the effects of different risk profiles indicate the relative importance of cumulative or interactive effects. The results provide more nuanced evidence to inform the design and delivery of a public health approach, improving our ability to better specify when and for whom certain risk profiles may be relevant predictors of radicalization leading to involvement in violent extremism. Ultimately, we call for a step change in how we devise and conduct risk assessment in this space and reiterate the need to move away from the study of single risk factors, and towards inferring the functional relevance of configurations of risk factors and how these relate to differential vulnerability to radicalization.

## *Background*

The approaches of Western countries to combatting ideologically motivated violence, or violent extremism, have changed considerably over the years. Whereas the immediate period following 9/11 placed a focus on counterterrorism, the last decade has seen the proliferation of a counter-radicalization paradigm (Borum, 2011; Horgan, 2008; Silva & Deflem, 2020). Whilst radicalization remains a contested term, Western countries conceive it as being the adoption of attitudes that justify violent extremism, and for some small proportion of those who hold such attitudes, the actual engagement in such violence. Public-health approaches to countering violent extremism are modelled closely after strategies combatting crime, with interventions at different levels targeted at combatting attitudinal and behavioral radicalization.

At the primary level, interventions seek to manage susceptibility to radicalization and address unmet needs. Such interventions intend to reduce the size of the pool from which violent extremists may emerge, thereby reducing the likelihood of harm—the focus of our study is at this level. At the secondary level, interventions target those who already hold radical attitudes and seek to prevent their turn towards violence. Tertiary level interventions target those who have already offended and aim to reduce the risk of recidivism (Weine et al., 2017). At all levels, interventions are usually designed to stymie or mitigate some risk factor and/or bolster protective factors (Bhui et al., 2012).

However, the identification and selection of risk factors used in risk assessments and subsequent management interventions preceded the development of a rigorous evidence base (Silva & Deflem, 2020). Indeed, many of the most commonly targeted factors (e.g. poor integration) have been found to have relatively weak relationships with vulnerability to radicalization (Wolfowicz et al., 2020). Findings also show that factors from different risk domains encompass a broad range of effect sizes (ibid). Such findings further emphasize the significant degree of overlap that exists between risk factors for radicalization and criminality, lending support to the public health model currently being implemented - also suggesting that theoretical and methodological approaches from Criminology offer significant promise for the development of an enhanced evidence-based approach (LaFree & Dugan, 2004).

For such an agenda to progress, research must be carried out in a systematic way, building from what is known, identifying knowledge gaps, and applying proven theoretical and methodological approaches to address them. What is currently known is that there are over a hundred risk factors for vulnerability to radicalization worthy of consideration, and the relative magnitude of their effects (Wolfowicz et al., 2020). However, it is also known that no single risk factor determines the likelihood that an individual will inevitably radicalize, let alone offend (Gill et al., 2014). Recently, Clemmow et al. (2022) applied psychometric network analysis, underpinned by the RAF, to model the many correlates of vulnerability to radicalization as a complex system. The results visualized how individual risk factors interact with and relate to one another. The images are a tangible demonstration of the multi- and equifinality of risk factors for vulnerability to radicalization (Gill et al., 2021). This work, and preceding scholarship developing the evidence base for risk factors for vulnerability to radicalization, directly informs the present study. Whilst Clemmow et al. (2022) demonstrated the mutually reinforcing and causal interactions among the many risk factors for vulnerability to radicalization, a core problem persists. Whereas scientific work developed an awareness of which factors, in isolation, are more commonly ***present*** within radicalized populations, real-world practice requires a robust scientific understanding of how different factors, combine to be ***relevant*** in the generation of the harmful outcome of interest. We suggest that, as with inquiries into other forms of deviance, it is now necessary to consider how ***sets*** of risk factors may relate to the causal mechanisms which underpin the phenomenon—the thinking being that whilst single risk factors may have differential effects, the underlying causal mechanisms which drive the phenomenon may be more stable grounds for decision-making (Bouhana, 2019).

In fact, the Criminological literature has demonstrated that risk and protective factors do not operate individually, and there is rarely a case in which only one risk factor is present (Hart et al., 2016). Rather, risk and protective factors can operate both ***cumulatively*** and ***interactively***. That is, it could be either the number of risk and protective factors or the particular combinations in which they present themselves, that increases or lessens individuals' risk. Our previous work alludes to this also being true of vulnerability to radicalization (Clemmow et al., 2022; Clemmow et al., 2022), however this remains to be examined empirically. We still understand little about the inter- and intra-domain cumulative and/or interactive effects of risk factors and how these relate differentially to vulnerability to radicalization leading to involvement in terrorism. This gap in the literature is the focus of the present study and how we build upon and extend our previous work.

To generate a more nuanced understanding of how risk factors within and across different domains relate to vulnerability to radicalization, a different approach to identifying "risk profiles" is warranted. One such approach often used in criminology is deductive techniques like cluster analysis or latent class analysis (LCA). Such analytical strategies detect unmeasured sub-groups, providing a data driven classification of groupings which exist naturally amongst data. An evaluation of statistical classification techniques suggests that LCA is superior to other commonly used classification techniques such as multi-dimensional scaling and cluster analysis (Fox & Escue, 2021). Hence there is evidence to suggest that LCA may be appropriate to examine the intra- and inter-domain interactive and cumulative effects of risk factors for vulnerability to radicalization. Nevertheless, data-driven, deductive techniques such as LCA are best implemented alongside a robust analytical framework to guide interpretation.

### *Analytical Framework*

In the present study, we employ the previously designed Risk Analysis Framework (RAF) to guide our conceptualization and interpretation (Bouhana et al., 2022). Built on the premise that radicalization is a specific case of a general process of criminal propensity development (Bouhana & Wikström, 2011), the RAF is a willfully criminological framework. It draws on Situational Action Theory (SAT) (Wikström, 2010)—a general theory of crime—to synthesize and organize observations about the multilevel factors associated with radicalization leading to violent extremism under a parsimonious set of fundamental causal mechanisms. Radicalization is theorized as the outcome of the interaction between individual susceptibility to moral change (pre-existing propensity), selection factors (situation), and radicalization settings (exposure), whose features afford terrorism-supportive radicalization.

Operationalizing the RAF, vulnerability to radicalization was conceptualized into three components: (1) *Propensity* refers to a person's pre-existing disposition to moral rule-breaking, notably their prior (or lack thereof) commitment to an action-relevant moral framework and their executive functioning capacity, two domains consistently associated with the development of a criminal propensity and involvement in crime (Wikström et al. 2012); (2) *Situation* refers to life circumstances which can induce a change an individual's lifestyle, habits, and activity fields that increases the risk of selection for exposure to settings with terrorism-supportive features. While changes in life circumstances have been traditionally interpreted as opportunities for cognitive openings to radicalizing influence, within the RAF they are conceptualized as events that move people in (new) space, creating opportunities for exposure to (potentially radicalizing) settings (Bouhana & Wikström, 2011; Wikström & Bouhana, 2016); (3) *Exposure* relates to the features of the terrorism-supportive people, places, and materials to which susceptible individuals can be exposed through situational selection. The indicators chosen to operationalize this domain reflect aims to capture some of the key features of radicalizing contexts, chiefly those which afford opportunities for contact and attachment to radicalizing agents and for exposure to radicalizing moral norms.

While criminological in formulation, these three domains can be mapped onto the kinds of factors and processes researchers have prioritized in their investigation of radicalization (see Bouhana et al. 2022, Bouhana, 2019, and Bouhana & Schumann, 2022 for an extensive discussion). Most importantly, developmental psychological frameworks of radicalization increasingly recognize the need to fully integrate individual-level processes and selection for exposure to radicalizing contexts in explanations of radicalization leading to involvement in violent extremism (see for example the development of the Quest for Significance theory into the 3 N model; Kruglanski et al., 2018), an integration which is a key dimension of the RAF.

### *The Present Study*

We examine how risk profiles across different domains (propensity, situation, exposure) relevant to risk assessment and management, as theorized by the RAF, relate to vulnerability to radicalization, and further explore the intra- and inter-domain cumulative and interactive effects among the identified risk profiles in a general population. We employ a three step person-centered analytic strategy using: (1) LCA, (2) a series of ANOVAs, and (3) moderator analyses with data from a sample of the UK population ($n = 1{,}500$). We further examine how age and sex affects risk profile membership. The resultant findings have important implications for the implementation of a public health approach, risk assessment and management, and future research for preventing and countering violent extremism.

## Method

### *Ethics*

The study received ethical approval from University College London's ethics committee, approval number 12359/002.

### *Sample*

We surveyed a sample of the UK general population. The sample was recruited from Prolific, an online access panel specifically for ***academic*** research. All participants who agreed to take part in the study provided informed consent. Prolific offers researchers the option to specify certain characteristics of their sample. One such function uses the most recent census information to determine sample quotas based on age, gender, and ethnicity. Hence, we recruited a sample representative of the UK general population on age, gender, and ethnicity. Upon inspection, the quotas established by Prolific were largely met, with discrepancies ∼0.1% or less.

Given the length and mode of survey delivery, we included nine attention checks (Oppenheimer et al., 2009). If a participant failed two or more attention checks, their data were flagged for review. Decisions about whether to exclude a participant or not

**Table 1.** Fit statistics for latent class analysis of the propensity component.

| NClass | Log-liklihood | Resid.df | BIC | aBIC | cAIC | Liklihood-ratio | Entropy |
|---|---|---|---|---|---|---|---|
| 2 | −13348.61 | 1453 | 27040.95 | 26891.64 | 27087.95 | 8566.21 | 0.80 |
| 3 | −13125.01 | 1429 | 26769.26 | 26543.71 | 26840.26 | 8119.01 | 0.79 |
| 4 | −12966.19 | 1405 | 26627.14 | 26325.35 | 26722.14 | 7801.38 | 0.75 |
| 5 | −12873.30 | 1381 | 26616.86 | 26238.83 | 26735.86 | 7615.58 | 0.77 |
| 6 | −12784.34 | 1357 | 26614.46 | 26160.19 | 26757.46 | 7437.66 | 0.78 |
| 7 | −12706.21 | 1333 | 26633.73 | 26103.22 | 26800.73 | 7281.42 | 0.78 |
| 8 | −12636.77 | 1309 | 26670.37 | 26063.62 | 26861.37 | 7142.54 | 0.79 |

were based upon consideration of the number of failed attention checks, the speed at which they completed the survey, and the quality of any free text responses. If the decision was made to reject a participant, their place in the study was reallocated to another suitable candidate, until the study quota was met ($n = 1,500$). The mean age of the sample was 47.76 years (range = 18—87, $SD = 15.70$), 51.5% were female, and 48.5% were male (see Table S1 for further descriptive statistics).

## Measures

The full survey can be accessed on the Open Science Framework (OSF)[1], here. It measures correlates of radicalization drawn from a wide range of expertise including academic literature review, previously designed data collection codebooks (see Gill et al., 2014), consultation with practitioners, and evaluation against open- and closed-source data on radicalization and violent extremism (see Clemmow et al., 2022 for a full account of survey development). Table S2 in the Supplementary Materials details the measures used in the present study.

Indicators were mapped onto the three domains previously described (propensity, situation, exposure; Table S2). The decision to use observable behavioral indicators was purposeful. Much of the work in this space operationalizes complex constructs with psychometric scales measuring latent traits. These measures often perform well and are considered good proxy measures for difficult to capture concepts. However, in the present study we sought to optimize the practical implications of our findings by taking well-known behavioral indicators of vulnerability to radicalization, and mapping these onto constructs theorized by the RAF. The aim was to demonstrate how to tie patterns of indicators which practitioners routinely observe, to the more stable causal mechanisms theorized to underlie the phenomenon.

Ideally, we would seek to validate this mapping via some sort of deductive analysis, such as exploratory or confirmatory factor analysis, however we felt this beyond the scope of the present study. That being said, previous work has taken both deductive and inductive approaches to this mapping, demonstrating, that although crude, there is evidence to suggest that these risk factors co-occur in predictable ways (see Clemmow et al., 2022; Clemmow et al., 2022; Clemmow et al., 2020; Corner et al., 2019).

[1]The data employed in the present study were collected as part of a wider survey, hence there are some measures that appear in the full survey on the OSF(https://osf.io/gjx4q/) that are not included in the current study.

Most items were measured dichotomously with two exceptions: *thrill-seeking* was measured with three, and i*mpulsivity* was measured with six scale items. All scale items were measured on a 7-point Likert scale ("Strongly disagree" to "Strongly agree"). Both measures demonstrated good reliability, where $\omega = 0.821$, and $\omega = 0.726$, respectively (see the full survey for item wording). It was necessary to dichotomize all continuous measures to be compatible with our analytical strategy. Mean scores were calculated and cut-off's of $> 4$ (Somewhat agree, Agree, Strongly agree) were applied. Scores above 4 were coded as present (1) and all other values were coded as absent (0).

### *Violent Extremist Intentions*

Violent extremist intentions was measured with four items from the Radicalism Intention Scale (RIS; Moskalenko & McCauley, 2009; see the full survey for item wording) The scale showed good reliability where, $\omega = 0.860$. Mean scores were calculated so that higher scores indicated higher violent extremist intentions.

### *Procedure*

Analysis proceeded in three phases. First, latent class analysis (LCA) determined unmeasured subgroups across each component (propensity, situation, exposure). Whilst there is no consensus about how to determine the optimum latent class solution, there is some agreement that final model selection be based on an assessment of multiple fit statistics whilst considering the theoretical interpretability of the final class solution (Muthén & Muthén, 2000; Nylund et al., 2007). We present the results of LCA for each of the components alongside how we determined the final class solution. We further examined differences by age and sex among different classes. Second, a series of ANOVAs and subsequent Cohen's *d* effect size calculations examined how the different classes scored on our proxy measure for vulnerability to radicalization (RIS). Third, we conducted moderator analyses testing for risk and protective interactive effects between the risk profiles across the different domains. All analyses were conducted in R.

## Results

### *Propensity*

Table 1 presents the fit statistics of latent class solutions for the propensity component from two to eight classes. To aid decision-making we created an elbow-plot summarizing aBIC, cAIC, entropy, and likelihood ratio statistics (Figure 1). The point at which the plot "levels off" or "the elbow" indicates declining improvement in fit, and thus provides information about the optimum number of classes. We also report the entropy of each model solution to provide an indication of the average amount of uncertainty that exists when assigning participants to a given latent class. Often, comparing fit statistics does not identify the same class solution, as in the present case. Here, a four-to-six class solution could be suitable, so we examined the composition of classes deducted by a four, five, and six class model and considered how these aligned with the existing evidence base and our theoretical framework. A four-class

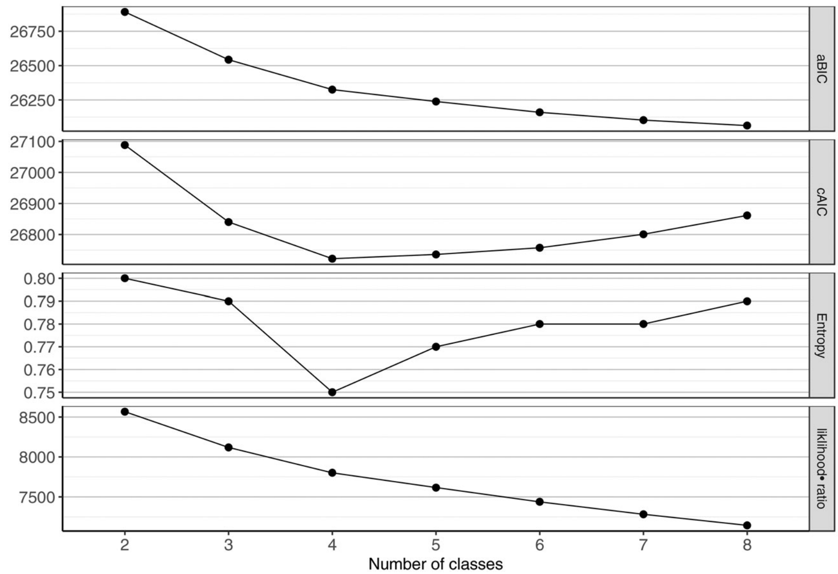


**Figure 1.** Elbow-Plot showing the parsimony and goodness-of-fit for propensity models.

solution was chosen as both a five and six class solution resulted in the same three classes and differed only in how they disaggregated the fourth class (i.e. in a five-class solution the fourth class was disaggregated into two classes, in a six-class solution the fourth class was disaggregated into a three-class solution). Moreover, the cAIC *increased* (rather than decreased) after extracting a fifth profile, suggesting model fit began to decline after the model with four latent classes.

To aid interpretation, here we present the class solutions as figures whilst Table S2 in the supplementary materials details the final class solutions in full. Risk profiles were labelled through an examination of the relative frequencies of the indicators and in consideration of the RAF. For propensity, four risk profiles were deduced and labelled *low propensity, high propensity, cognitive susceptibility, and moderate propensity* (Figure 2).

The low propensity profile is classified by relatively low frequencies of all propensity indicators including those relating to a pre-existing commitment to moral rule breaking (i.e. previous offending), and capacity for executive functioning (psychological distress) and self-regulation (self-control). None of the cases in this class were violent as a child nor committed a non-violent offence, and only 3.88% reported a diagnosed mental disorder. In contrast, the high propensity profile demonstrates relatively high frequencies of both moral commitment and executive functioning indicators. For instance, 61.09% of cases had committed a non-violent offence, 51.49% and 52.21% demonstrate thrill-seeking and impulsivity, respectively, 88.27% reported psychological distress, and 48.11% reported a diagnosed mental disorder.

The cognitive susceptibility profile demonstrates high rates of executive functioning indicators and relatively low frequencies of moral commitment indicators—this is how it differs from the high propensity profile. Where 92.99% reported psychological distress, 47.91% reported a diagnosed mental disorder, and 65.65% reported chronic stress, just 1.86% were arrested as children/adolescents, and none (0%) had committed

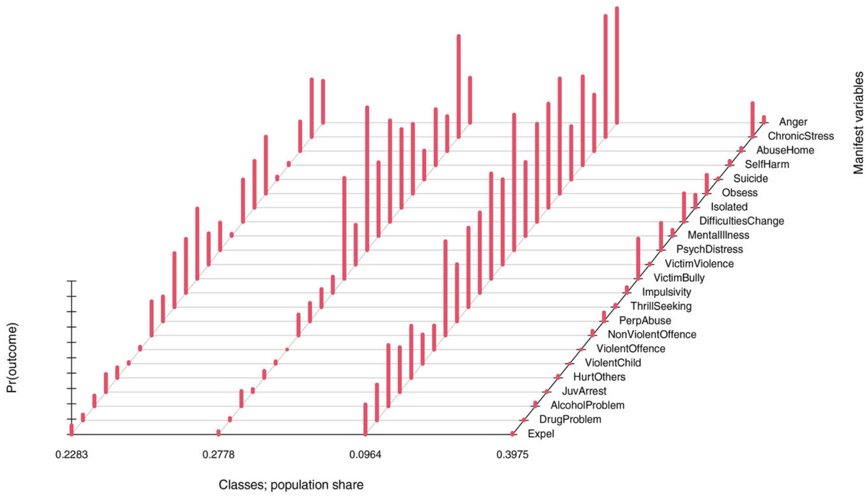


**Figure 2.** Posterior probability of manifest variable responses across classes for propensity. From left to right profiles are labelled **Moderate propensity, Cognitive susceptibility, High propensity, Low propensity.**

**Table 2.** Fit statistics for latent class analysis of the situation component.

| NClass | Log-liklihood | Resid.df | BIC | aBIC | cAIC | Liklihood-ratio | Entropy |
|---|---|---|---|---|---|---|---|
| 2 | −10995.54 | 1463 | 22261.66 | 22144.12 | 22298.66 | 6052.97 | 0.88 |
| 3 | −10709.07 | 1444 | 21827.69 | 21649.79 | 21883.69 | 5480.05 | 0.80 |
| 4 | −10543.51 | 1425 | 21635.52 | 21397.27 | 21710.52 | 5148.93 | 0.80 |
| 5 | −10459.52 | 1406 | 21606.48 | 21307.86 | 21700.48 | 4980.93 | 0.81 |
| 6 | −10395.72 | 1387 | 21617.83 | 21258.86 | 21730.83 | 4853.34 | 0.80 |
| 7 | −10330.79 | 1368 | 21626.92 | 21207.59 | 21758.92 | 4723.48 | 0.80 |
| 8 | −10289.58 | 1349 | 21683.45 | 21203.77 | 21834.45 | 4641.06 | 0.80 |

a violent offence. Interestingly, this profile demonstrated relatively low levels of indicators related to self-regulation, including low self-control, thrill-seeking (11.70%) and impulsivity (10.54%). Hence this group demonstrate a *cognitive* susceptibility without the moral commitment and self-regulation risk factors experienced by the high propensity profile.

The moderate propensity profile is characterized by *relatively* high self-reported thrill-seeking (34.83%) and impulsivity (34.94%), alongside moderate frequencies of moral commitment indicators, including non-violent offending (22.17%), arrest as a child/adolescent (11.66%), and domestic violence perpetration (16.09%).

### Situation

Table 2 and Figure 3 present the fit statistics of latent class solutions from two to eight classes for the situational component. Here, a four-to-five class solution could be suitable. As above, we compared the classes deducted by a four- and five-class solution by examining how these aligned with the existing evidence base, alongside consideration of various fit statistics. As cAIC appeared to plateau at four-to-five classes, we selected the more parsimonious solution.

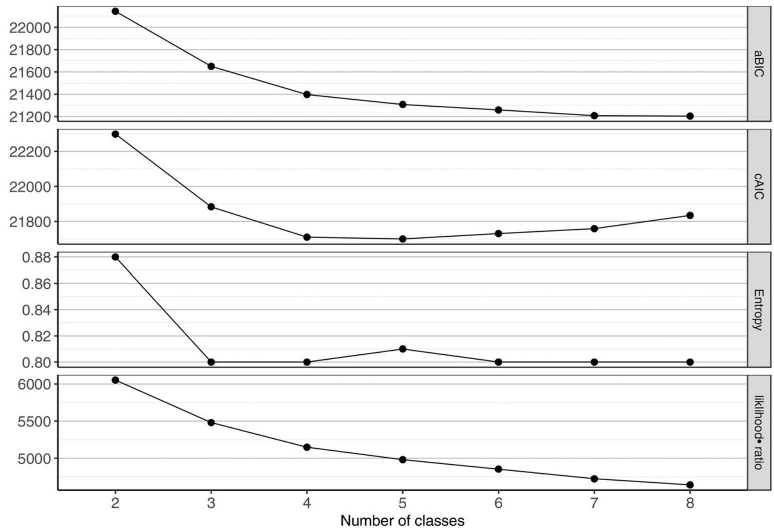


**Figure 3.** Elbow-Plot showing the parsimony and goodness-of-fit for situation models with varying number of classes.

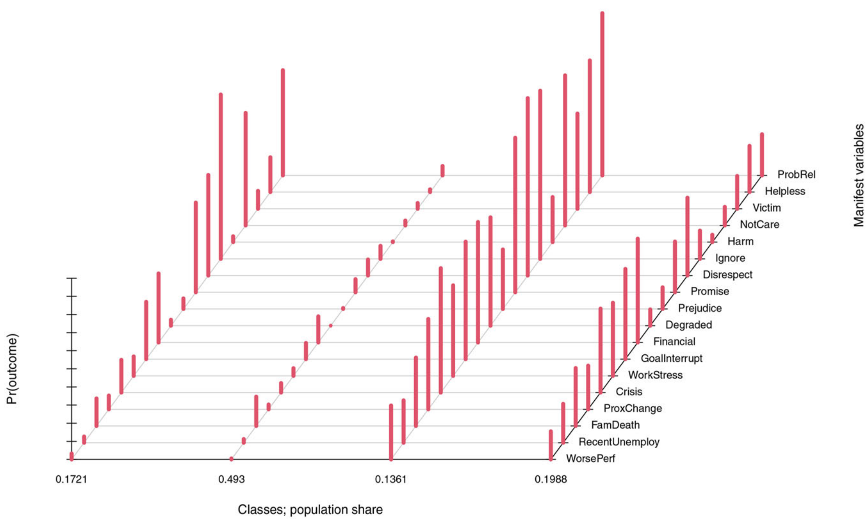


**Figure 4.** Posterior probability of manifest variable responses across classes for situation. From left to right profiles are labelled **Interpersonal stress, Low stress, High stress, Proximate crisis.**

The final class solution is summarized in Figure 4 (see Table S1 for full details). As previously, risk profiles were labelled based on the presenting pattern of indicators. Risk profiles were labelled *interpersonal stress, low stress, high stress*, and *proximal crisis*. The interpersonal stress profile is characterized by relatively high frequencies of indicators suggesting difficulties with relationships with others. Salient stressors include being ignored by someone important (90.67%), not being cared for by someone important (62.11%), and problematic personal relationships (58.03%). The low stress profile is characterized by markedly lower frequencies of stressors than all other groups, including low rates of recent unemployment (2.02%), proximate life change (5.20%) and prejudice (0.58%). The high stress profile in contrast demonstrates high frequencies across all situational indicators. For instance, 68.62% reported proximate crisis, 97.90% reported being disrespected, and 72.65% felt like a helpless victim. Lastly, the proximal crisis profile demonstrates relatively high frequencies of indicators related to work and life goals, such as financial problems (57.27%), work stress (40.34%), and life goals interrupted (49.76%).

### *Exposure*

Table 3 and Figure 5 present the fit statistics of latent class solutions from two to eight classes for the exposure component. Following the same procedure as previously described, a four-class solution was identified.

The final class solution is summarized in Figure 6. Risk profiles were labelled *high contact/attachment, high exposure to radicalizing moral norms, moderate contact/attachment*, and *low exposure*. The high contact/attachment profile is characterized by high frequencies of indicators relating to opportunities for contact and attachment to radicalizing agents, including face-to-face interactions with extremists (80.37%), and searching online for extremist content (82.98%). The high exposure to radicalizing moral norms profile demonstrates high frequencies of indicators related to people, settings, and materials conducive to radicalizing moral norms, for instance witnessing threats of political violence (100%) and being aware of extremism in the community (82.82%). The moderate contact/attachment exposure profile demonstrates relatively high frequencies of contact and attachment related exposure indicators. For instance, 41.70% chose to spend time with friends with extremist views, and 29.07% engaged with extremist propaganda. The low exposure profile demonstrates low frequencies of all exposure-related indicators.

Finally, we examined how age and sex affected profile membership. A series of chi-square tests identified several significant differences (Table 4). Men were significantly more likely to demonstrate the moderate propensity, goal interrupted, high contact/attachment, and moderate contact/attachment risk profiles than women. Women were more likely to demonstrate the high stress, and low exposure profiles than men.

In terms of age, 18—29-year old’s were more likely to demonstrate the high stress, and moderate contact/attachment exposure profiles and less likely to demonstrate the low propensity, low stress, and low exposure profiles. 30—49-year old’s were more likely to demonstrate the high propensity and goal interrupted profiles. 50+ year old’s were more likely to demonstrate the low propensity, low stress, and low exposure

**Table 3.** Fit statistics for latent class analysis of the exposure component.

| NClass | Log-liklihood | Resid.df | BIC | aBIC | cAIC | Liklihood-ratio | Entropy |
|---|---|---|---|---|---|---|---|
| 2 | −4069.22 | 1475 | 8321.28 | 8241.86 | 8346.28 | 1331.23 | 0.89 |
| 3 | −3955 | 1462 | 8187.9 | 8067.18 | 8225.9 | 1102.77 | 0.88 |
| 4 | −3878.06 | 1449 | 8129.1 | 7967.08 | 8180.1 | 948.9 | 0.88 |
| 5 | −3840.57 | 1436 | 8149.19 | 7945.88 | 8213.19 | 873.93 | 0.90 |
| 6 | −3807.01 | 1423 | 8177.15 | 7932.54 | 8254.15 | 806.81 | 0.90 |
| 7 | −3785.08 | 1410 | 8228.35 | 7942.44 | 8318.35 | 762.94 | 0.88 |
| 8 | −3770.75 | 1397 | 8294.77 | 7967.57 | 8397.77 | 734.29 | 0.86 |

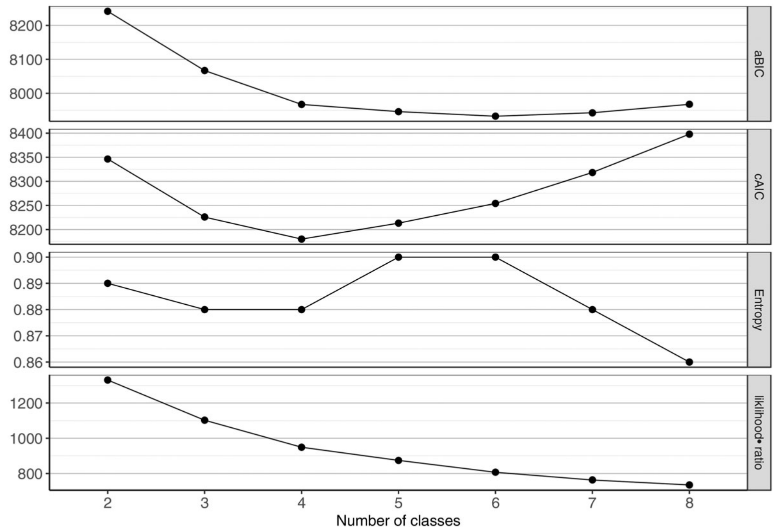


**Figure 5.** Elbow-Plot showing the parsimony and goodness-of-fit for exposure models with varying number of classes.

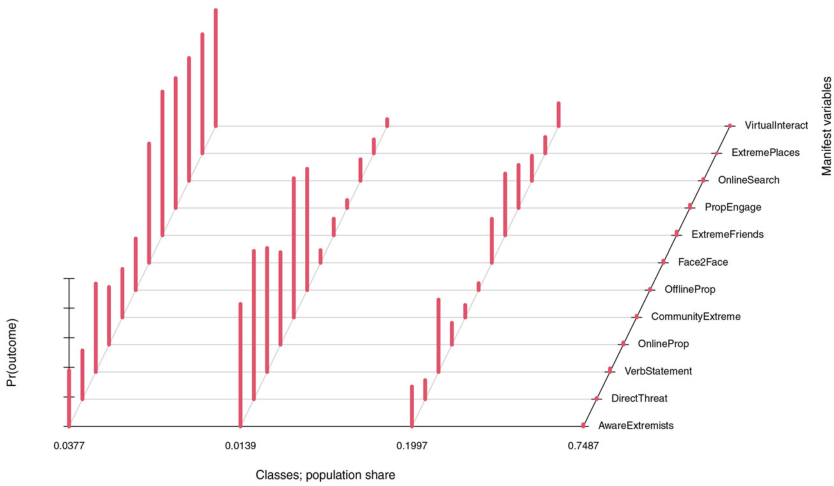


**Figure 6.** Posterior probability of manifest variable responses across classes for exposure. From left to right profiles are labelled **High exposure to radicalizing moral norms, High contact/attachment, Moderate contact/attachment, Low exposure.**

profiles and less likely to demonstrate the high propensity, cognitive susceptibility, and high stress profiles.

## *Interactions between Risk and Protective Profiles*

We were further interested to see whether the risk profiles would interact with each other to increase the effects upon violent extremist intentions. In addition, we tested whether the protective profiles may dampen the adverse effects of risk profiles upon violent extremist intentions.

**Table 4.** Chi-Square tests examining age and sex differences in risk profile membership.

| Component | Profile | Sex | | | | | Age | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Female | Male | $X^2$ | df | $p$ | 18–29-year-old's | 30–49-year-old's | 50+ year old's | $X^2$ | df | $p$ |
| Propensity | | | | 15.751 | 3, 1 | .001 | | | | 68.454 | 6, 1 | <.001 |
| | Moderate propensity | 18.00%** | 24.30%** | | | | 25.90% | 18.70% | 20.80% | | | |
| | Cognitive susceptibility | 29.80% | 25.00% | | | | 34.00% | 29.80% | 22.70%*** | | | |
| | High propensity | 7.90% | 10.90% | | | | 13.10% | 12.40%** | 5.20%*** | | | |
| | Low propensity | 44.40% | 39.80% | | | | 26.90%*** | 39.40% | 51.30%*** | | | |
| Situation | | | | 21.038 | 3, 1 | <.001 | | | | 159.81 | 6, 1 | <.001 |
| | Interpersonal stress | 19.10% | 14.60% | | | | 20.90% | 16.50% | 15.50% | | | |
| | Low stress | 49.20% | 52.10% | | | | 28.60%*** | 46.10% | 64.00%*** | | | |
| | High stress | 15.90%** | 10.90%** | | | | 30.00%*** | 13.70% | 6.00%*** | | | |
| | Goal interrupted | 15.80%*** | 22.40%*** | | | | 20.50% | 23.80%*** | 14.50%*** | | | |
| Exposure | | | | 54.554 | 3, 1 | <.001 | | | | 51.011 | 6, 1 | <.001 |
| | High contact/ attachment | 2.50%** | 5.10%** | | | | 7.10%*** | 3.20% | 2.70% | | | |
| | High exposure to radicalizing moral norms | 1.40% | 1.20% | | | | 2.70% | 1.70% | 40.00% | | | |
| | Moderate contact/ attachment | 10.60%*** | 23.40%*** | | | | 26.60%*** | 14.20% | 14.50% | | | |
| | Low exposure | 85.50%*** | 70.30%*** | | | | 63.60%*** | 80.90% | 82.40%*** | | | |

*Notes.* Adjusted for multiple comparisons (Bonferroni correction). ***$p < .000$. **$p < .01$, * $p < .05$.

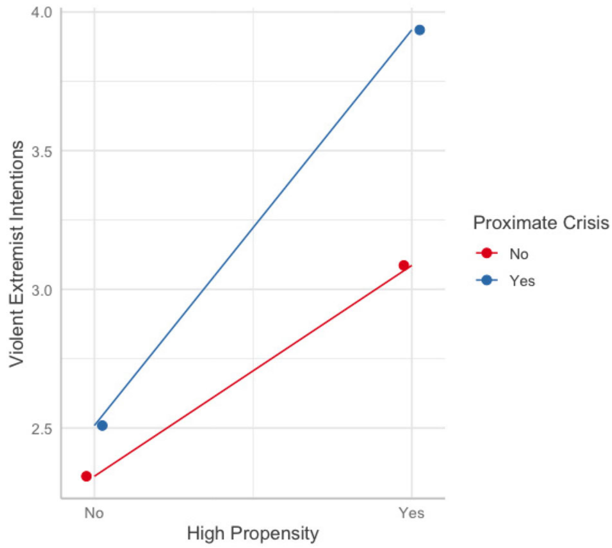


**Figure 7.** Interaction of high propensity and proximate crisis on violent extremist intentions.

For each domain, we identified the risk and protective profiles with the strongest effect size to determine the most relevant profiles. The three most relevant risk profiles for violent extremist intentions included (1) high propensity, (2) proximate crisis, and (3) high contact/attachment. The three most significant protective profiles against violent extremist intentions were (1) low propensity, (2) low situational stress, and (3) low exposure.

First, we ran three separate moderation analyses, one for each of the most relevant risk-risk combination: (1) high propensity- proximate crisis, (2) high propensity-high contact/attachment, and (3) proximate crisis- high contact/attachment.

Second, we examined if the protective profiles were able to buffer against the effects of the risk profiles on violent extremist intentions. As such, we ran six risk-protective profile moderation models in total, one interaction analysis for the most relevant risk profile with each of the most significant protective profiles across the other domains: (1) high propensity- low situational stress, (2) high propensity-low exposure, (3) proximate crisis-low propensity, (4) proximate crisis-low exposure, (5) high contact/attachment - low propensity, and (6) high contact/attachment - proximate crisis.

### *Risk-Risk Interactions*

***High Propensity – Proximate Crisis.*** Proximate crisis significantly moderated the effects of high propensity on violent extremist intentions ($b$ = .67, 95% CI [.12, 1.22]). To illustrate the significant interaction of high propensity and proximate crisis, we computed simple effects. The plotted values of the predictors represent 0 (absent) and 1 (present). The simple effects (Figure 7) show that when proximate crisis is present, high propensity has strong positive effects on violent extremist intentions ($b$ = 1.43, 95% CI [.93, 1.92]). These effects are attenuated when proximate crisis is absent ($b$ = .76, 95% CI [.52, 1.00]).

***High Propensity – High Contact/Attachment.*** The interaction between high contact/attachment and low propensity proved to be non-significant for violent extremist

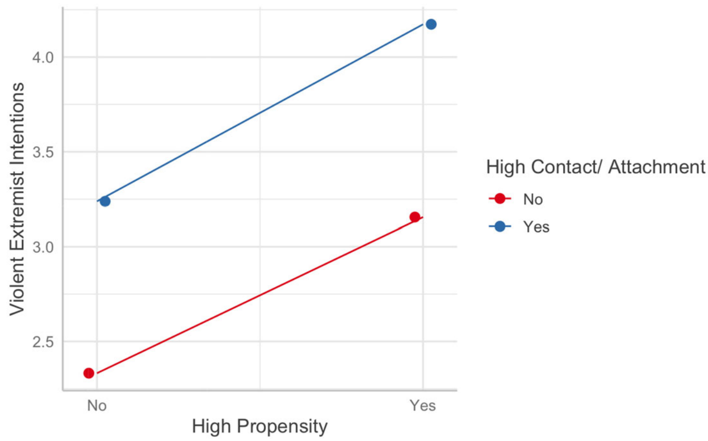


**Figure 8.** Interaction of high propensity and high contact/attachment on violent extremist intentions.

intentions ($b$ = .04, 95% CI [-.45, .53]). The simple effects plot shows that when high propensity and high contact/attachment are present, the effects are higher compared to when only one is present (Figure 8). Yet, the lines connecting the dots are almost parallel, indicating that the effects for high contact/attachment being present or absent are increasing at a similar rate and thus, no interaction effect is present.

***Proximate Crisis - High Contact/Attachment.*** The third risk-risk interaction model showed that high contact/attachment does moderate the effects of proximate crisis on violent extremist intentions ($b$ = .41, 95% CI [.01, .08]). The simple effects plot highlights the significant interaction and shows that when high contact/attachment is present, the effects of proximate crisis on violent extremist intentions are amplified ($b$ = .34, 95% CI [.09, .62]) compared to when high contact/attachment is absent ($b = -.07$, 95% CI [-.15, −.001]) (Figure 9).

### *Risk-Protective Factor Interactions*

***High Propensity- Low Situational Stress.*** We conducted a simple effects analysis to explore the potential interaction of high propensity and low situational stress (Figure 10). We computed a graph for the effects of no (0), and yes (1) low situational stress. We were interested to see whether low situational stress might be able to reduce the risk effects of high propensity on violent extremist intentions. Yet, no evidence was found for the moderating effects of low situational stress on the relationship between high propensity on violent extremist intentions and thus, no protective buffering effect was detected ($b$ = .37, 95% CI [-.19, .94]).

***High Propensity- Low Exposure.*** The interaction between high propensity and low exposure was non-significant ($b = -.15$, 95% CI [-.58, .29]). While the effects of high propensity are lower when low exposure is present, the simple effect plot illustrates two almost parallel lines and therefore, no protective interaction effect was found (Figure 11).

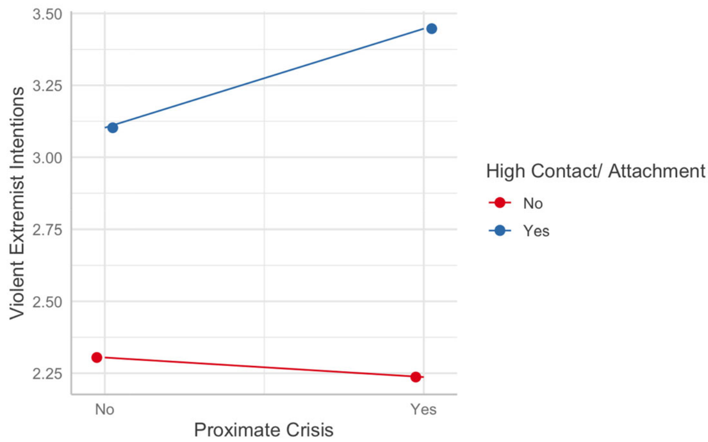


**Figure 9.** Interaction of proximate crisis and high contact/attachment on violent extremist intentions.

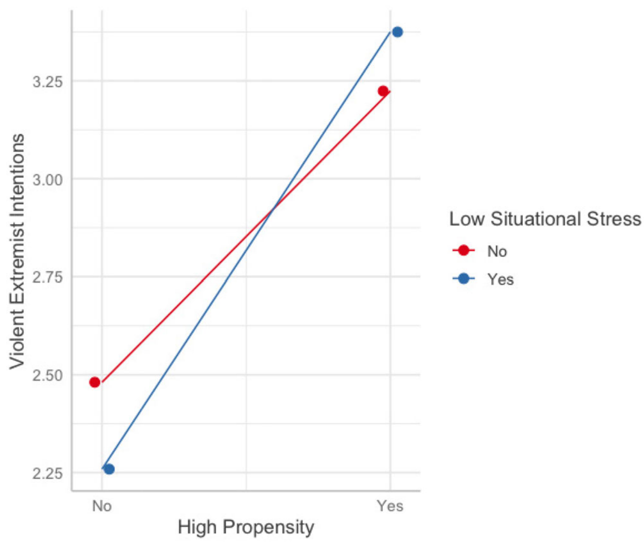


**Figure 10.** Interaction of high propensity and low situational stress on violent extremist intentions.

***Proximate Crisis – Low Propensity.*** Proximate crisis showed a significant negative interaction with low propensity ($b = -.37$, 95% CI [-.72, $-.02$]). The simple effects analysis (Figure 12) shows that proximate crisis increases when low propensity is absent ($b =$ .36, 95% CI [.16, .56]), while the effects almost remain unchanged when low propensity is given ($b = -.01$, 95% CI [-.29, .28]). This indicates that low propensity represents a buffering protective factor for the effects of proximate crisis on violent extremist intentions.

***Proximate Crisis – Low Exposure.*** Low exposure did not moderate the effects of proximate crisis on violent extremist intentions ($b = -.30$, 95% CI [-.69, .09]). Despite the dots indicating that when low exposure is present, the effects of proximate crisis on

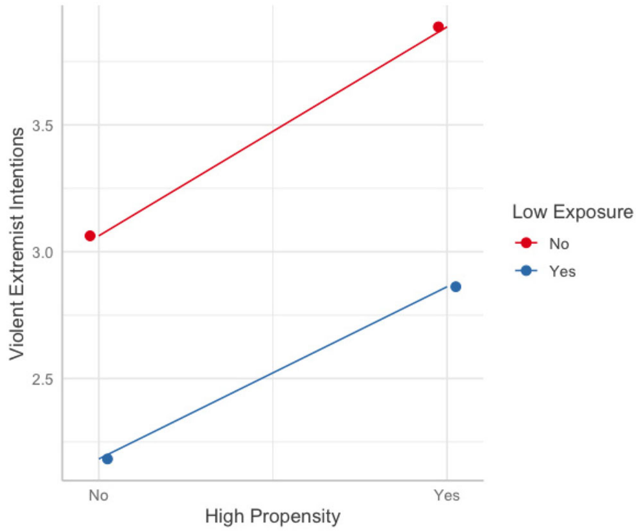


**Figure 11.** Interaction of high propensity and low exposure on violent extremist intentions.

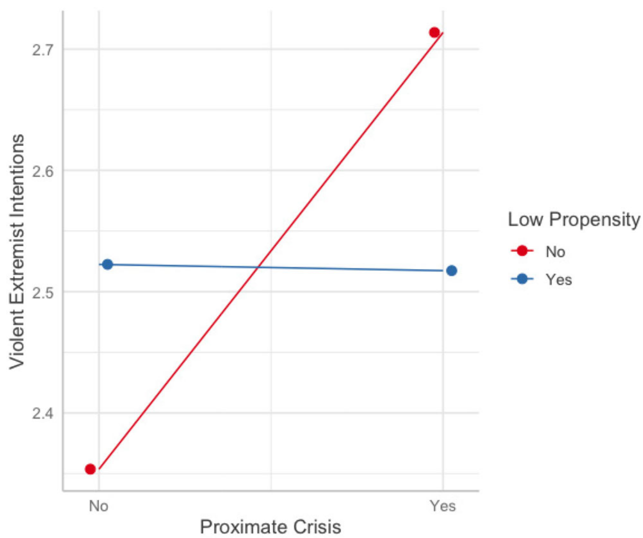


**Figure 12.** Interaction of proximate crisis and low propensity on violent extremist intentions.

violent extremist intentions are lessened, the interaction was non-significant (Figure 13).

***High Contact/Attachment – Low Propensity.*** The interaction between high contact/attachment and low propensity proved to be significant for violent extremist intentions ($b = -.58$, 95% CI [-.94, −.22]). When low propensity is given the effects are weakened ($b = .47$, 95% CI [.17, .77]), while they are increased when low propensity is absent ($b = 1.05$, 95% CI [.85, 1.25]) (Figure 14). Thus, the results confirm that the effects of high contact/attachment on violent extremist intentions are conditional upon low propensity, rendering low propensity a protective buffering factor.

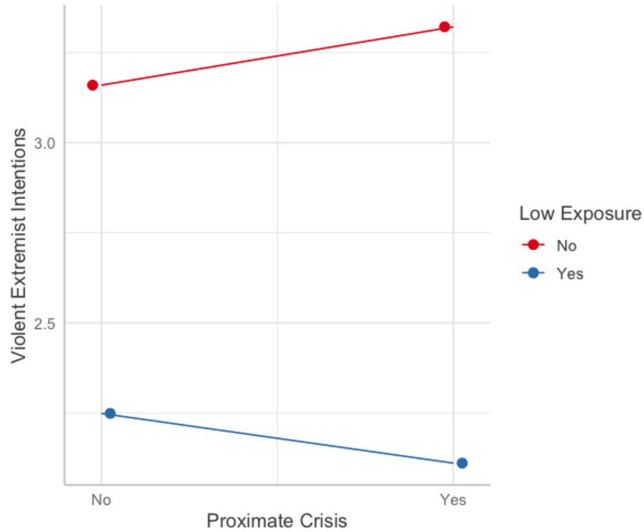


**Figure 13.** Interaction of proximate crisis and low exposure on violent extremist intentions.

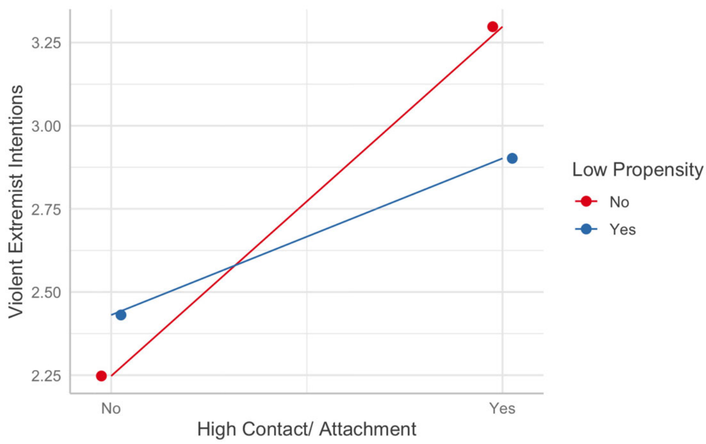


**Figure 14.** Interaction of high contact/attachment and low propensity on violent extremist intentions.

***High Contact/Attachment – Low Stress.*** The interaction between high contact/attachment and low situational stress proved to be non-significant ($b = -.32$, 95% CI [-1.02, .38]. The simple effects plot shows that the effects of high contact/attachment on violent extremist intentions are weakened when low situational stress is present, yet these marginal differences are not statistically significant (Figure 15).

## Discussion

The present study aimed to build upon and extend our knowledge of risk factors for vulnerability to radicalization leading to violent extremism. The goal was to move beyond examining individual risk factors by exploring how risk factors co-occur as "risk

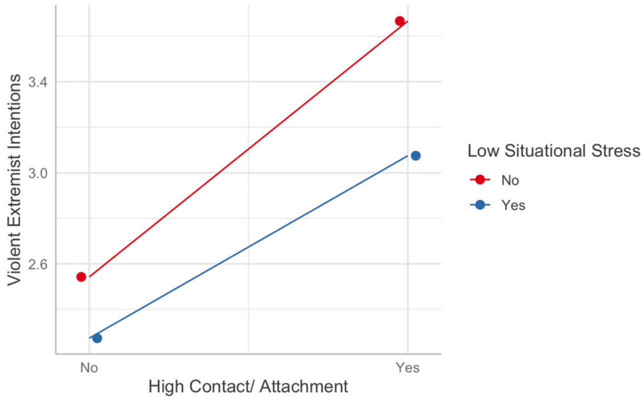


**Figure 15.** Interaction of high contact/attachment and low situational stress on violent extremist intentions.

profiles" across different domains relevant to risk assessment, and explore the inter and intra-domain cumulative and interactive effects among said profiles. Our analysis focused on the risk of developing an extremist propensity, as measured by willingness to engage in violent extremism. While only a very small percentage of radicalized individuals will ever engage in an act of violent extremism, an extremist propensity (action-relevant moral beliefs supportive of extremism) is almost always a necessary precursor for it (Moskalenko & McCauley, 2020). It is this type of susceptibility to involvement in violent extremism that is targeted by primary level interventions which are central to preventing and countering extremism and thus, our study provides important contributions for both scientific research as well as policy and practice.

We deducted risk profiles across propensity, situation, and exposure domains, and examined how the identified profiles related to self-reported violent extremist intentions, a proxy measure for vulnerability to radicalization. We found that the strongest effects were for the risk profiles related to exposure to violent extremism (high and moderate contact/attachment). The high propensity profile similarly demonstrated a large effect on violent extremist intentions. This is perhaps unsurprising given that this profile is characterized by high frequencies of criminogenic and psychological risk factors. However, a meta-analysis found that effect sizes for individual propensity factors were often larger than exposure factors, sometimes quite considerably (Wolfowicz et al., 2020). For example, having deviant peers and radical media consumption were found to have *r* correlations of .17 and .26 respectively, whereas propensity factors such as low self-control, criminal history, and thrill-seeking had estimates of .25, .29, .31, respectively. In the present study, the moderate propensity and cognitive susceptibility risk profiles demonstrated relatively small effect sizes. As such our results suggest it may be more important to consider ***intra-domain interaction effects among risk factors***, rather than examining their independent effects.

For instance, the moderate propensity profile demonstrates a pattern of risk factors which, individually, have been found to have relatively large effect sizes, such as impulsivity, and non-violent offending. However, compared to the high propensity profile, the moderate propensity profile demonstrates lower frequencies of risk factors related to previous violence, such as committing a violent offence or engaging in violence as a child, as well as lower frequencies of psychological risk factors such as self-harm, suicide attempts, and psychological distress. Similarly, the cognitive susceptibility profile demonstrates high frequencies of diagnosed mental disorder, psychological distress, and chronic stress, however markedly lower frequencies of risk factors relating to previous violence, previous criminality, and low self-control, compared to the high propensity profile. Therefore, the intra-domain interactive effects of risk factors, rather than the magnitude of the effects of individual risk factors, may be key to understanding vulnerability to radicalization, as well as informing how we design interventions.

Conversely, the effect sizes for the situational profiles were comparably small. Many of the factors in the situational domain have been found to have relatively small effect sizes individually, such as victimization, discrimination, and disadvantage (Wolfowicz et al., 2020). However, it is not necessarily the case that situational risk factors are not relevant to vulnerability to radicalization, as demonstrated by the results of the moderator analysis examining the interactive effects among the risk profiles.

For instance, our results show that when proximate crisis (a situational domain profile) is present, the effects of high propensity on violent extremist intentions are amplified. That is, when proximate crisis occurs alongside high propensity, their joint influence is greater than the sum of their parts—their effect is interactive, rather than cumulative. Therefore, it may be highly relevant to consider the interactive effects of proximate crisis, particularly for individuals who exhibit a high propensity for radicalization. Similarly, high contact/attachment moderates the effect of proximate crisis on violent extremist intentions. The joint effects of proximate crisis and high contact/attachment amplifies the effect of proximate crisis on violent extremist intentions. In this instance, situational risk factors, which individually may have relatively small effect sizes, may in fact be highly relevant to vulnerability to radicalization.

High contact/attachment was not found to have an interactive effective with high propensity. This does not suggest that high contact/attachment is not relevant to high propensity, rather that the effect of high contact/attachment on high propensity is cumulative, rather than interactive. That is, here, more risk factors simply translate to more risk. Whereas in the instance of an interaction, the combined effect of two profiles exerts an increased effect on violent extremist intentions, where the effect of one is contingent upon the other. Taken together, our findings highlight what is the key contribution of our approach to further theoretical development and case assessment practice in this problem domain: radicalization risk emerges fundamentally from both the interaction or cumulation of processes at different levels of analysis (e.g. individual; situational) and is therefore highly context dependent. It also suggests that risk analysis should rely less on specific indicators rather than correctly inferring the function they serve (e.g. propensity or selection markers) and ensuring that markers are present that stand in for each level of explanation (Bouhana, 2019; Bouhana & Wikström, 2011).

In terms of protective effects, our results suggest that the high propensity profile may prove such a strong constellation of risk factors that seemingly protective patterns of factors, such as low exposure, and low situational stress, do not buffer against its effects. This is in line with criminological literature which identifies a high criminal propensity as the main predictor of criminal involvement (Wikström et al., 2012) and with work in the radicalization space which finds indicators of a pre-existing criminal propensity to be among the top predictors of involvement in extremism (Perry et al., 2018; Nivette et al., 2017; Ljujic et al., 2017; Jensen et al., 2020; Lösel et al. 2018; Wolfowicz et al., 2020). Conversely, low propensity is a buffering protective factor, when proximate crisis is present and, importantly, when high contact/attachment is present. This again speaks to *relevance*, as although high contact/attachment demonstrates the greatest effect on violent extremist intentions, when propensity is low, the effects of high contact/attachment are likely to be dampened. This accords with previous research which finds that not all experience negative consequences from engaging with extremist materials (Gerstenfeld et al., 2003; Keipi et al., 2017). Our results go some way to understanding why.

Understanding how age and sex relate to the risk profiles provides further insight. Both men and younger adults were generally significantly more likely to demonstrate risk profiles than protective profiles. Particularly pertinent were findings related to exposure. As previously described, exposure profiles demonstrated the largest effect sizes. Men and younger adults were significantly more likely to demonstrate both the high contact/attachment and the moderate contact/attachment exposure profiles. Relating back to the RAF, vulnerability is theorized as susceptible people at risk of exposure. If men and younger adults are more likely to demonstrate exposure profiles, this may be one reason why these characteristics are disproportionately represented across CVE. In other words, in our sample, women and older adults are both less likely to be susceptible—that is to demonstrate characteristics which make them more susceptible to radicalization, and also less at risk of exposure to radicalizing influences.

Overall, our results suggest that known effect sizes for risk factors may not necessarily determine their cumulative and interactive effects. These results are particularly relevant to preventing and countering extremism. As such, a "one size fits all" approach to prevention is cautioned against, and careful consideration should be given as to "what" and "when" should be targeted in the context of primary level interventions. Another area in which our findings should be considered is risk assessment. To date, risk assessment has mostly taken a nominal approach to scoring, where some use a cumulative risk score (Lösel et al., 2018); that is, all factors are essentially given the same weight. It has therefore been suggested that the next stage in risk assessment will be one in which the relative weights of different factors are considered (Silke, 2014). While we agree with this general sentiment, our results suggest that going a step further and considering specific combinations of risk factors may also be helpful. As such, more research is needed to identify the way in which effects vary in the presence of other factors.

## *Practical Implications*

Practically, our findings have implications for the prevention and management of vulnerability to radicalization. First, in terms or risk assessment and management, structured professional judgement tools necessitate empirically grounded guidance to help inform expert decision-making (Logan & Lloyd, 2019; Monahan, 2012, 2017). Our findings demonstrate one instance of how to tie observable indicators to theory informed judgements utilizing the RAF. Rather than focusing on the presence or absence of a single risk factors, our results demonstrate how patterns of risk factors relate to the mechanisms theorized to drive vulnerability to radicalization.

In a similar vein, our findings highlight how establishing relevance is importance. Previous research on the effects of single risk factors finds the effects of individual situational indicators to be relatively small. However, our findings demonstrate *when* and *how* patterns of situational indicators may be highly relevant to vulnerability to radicalization. Establishing relevance, or when and for whom certain patterns of risk factors matter, is again key to providing scientific evidence to inform structured professional judgement approaches to the assessment of risk.

In terms of interventions, when resources are limited, decision-making about where and how to intervene is crucial. Our findings provide further scientific evidence to help guide practice and policy decision making. A finding highlighted throughout our analyses, is the importance of exposure. Exposure profiles demonstrated the greatest effect on vulnerability to radicalization. We also highlighted how young people and men were more likely to demonstrate exposure profiles. Referring back to the RAF, vulnerability is conceptualized as the interaction of individual susceptibility and the risk of exposure enabled by selection mechanism. Exposure occurs across mediums, online and offline, in the "real world" amongst other people, and in different settings, which suggests that intervening to disrupt or prevent the emergence of radicalizing settings may be the most effective at reducing risk.

## Limitations

It is important to consider the limitations of our study. First and foremost, we acknowledge that cross-sectional data is limited in that it can only examine multiple exposure to risk factors and not persistent exposure. Longitudinal research is required to make inferences about cause and effect. Second, as an online platform, the sample is likely subject to a selection bias, where only participants who have internet access and who sign up to participate on Prolific, are eligible. Individuals experiencing digital poverty for instance will not be sampled here. Whilst no sample will be completely free of bias (Gomes et al., 2019), it is still important to consider how any practical implications may be impacted. That being said, Prolific affords researchers access to more novel populations than the traditional subject pool, i.e. undergraduate psychology students, and so may facilitate greater generalizability than is normally afforded.

Third, it is important to consider the limitations of LCA. A recent study compared LCA with multidimensional scaling and cluster analysis and concluded that LCA was superior due to its ability to handle missing data, objectively evaluate model fit, the balance of parsimony and complexity, and the predictive utility of the resultant classes (examined in a sample of 405 burglaries) (Fox & Escue, 2022). However, LCA is not without limitations, and it is important to understand these when considering the practical implications of the present study. Interpreting and labelling of LCA classes is largely subjective. Even employing a theoretical framework to guide decision-making still relies upon researcher inference.

Similarly, as a data-driven classification technique, LCA results in classes which make the most sense statistically—however these may not reflect what makes the most sense theoretically. In some instances, some classes may not make sense or reflect what is expected based on prior knowledge. Therefore, drawing from a theoretical framework is helpful, however no LCA solution will be perfect. In a similar vein, LCA classes are not absolutes. For instance, the low propensity profile does in fact demonstrate some prevalence of propensity indicators. Therefore, these profiles are not intended to be applied to a set of cases as a categorical "typology" which arbitrarily assigns a risk rating. Rather we reiterate the relevance of our findings for providing evidence to inform expert judgements and to guide decision-making in case formulation.

Fourth, there are limitations to how we operationalized vulnerability to radicalization. Our measure (RIS) captures violent extremist *intentions*, not actual behavior. That is, a person's self-reported willingness to engage in violent extremism, not actual behaviors associated with radicalization. However, in the present case, we consider intentions a sufficient proxy for *vulnerability* to radicalization, as we wouldn't necessarily expect to observe radicalized behaviors at this stage. Equally, research demonstrates that in fact intentions do often predict behavior (Banaji & Heiphetz, 2010).

Intentions are also more closely related to behaviors than attitudes (Ajzen & Fishbein, 1980). However, an exceptionally small proportion of radicalized individuals will ever go on to engage in violent extremist behavior, even if they express intentions to do so (McCauley & Moskalenko, 2017). We must therefore avoid conflating vulnerability to radicalization, radicalization, and violent extremism, which are related but distinct outcomes for which risk factors may operate differently (ibid). Vulnerability to radicalization is a key risk factor for violent extremism, and for this reason it is the target of primary level P/CVE, and it is only at this level that our results should be considered relevant.

## Conclusion

In line with Aristotle's observation that "the whole is greater than the sum of its parts," we identified that the individual, relative effect sizes of risk factors may be less important than intra- and inter-domain effects, which demonstrate a greater relative relationship with vulnerability to radicalization. A key dimension of risk assessment and management requires first understanding what the risk is, and then considering if and when that risk realizing is probable. Therefore, understanding functional relevance is key, and practice requires empirically based knowledge which goes beyond describing the presence or absence of the many correlates of vulnerability to radicalization.

Research on vulnerability to radicalization has come a long way however, unlike analogous outcomes such as criminal attitudes and behaviors, the evidence base has developed alongside P/CVE, given the field's relative infancy and the need to tackle an ever-evolving threat. Nevertheless, it is important for research to continue to progress, and to treat the development of the body of knowledge in the same systematic way as more established fields. In this way, we hope our findings provide a bridge between ***identifying risk factors*** and understanding ***how they may be relevant*** to vulnerability to radicalization

## Disclosure Statement

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