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Can you identify violent extremists using a screening checklist and open-source intelligence alone?

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ABSTRACT

Checklist-based screening instruments have a role in the assessment of mentally disordered and criminal offenders, but their value for screening for vulnerability to violent extremism remains moot. This study examined the effectiveness of using the Identifying Vulnerable People (IVP) guidance to identify serious violence in persons convicted or killed in the process of committing a violent-extremist offence using open-source intelligence (i.e., publically available archival material). Of 182 specific participants identified, specific offence data was available for 157 individuals. Blind kappas for individual items of the 16-item IVP guidance ranged from 0.67 to 1.00. IVP guidance was more reliable when applied to conventional terrorist groups, but missing information significantly reduced reliability. Weighting items thought more central to violent extremism (death rhetoric, extremist group membership, contact with recruiters, advanced paramilitary training, overseas combat) did not improve reliability or prediction. Although the total unweighted IVP score predicted some acts of violence, test effectiveness statistics suggested IVP guidance was most effective as a negative predictor of grave outcomes, and best applicable to conventional ideological violent extremists who came to this position through typical "terrorist" trajectories. Results suggest the IVP guidance has potential value as an initial screening tool, but must be applied appropriately to persons of interest, is strongly dependent on the integrity and completeness of information, and does not supercede human-led risk assessment of the case and acute risk states.

Keywords: VIOLENT EXTREMISM; TERRORISM; RISK ASSESSMENT; SCREENING TESTS; VIOLENCE; IDEOLOGY; SCHOOL SHOOTERS; MASS MURDER.

POSITIVECAN YOU IDENTIFY PEOPLE VULNERABLE TO VIOLENT EXTREMISM USING A SIMPLE CHECKLIST AND OPEN SOURCE INTELLIGENCE ALONE?

INTRODUCTION

While the ideologies of violent extremism span a wide variety of religious, political, and social views, such views tend to be expressed relatively consistently; they tend to be uncompromising, certain, intolerant, and inclined to dehumanise the opposition. The most extreme adherents of such views rationalise violence as a necessary part of their group's agenda (Wintrobe, 2006). Cognitive cues such as ideology, affiliation, grievance thinking, self-righteous morality, and moral disengagement (Bandura, 1999) are all plausible constructs to explain why some persons engage in politically-motivated violent extremism (Monahan, 2012). Others describe individuals having a "fused identity", whereby an individual's identity becomes so synonymous with that of a collective or social self as to make them willing to sacrifice themselves (sometimes literally) for their beliefs (Swann, Jetten, Gómez, Whitehouse, & Bastian, 2012). Different ideologies and trajectories may radicalise individuals differentially (Borum, 2011, 2014). However, before one can investigate the psychology of violent extremism, persons who present such a threat need to identified. The current study examines the effectiveness of one potential set of guidelines – the UK's Identifying Vulnerable People (IVP) guidance – using a sample of persons involved with or convicted of violent extremism who have data available in the public domain.

Screening for vulnerability.

The UK Government's counter-terrorism strategy policy comprises four goals; to prevent, pursue, protect, and prepare (HM Government, 2006). Prevention interventions generate a range of moral and ethical dilemmas for practitioners, which include the identification and engagement of individuals who have not actually done anything illegal, on the premise that they might. Axiomatic to forensic psychology is the observation that extremes of character and focus often predict antisocial and violent behavior (Egan, 2011; 2013; Egan, Austin, Elliot, Patel, & Charlesworth, 2003). Assessment of an individual's historical, clinical and relapse-associated factors are moderately effective predictors of future risk in violent, sexual, and mentally-disordered offenders (Yang, Wong, & Coid, 2010). Yang et al conclude that while most violence risk assessment tools employed to predict violence are interchangeable, they are not equally accurate. Methods for assessing violence risk in offenders and mentally disordered offenders are now well-established; less well-established and more sceptically regarded is the notion that one can apply such principles to assess violent extremists. Misgivings about the use of such methods in what is a highly nuanced and political arena are not without foundation (Silke, 1998; 2001).

Problems with screening for vulnerability.

Paul Meehl observed that what one can predict statistically in a population is difficult for an individual (Grove, 2005). Even with fair test-retest reliability and small standard errors, confidence limits around the scores from instruments predicting risk of violence are considerable for groups, and, some argue, can be so large for an individual that specific clinical prediction is essentially meaningless (Hart, Michie, & Cooke, 2007). While the limits of such instruments ostensibly preclude their being used in isolation for any decision-making in the criminal justice system (Yang et al, 2010, pp. 740), in practice this is not the case (Cooke & Michie, 2014). This is because such instruments may assist prioritisation of cases for closer review (ideally using proper structured professional judgment instruments), in the same way screening instruments are used in other domains of applied psychology. Whilst a psychometric instrument may lack reliability, applied psychologists sometimes use inexact indices with partial validity that allow probabilistic inferences to be made (Harris, Rice, & Quinsey, 2007; Harris & Rice, 2007). Practitioners routinely work with uncertainty and inexact or missing data to make real-world decisions (Gray, Snowden, MacCulloch, Phillips, Taylor, & MacCulloch, 2004; Gray, Taylor, & Snowden, 2008), for example the FBI's evaluation of death threats sent to high-profile targets (Borum, Fein, Vossekuil. & Berglund, 1999).

Can risk assessment paradigms be applied to risk of violent extremism?

Applying the conventional risk assessment approach prospectively to violent extremism is problematic. Firstly, screening for a given construct with a low base rate will inevitably produce poor predictive values, as the intended outcome criterion may be rare; inappropriate use of screening instruments with a healthy population to spot an increased risk of a disease can generate harmful outcomes, as well as waste limited resources best directed to those who need them (Grimes & Schulz, 2002). Some believe sociological and cultural approaches better describe the forces leading to violent extremism (Schbley, 2003), in which case methods deriving from clinical and individual psychology traditions may be inappropriately applied to such concerns (Dernevik, Beck, Grann, Hogue, & McGuire, 2009). Others suggest that the empirical claims of contemporary risk assessment methodology to assist in this area are exaggerated. For example, the receiver-operated-characteristic (ROC) methods commonly used to evaluate risk assessment instruments against specific outcomes work better for high-probability, low-impact events (e.g., generic reconviction) than low-probability, high-impact events (e.g., a mass killing, or a terrorist attack) (Sjöstedt & Grann, 2002). Meta-analysis of the predictive validity for tools commonly used to assess risk of violence, sexual, and criminal behavior suggests the positive and negative predictive values they generate are insufficient to justify being the sole factor in determining an individual's detention, sentencing, and release (Fazel, Singh, Doll, & Grann, 2012). Moreover, general factors predicting violence (*viz*. gender, social class, education. mental illness, criminal history, substance misuse, extremes of personality, and personality disorder) are not so clear in the case histories of persons identified as terrorists (Monahan, 2012; Silke, 1998). Given these technical and epistemological concerns, critics claim the development of screening instruments for risk of violent extremism (and the technology and systems of governance and control they require or may set in motion) is unethical, potentially leading to illegal activity and human rights abuse by the State (Monahan, 2011; Sims 2007).

To grossly reject proven methods as a possible approach to violent extremism is to reject a large body of potentially useful knowledge and expertise (Gudjonsson, 2009). For example, Roberts and Horgan (2008) suggest an instrument akin to the third revision of the Historical Clinical Risk-20 (HCR-20 V3: Douglas, Hart, Webster, & Belfrage, 2013)) or the screening version of Hare's revised Psychology Checklist (Hart, Cox, & Hare, 1995) is potentially applicable to guide assessments of violent extremists. Kennedy, Homant, and Barnes (2008) used a checklist developed by US security to screen for members of possible terrorist sleeper cells. Tested on a Muslim cohort, these criteria formed a single dimension related to concern about terrorism. Psychometric and risk-assessment approaches have also proven informative for understanding the structure of violent militant mindset (Saucier, Akers, Shen-Miller, Kneževié, & Stankov, 2009; Stankov, Saucier, & Knezevic, 2010).

---- Insert table 1 here ---

The Identifying Vulnerable People (IVP) guidance.

The Identifying Vulnerable People (IVP) guidance (available from www.tacticaldecisionmaking.org) was developed as part of a project to provide public sector frontline practitioners (e.g., school teachers, health care workers, and Police Officers) with a checklist of key behaviors that might assist the identification of individuals vulnerable to recruitment into violent extremism, or contributing to such activity. For example, risk-taking behavior can be inferred by an individual's lifestyle, whereas travel and residence abroad could be inferred by a person's movements through official border checks. The IVP guidance criteria derive from a thematic analysis of open source material on British Muslims (Cole & Cole, 2009) who had engaged in or been convicted of terrorist offences (Cole, Alison, Cole, & Alison, 2009; Cole, Cole, Alison, & Alison 2010; Weyers & Cole 2014). IVP items range from the very non-specific (e.g., familial conflict), through to very specific risk factors (e.g., engagement in overseas combat). The IVP's non-specific criteria indirectly indicate the importance of considering common behavioral problems (e.g., criminality, substance use) commonly associated with violence (Dolan & Rennie, 2008). Criminality and substance use is captured in the IVP by the item 3: "risk-taking behaviour".

Intentions of study.

The current study (the first to use the IVP) examines whether the IVP items cohere as a useful screening metric when used to evaluate known violent extremists for whom publically available data was available, using open source intelligence sources (OSINT; Stottlemeyer, 2015). This method tests the IVP in a criterion group of heterogeneous individuals convicted of a variety of offences involving violent extremism deriving from a variety of ideologies. This provides a strong test of the ideological neutrality of the IVP, given it was developed primarily to address persons inspired by violent Islamism. To examine if the IVP reflected generic factors, we also included a cohort of school shooters as an ideologically-neutral but alienated criterion group. Lastly, the IVP was examined for association with the real-world violent outcomes in the individual cases; committing or being convicted of acts that led to the death, injury, or potential/actual bombing of civilians.

METHOD

Sample

The cohort comprised an opportunistic sample of 182 named persons who had committed offences involving violent extremism for whom case information was available in the public domain via on-line searches using "Google". The sample comprised 90 (49.2%) primarily UK-based persons arrested for terrorist offences inspired by Islam. There were also 20 (10.9%) animal rights activists, 33 (18.0%) school shooters, 17 far-right activists (9.3%), 18 Irish Republican Army activists (9.8%), and 4 (2.2%) violent Sikh militants. The cohort was almost completely male; 176 (96.2) out of 182 persons. Public domain information specifically linking the persons to an offence was available for 157 of these persons, and indicated that 47 of the persons had been in incidents that led to the death of 1 to 13 persons, with another 56 involved in incidents leading to the injury of between 1 and 200 persons. Eighty-seven persons had been convicted for involvement in bomb-making activities, while 41 could be described as isolated, self-styled violent extremists. Our classification was based on OSINT. The name of the individuals rated and the violent extremist group they were allegedly involved with is presented at appendix A.

Procedure.

We used an OSINT method (Burke, 2007) to code and classify the individuals in this study. OSINT comprises publically-available content potentially available to anyone. Google Search was used to identify official newspaper reports of the trials of the named offenders, and to codify offence history, with supplementary data being obtained from further on-line articles and, if available, Wikipedia entries on the individuals. While subject to all the caveats Internet-held information provokes, Wikipedia is self-correcting (Anthony, Smith, & Williamson, 2009). OSINT data is no more unreliable than any other intelligence, and has the virtue of often being open to easier corroboration and checking by an independent reviewer than information acquired by state agencies that may have to conceal sources (Hulnick, 2010). Classification using IVP criteria was conducted conservatively, with persons being rated for each of the 16 criteria as 0 (no record/ not known), 1 (low evidence), 2 (medium evidence), and 3 (good evidence for the construct).

---- Insert table 2 here ----

To examine the integrity of OSINT IVP ratings, two additional raters blind-classified 16% (30) of the cases, these cases being the members of the cohort with the greatest amount of information available for them. Cohen's Kappa (Cohen, 1960) was calculated to determine agreement (table 2). These results show IVP ratings ranging from 0.63 to 1.00, and all were significant at $P<.001$. The mean kappa was 0.80; when the information was available, using OSINT to code IVP constructs is generally very reliable.

Plan of analysis

To examine whether the IVP items cohered as a useable metric, the reliability and validity of the measure was examined within and between extremist groups. All missing data were scored as 0 (construct not present) to reduce chance effects and enable the data to be approached using multivariate methods. This approach could be seen as being the equivalent of being presumed innocent until there is positive evidence for guilt (though may exaggerate effects for persons better documented within the public domain). As no criterion group had more than 100 persons, differences in alpha reliability between groups were compared using the Fisher-Bonnett test (Kim & Feldt, 2008; www.bgu.ac.il/~baranany/Feldt.xls). We tested whether IVP items were more effective if weighted using reliability and ANOVA measures, also testing whether IVP scores differed across extremist types. We used ROC and AUC to test if IVP screening scores predicted one of three violent outcomes: killing, injuring, or bombing. Lastly, we used diagnostic test statistics (sensitivity, specificity, positive and negative predictive values) to evaluate IVP performance.

RESULTS

---- Insert table 8 here ----

Functioning of the IVP across groups

Initial analysis found persons typically had about seven items of the IVP missing from OSINT (table 3); this was differentially distributed through the extremist groups: $F(4, 173) = 24.89$, $P<.001$, school shooters and animal rights activists had significantly more information missing to all other groups using post-hoc Scheffe test at $P < .01$ or below. Tests of reliability (table 4) across extremist groups indicated differential functioning of the IVP in terms of internal reliability. The IVP was more reliable screening Irish Republicans and Islamists, but particularly unreliable for screening of animal rights activists and school shooters. The difference of reliability between lowest and highest alpha reliability (animal rights activists versus Irish republicans) using the Fisher-Bonnett test was $z = -2.81$, $P = 0.003$; the difference of IRA and Islamist reliabilities was $z= -1.92$, $P = 0.027$. A regression predicting IVP total from extremist group membership, missing items, and the interaction of these was highly significant; $R=0.89$, adjusted $R^2 = 0.78$, $F(3, 174) = 209.31$, $P<.001$. Neither group, or the group x missing items interaction significantly independently contributed to this outcome, although missing data had a strong influence on total IVP ($t = -9.94$, $P<.001$). Some IVP items were more salient for some groups than others; for example, the animal rights activists did not present as isolated, did not show changes in religious practice, had not travelled or lived overseas, and had no experience of overseas combat. In other cases, the items lacked variance; all school shooters were alienated from their peers (IVP item 7); and all Irish Republicans were integrated with their families (IVP 2) while being members of an extremist group (IVP 13). The reliability of the IVP for Irish Republicans, Islamists and right-wing extremists together was the same as to the alpha reliability of the IVP for the full sample: 0.64. Results indicated removal of items would not increase the reliability of the scale. Weighting items hypothesised as more salient by 2 to 4 times did not improve reliability or validity, justifying the use of a single total IVP total score in subsequent analyses.

---- Insert table 5 here ----

Comparison of IVP across extremist groups.

Summary scores (mean and standard deviation) were calculated for the total IVP measure, and broken down by extremist group, excluding the extremist Sikhs (of whom there were only 4 participants) and a single radical libertarian (table 5). The difference across groups was highly significant: $F(4, 173) = 15.48$, $P<.001$, partial eta squared = 0.264, Power = 1.00. Post-hoc Bonferroni comparisons found that animal rights activists and school shooters had significantly lower IVP scores than Irish republican, Islamist, and right-wing extremists, who did not differ significantly between themselves.

---- Insert table 6 and 7 here ----

ROCs predicting violent offences from IVP total score.

To test whether the IVP related to specific harmful behaviors, ROC curves were calculated between scores for total IVP and three categorical criminal outcomes; the person being involved in an offence that led to a conviction for injury, a killing, or a bombing. The higher the area under the curve (AUC) produced by an ROC analysis, the more sensitive the measure is able to identify the particular outcome. An AUC over 0.7 is regarded as fair, while 0.8 is good. The ability of the IVP to predict injury, killing, or involvement in a bombing was greater for more established politicised violent extremist groups than for animal rights activists or school shooters. A similar ROC analysis was conducted on whether the violent extremist was apparently working alone (a lone actor) as compared to in a group. The AUC for a total IVP score predicting membership of the lone actor category was low and non-significant: 0.40 (95% confidence interval = .31 to .50).

Finally, to explore the value of the IVP for evaluating risk of genuine harm in a criterion group of persons who had been committed violent acts that involved a bombing campaign, persons being injured, or persons being killed, a sensitivity/ specificity analysis was conducted (table 7). Total IVP scores were examined in relation to the outcomes used in the AUC analysis using the sensitivity/ specificity analyses provided by the online medical calculator, *MedCalc* (http://www.medcalc.org/calc/diagnostic_test.php). These results show that specificity and sensitivity of the IVP was modest, as was the positive predictive value; however, the measure appeared to have a fair negative predictive value in accurately identifying persons who would not be involved in injurious or homicidal events.

DISCUSSION

The IVP guidance was developed for UK Government as an ideologically neutral tool to provide frontline practitioners from a wide range of UK public agencies (i.e. primary schools through to prisons) with a checklist of behaviors that potentially indicated vulnerability to violent extremism in their service users. The current study is the first to explore the properties of the checklist, and used a convenience sample comprising persons who could be unambiguously seen as the kinds of individuals the instrument was intended to identify (i.e., “true positives”). Persons were rated on the IVP using OSINT. Data were sought from publically- available information on the Internet and contemporaneous newspaper reports of the trials describing the persons in the database. Information to score items was often missing, and this influenced total scores on the IVP. The reliability of the measure was greater for cohorts with more information, and less effective for those with more missing information. Data were approached conservatively, and we were mindful of the many difficulties with the kind of information we used to rate persons. Generally, as the amount of OSINT increased, so did the number of criteria the individual scored against. The information used here was based on that available in the public domain, and may not reflect official knowledge of the individuals involved.

Implications

Taking these caveats into account, our exploratory findings indicate that using the total unweighted IVP score is the optimal way of using the IVP, and that it is best applied to screening for conventional violent extremists. The IVP checklist total was not systematically sensitive or specific for identifying persons convicted for injuring, killing, or being involved in a bombing campaign, though showed sporadic associations with these outcomes in subgroup analyses. The confidence limits on the AUCs were such that with better data, a more conclusive result could be made of the measure's validity. The IVP guidance was developed to identify all types of violent extremists (including recruiters and facilitators), so our specific (and more violent) outcomes perhaps focus on severe outcomes relative to process and "joint enterprise" type offences committed by persons included in the cohort.

Our results underline the importance of using systematic data using official information to assess risk, and that use of the IVP (or any other screening device) should be under strong professional review. For example, individual items need to be scored carefully; for example, the link between low level criminality and apparent terrorism is sometimes more pragmatic than sincere. In lawless and unstable states, criminals sometimes adopt the signifiers and rhetoric of broader conflict to justify offences; for example, dacoit kidnapping and extortion in India and Pakistan (Sahito, Farooq, & Chandio, 2009), or piracy in the Horn of Africa (Ohnuoha, 2009), both of which existed long before they became rationalised by reference to Islamic struggles. "Travelling abroad" and "religious practice" are also somewhat non-specific and over-general; many persons travel internationally to visit family, and observing a socially conservative faith is common for many believers, so not inherently an indicator of risk or behavioral pathology; "radical" (or reactionary) does not mean "terrorist" (Bartlett & Miller, 2012). A recognised risk for radicals "inspired" by Islam is lack of objective religious knowledge, or an aggressively conservative interpretation of the faith, rather than a sudden change in religious behavior *per se* (Loza, El-Fatah, Prinsloo, Hesselink-Louw,& Seidler, 2011). Ignorance or polarised views can be easily exploited by recruiters and ideologues (Cole, Alison, Cole, & Alison, 2009).

Limitations

The effects here might be thought modest, and to preclude further development of the IVP. That is unduly pessimistic, and reflects the heterogeneity of participants, and the informational limitations described. Despite their modest predictive values, soft behavioral signs are commonly considered in a variety of disciplines. For example, while "oddness" and "social withdrawal" are seen as cardinal prodromal antecedents to psychosis, positive predictive values for developing frank psychosis are below our equivalent values for prediction of violent outcome (Johnstone, Ebmeier, Miller, Owens, & Lawrie, 2005). Likewise, our data generated predictive values comparable to those found when screening for lower level mental disorders in primary health care using a standard clinical instrument. Such predictive values in a healthcare setting invited the authors to propose that the SCL-90 provides a rough index of concern, which they recommended be followed-up with more specific clinical assessment (Schmitz, Kruse, Heckrath, Alberti, & Tress, 1999).

Monahan (2012) calls for the development of structured individualised risk assessment instruments involving professional judgement specific to terrorism and violent extremism, focussing on the ideological, affiliative and grievance/ self-righteously based factors in the histories of such individuals. He acknowledges that risk assessment instruments addressing terrorism and violent extremism are not easily validated in prospective studies of the ‘capture-recapture’ kind used in general violence risk assessment research, but may nevertheless differentiate persons at differential risk within a population of interest. We also note that it is axiomatic to epidemiology that the prevalence of a construct in a sample affects the results of a screening test; in a low-prevalence setting, even a very strong psychometric instrument has poor predictive values (Grimes & Schulz, 2002).

Intelligent use of screening information.

It is wrong to conflate screening and risk assessment; the IVP is intended as a screening device, with risk assessment of individuals occurring at a higher level in the PREVENT process. The use of screening tests generates ‘false positives’ and ‘false negatives’. False positives and negatives arise from brief measures, and using unreliable outcomes uncritically underlines the importance of any screening being supplemented by specific intelligence (akin to clinical information) regarding the person of interest (Miller & Brodsky, 2011). This approach is inherent within the third- and fourth-generation violence risk assessments used by clinical practitioners and public protection panels that have to interpret the probabilistic risk information they generate. Classically, once information from a checklist or risk screening instrument is subjected to what is known more specifically about the person in question, risk is mostly moderated downwards (Douglas & Kropp, 2002). Revising provisional decisions reflects an awareness of the dynamic and risk-reducing factors that increase or decrease an individual’s risk-state (Douglas & Skeem, 2005), and are crucial given the potential expense, resources, and potential violations of human rights caused by over-reacting to false positives with a criminal justice response.

The potential threat posed by false negatives indicates that focusing on the false positive rate is only one side of the debate. The key point for IVP guidance is that all of the dataset in this study was scored using IVP guidance and would have thus potentially identified concerns prior to the commission of their offence by at least one statutory agency screening with the instrument. In theory, effective prevention interventions could have been employed to obstruct the development of extremist behaviour in these individuals. Therefore the correct way to interpret the utility of screening tools, such as the IVP guidance, is to balance the problems of both false positives and negatives, rather than just focus on the potential for false positives. In over 5 years of widespread use there has been no indications of the problems often associated with false positives, and, to the best of our knowledge, only one false negative (Weyers & Cole, 2014). In the latter case, an individual meeting only one IVP criteria was not passed onto a law enforcement agency when identified as part of a research study into online radicalisation, and several months later killed one person and injured another. On the other hand, multiple people and internet sites have been reported to law enforcement agencies resulting in the disruption of terrorist networks, seizure of illegal weapons, convictions for terrorist-related activities, and removal of terrorist-related online content (Weyers & Cole, 2014).

Future directions and conclusions

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The IVP guidance is currently the only ideologically neutral screening tool for violent extremism available in the public domain and open to scientific study. It is being used in multiple countries by a range of statutory agencies for screening and there is no indication to date that there is any evidence of widespread misuse or inappropriate reaction to identification. Violent activity from a range of violent extremist groups (i.e. not just

Islamists) has been brought to the attention of law enforcement agencies through the use of the IVP guidance resulting in criminal justice interventions (i.e. true positives). The death and injuries associated with the one known false negative to date underscore the price to be paid for a failure to effectively screen individuals who are beginning to engage with violent extremist activity. Analysis of *de novo* datasets are currently underway (Weyers & Cole, 2014). One of the problems of using *post hoc* OSINT to test the properties of a screening tool, such as the IVP guidance, is that the analyses are dependent on, and restricted by, the amount of information available. Until agencies with access to more information are willing to either provide access to that information or conduct the screening themselves, it will difficult to know whether the IVP guidance - or any other screening tool for violent extremism - is valid and reliable.

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Table 1: IVP Checklist items.

1. Cultural and religious isolation
2. Isolation from family
3. Risk taking behavior
4. Sudden change in religious practice
5. Violent rhetoric
6. Negative peer influences
7. Isolated from peer group
8. Hate rhetoric
9. Political activism
10. Basic paramilitary training
11. Travel/ residence abroad
12. Death rhetoric – increased salience
13. Extremist group membership – increased salience
14. Contact with known recruiters and extremists – increased salience
15. Advanced paramilitary training – increased salience
16. Overseas combat – increased salience

Table 2: Blind kappa agreement between raters for the 16 items of the IVP.

	Kappa	95% confidence interval
Cultural and religious isolation	.72	.94, .49
Isolation from family	.84	1, .63
Risk taking behavior	.63	.87, .39
Sudden change in religious practice	.87	1, .69
violent rhetoric	.69	.90, .49
Negative peer influences	.79	.98, .61
Isolated from peer group	.83	1, .66
Hate rhetoric	.80	1, .60
Political activism	.77	.98, .56
Basic paramilitary training	.85	1, .70
Travel/ residence abroad	.88	1, .76
Death rhetoric	.68	.94, .42
Extremist group membership	.89	1, .77
Contact with known recruiters and extremists	.88	1, .76
Advanced paramilitary training	.64	.79, .49
Overseas combat	1.00	0 to 0

Table legend: all kappa coefficients significant (P<.001)

Table 3: percentage missing data for IVP items in sample.

	Missing (%)
Cultural and religious isolation	7.1
Isolation from family	21.0
Risk taking behavior	13.7
Sudden change in religious practice	29.0
violent rhetoric	65.0
Negative peer influences	65.6
Isolated from peer group	94.0
Hate rhetoric	39.3
Political activism	56.3
Basic paramilitary training	69.9
Travel/ residence abroad	33.9
Death rhetoric	47.0
Extremist group membership	37.2
Contact with known recruiters and extremists	66.7
Advanced paramilitary training	65.0
Overseas combat	68.3

Table 4: Alpha reliability of the total unweighted IVP score across extremist groups.

	n	*n* items	Alpha reliability
Animal rights	20	12	0.32
School shooters	33	15	0.38
Islamists	90	16	0.65
Irish Republicans	18	14	0.84
Right wing extremists	17	16	0.61
All	182	16	0.64

Table 5: One way ANOVA comparing violent extremists on IVP total.

	Animal rights		School shooters		Islamists		Irish Republicans		Right-wing extremists		F-ratio (4, 173)	P<
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD		
IVP Total score	11.8	2.88	14.94	5.30	21.40	7.39	23.17	9.46	24.7	6.44	15.48	.001

Table legend: SD = standard deviation.

Table 6: ROC analyses (AUC) of IVP total/ violent outcomes for extremist groups.

	Cause injury	Kill	Bombing
Animal rights activists	0.53	-	0.54
95% CI	.24, .78	-	.23, .85
School shooters	0.67	0.64	0.49
95% CI	.43, .91	.47, .81	.31, .67
Islamists	0.63	0.66	0.59
95% CI	.47, .79	.50, .82	.43, .75
Irish Republicans	0.43	0.86 *	0.37
95% CI	.13, .72	.67, 1.00	.11, .63
Right wing extremists	0.89 **	1.00 *	0.28
95% CI	.71, 1.00	1.00, 1.00	.03, .52
Islamists, Irish republicans right-wing extremists alone	0.60	0.73 **	0.48
95% CI	.47, .73	.61, .85	.35, .61
All groups	0.51	0.49	0.63 **
95% CI	.42, .61	.39, .58	.55, .72

Table legend; AUC = area under curve.; 95% CI = 95% confidence interval. ROC/IVP for animal rights activists not calculated as no persons killed by this group. Significance * = P<.05; ** = P<.01.

Table 7: Sensitivity and specificity of the total unweighted IVP score in relation to violent outcomes.

	Sensitivity (%)	*Specificity (%)*	*Positive predictive value (%)*	*Negative predictive value (%)*
Injury	58.3	55.9	30.0	80.5
95% CI	40.8, 74.5	46.1, 65.3	19.6, 42.1	69.9, 88.7
Kill	66.7	57.9	31.4	85.7
95% CI	48.2, 82.0	48.3, 67.1	20.9, 43.6	75.8, 92.7
Bombing	60.0	63.6	60.0	63.6
95% CI	47.6, 71.5	51.9, 74.3	47.6, 71.5	51.9, 74.3

Table legend. *95% CI* = 95% confidence interval; *Sensitivity*: the probability that a test result will be positive when the construct is present (true positive rate); *Specificity*: the probability that a test result will be negative when the construct is not present (true negative rate); *Positive predictive value*: the probability that the construct is present when the test is positive; *Negative predictive value*: the probability that the construct is not present when the test is negative.

Table 8: learning points from this study.

- Open-source intelligence may lack detail available to official agencies, reducing the amount of risk-related information in quick screening instruments.
- Different violent extremist cohorts have present different profiles of risk reflecting their prior history and the trajectory that brought them to the current position.
- Weighting item information deemed to be more salient (or not) did not improve reliability or validity of measurement using the IVP.
- Screening instruments must be followed by a human-driven risk assessment of the individual to optimise judgement of the risk and risk state.

Appendix A: Persons included in the analysis and their associated preferred ideology.

	Name	Extremist movement
1.	Greg Avery	Animal rights
2.	Natasha Avery	Animal rights
3.	Heather Nicholson	Animal rights
4.	Gavin Medd-Hall	Animal rights
5.	Gerrah Selby	Animal rights
6.	Daniel Wadham	Animal rights
7.	Daniel Amos	Animal rights
8.	Deborah Morrison	Animal rights
9.	Diane Jamieson	Animal rights
10.	Donald Currie	Animal rights
11.	Robert Cogswell	Animal rights
12.	Jon Curtin	Animal rights
13.	Barry Horne	Animal rights
14.	Charlotte Lewis	Animal rights
15.	Joseph Harris	Animal rights
16.	Jon Ablewhite	Animal rights
17.	Josephine Mayo	Animal rights
18.	John Smith	Animal rights
19.	Kerry Whitburn	Animal rights
20.	Laurence McKeown	Irish Republican Army
21.	Sean O'Callaghan	Irish Republican Army
22.	Eamon Collins	Irish Republican Army
23.	Kieran Doherty	Irish Republican Army
24.	Martin Meehan	Irish Republican Army
25.	Joe Cahill	Irish Republican Army
26.	Bobby Sands	Irish Republican Army
27.	Phil O'Donnell	Irish Republican Army
28.	Patrick Magee	Irish Republican Army
29.	Martin McGuinness	Irish Republican Army
30.	Gerry Adams	Irish Republican Army
31.	Dominic McGlinchey	Irish Republican Army
32.	Gerry Kelly	Irish Republican Army
33.	Noel Maguire	Irish Republican Army
34.	Robert Hulme	Irish Republican Army
35.	Aiden Hulme	Irish Republican Army
36.	James McCormack	Irish Republican Army
37.	John Hannan	Irish Republican Army

38. Mohammed Kamel	Islamist (home)
39. Mohsin Ghalain	Islamist (home)
40. Samad Ahmed	Islamist (home)
41. Shahid Butt	Islamist (home)
42. Malik Harhara	Islamist (home)
43. Iyad Hussein	Islamist (home)
44. Shazad Nabi	Islamist (home)
45. Ghulam Hussein	Islamist (home)
46. Richard Reid	Islamist (home)
47. Sajid Badat	Islamist (home)
48. Moinul Abedin	Islamist (home)
49. Omar Sheik	Islamist (home)
50. Asif Hanif	Islamist (home)
51. Omar Sharif	Islamist (home)
52. Mohammed Khan	Islamist (home)
53. Shezaad Tanweer	Islamist (home)
54. Germaine Lindsay	Islamist (home)
55. Hasib Hussain	Islamist (home)
56. Muktar Ibrahim	Islamist (home)
57. Ramzi Mohammed	Islamist (home)
58. Yassin Omar	Islamist (home)
59. Hussein Osman	Islamist (home)
60. Manfo Asiedu	Islamist (home)
61. Aadel Yahya	Islamist (home)
62. Abu Mansha	Islamist (home)
63. Omar Khyam	Islamist (home)
64. Salahuddin Amin	Islamist (home)
65. Jawad Akbar	Islamist (home)
66. Waheed Mahmood	Islamist (home)
67. Anthony Garcia	Islamist (home)
68. Dhiren Barot	Islamist (home)
69. Qaisar Shaffi	Islamist (home)
70. Mohammed Bhatti	Islamist (home)
71. Junade Feroze	Islamist (home)
72. Zia ul-Haq	Islamist (home)
73. Abdul Aziz Jalil	Islamist (home)
74. Hamid Elasmar	Islamist (home)
75. Attilla Ahmet	Islamist (home)
76. Mohammed al-Figari	Islamist (home)
77. Kibley Da Costa	Islamist (home)
78. Kidar Ahmed	Islamist (home)
79. Mohammed Kyriacou	Islamist (home)
80. Yassin Mutegombwa	Islamist (home)
81. Hassan Mutegombwa	Islamist (home)

82. Abdullah Ahmed Ali	Islamist (home)
83. Kazi Nurur Rahman	Islamist (home)
84. Andrew Rowe	Islamist (home)
85. Arafat Waheed Khan	Islamist (home)
86. Waheed Zaman	Islamist (home)
87. Ibrahim Savant	Islamist (home)
88. Umar Islam	Islamist (home)
89. Tanvir Hussain	Islamist (home)
90. Assad Sarwar	Islamist (home)
91. Sohal Queshi	Islamist (home)
92. Younis Tsouli	Islamist (home)
93. Tariq Al-Daour	Islamist (home)
94. Ali al-Tamimi	Islamist (home)
95. Kamal Bourgass	Islamist (home)
96. Hassan Tabbakh	Islamist (home)
97. Faisal Mostafa	Islamist (home)
98. Kamel Merzoug	Islamist (home)
99. Parviz Khan	Islamist (home)
100. Mohammed Irfan	Islamist (home)
101. Bassiru Gassama	Islamist (home)
102. Zahoor Iqbal	Islamist (home)
103. Nicky Reilly	Islamist (home)
104. Bilal Abdullah	Islamist (home)
105. Kafeel Ahmed	Islamist (home)
106. Michael Adebolajo	Islamist (home)
107. Michael Adebowale	Islamist (home)
108. Abu Hamza	Islamist (home)
109. Andrew Ibrahim	Islamist (home)
110. Aabid Khan	Islamist (home)
111. Krenar Lusha	Islamist (home)
112. Matthew Newton	Islamist (home)
113. Munir Farooqi	Islamist (home)
114. Israr Malik	Islamist (home)
115. Mohammed Hamid	Islamist (home)
116. Irfan Naseer	Islamist (home)
117. Irfan Khalid	Islamist (home)
118. Ashik Ali	Islamist (home)
119. Rahin Ahmed	Islamist (home)
120. Bahader Ali	Islamist (home)
121. Mohammed Rizwan	Islamist (home)
122. Mujahid Hussain	Islamist (home)
123. Shaaq Hussain	Islamist (home)
124. Khobalb Hussain	Islamist (home)
125. Shahid Khan	Islamist (home)

126.	Naweed Ali	Islamist (home)
127.	Abdullah el-Faisal	Islamist (home)
128.	Miles Cooper	libertarian paranoid
129.	David Copeland	Right-wing extremist
130.	Martyn Gilleard	Right-wing extremist
131.	Neil Lewington	Right-wing extremist
132.	Robert Cottage	Right-wing extremist
133.	David Jackson	Right-wing extremist
134.	Alan Boyce	Right-wing extremist
135.	Terry Collins	Right-wing extremist
136.	William Thompson	Right-wing extremist
137.	Nathan Worrell	Right-wing extremist
138.	John Laidlaw	Right-wing extremist
139.	David Tovey	Right-wing extremist
140.	Darren Wells	Right-wing extremist
141.	Will (a.k.a. Bill) Browning	Right-wing extremist
142.	Charlie Sargent	Right-wing extremist
143.	Tony Lecomber	Right-wing extremist
144.	Mark Atkinson	Right-wing extremist
145.	Del O'Connor	Right-wing extremist
146.	Eric Harris	School shooter
147.	Dylan Klebold	School shooter
148.	Pekka-Eric Auvinen	School shooter
149.	Tim Kretchmer	School shooter
150.	Cho seung hui	School shooter
151.	Jeffrey Weise	School shooter
152.	Matti Juhani Saari	School shooter
153.	Kimveer Gill	School shooter
154.	Thomas Hamilton	School shooter
155.	Robert Stenhauser	School shooter
156.	Steven Kazmierczak	School shooter
157.	Kipland Kinkel	School shooter
158.	Asa Coon	School shooter
159.	Charles Carl Roberts	School shooter
160.	Latina Williams	School shooter
161.	Drew Golden	School shooter
162.	Mitchell Johnson	School shooter
163.	Michael Carneal	School shooter
164.	Luke Woodham	School shooter
165.	Sebastian Bosse	School shooter
166.	Alvaro Castillo	School shooter
167.	Adam Lanza	School shooter
168.	Charles Andrew Williams	School shooter
169.	Farda Gadirov	School shooter

170.	Wellington Oliveira	School shooter
171.	Tyrone Mitchell	School shooter
172.	Marc Lepine	School shooter
173.	Mamoru Takuma	School shooter
174.	Alaa Abu Dhein	School shooter
175.	One Goh	School shooter
176.	Mohammed Nazari	School shooter
177.	Patrick Purdy	School shooter
178.	Kim De Gelder	School shooter
179.	Inderjit Singh Reyat	Sikh extremist
180.	Karamajit Singh Chahal	Sikh extremist
181.	Sukhwinder Singh Gill	Sikh extremist
182.	Jarnail Singh	Sikh extremist