Learning from The Parallel Field of Terrorism Studies[1]

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Briggs and Pollard (this issue) make a convincing case for the advancement of computational modelling and simulation of mass violence for threat assessment and management. The purpose of this commentary is to look into the analogous study of terrorism to pinpoint recent areas of advancement. We narrow our focus to three core areas, two of which heavily overlap with core areas identified by Briggs and Pollard: (a) computational linguistic approaches (b) spatial modelling and (c) network based designs. Historically, the fields of both (a) threat assessment and management and (b) terrorism studies grew in silos. The aim here is for a much greater alignment in research agendas moving forward.

Linguistic Modelling of Radicalisation and Terrorism

Psychological and computational research increasingly examines language use to gain insight into psychological processes. The relative success of linguistic analysis within the field of psychology suggests that a similar approach is worthwhile within the specific domain of studying lone-actor terrorism. Approaches to automatically analysing radicalised language can be broadly categorised into wordcount-based approaches and weight-based approaches. A wordcount-based approach includes studies which make use of a dictionary, which are often used to measure psychological concepts in a piece of text (e.g. power, anxiety). One such example is LIWC software (Pennebaker et al., 2015), which processes each word in a text that is to be analysed, and determines whether the same word appears in an internal dictionary. The resulting output shows the frequencies and proportions of words that belong to each word category. For example, the software may show that 5% of words in a terrorist manifesto relate to power, and 7% to anxiety.

Several studies have examined the language of lone-actor terrorists using this method, identifying differences in language use between these violent individuals and the general population. For instance, Baele (2017) examined pieces of text written by lone-actor terrorists, measuring various psycho-social variables using LIWC software. The aim of the study was two-fold. First, the study assessed whether texts written by lone-actor terrorists were characterized by higher levels of anger and negative emotion than texts written by nonviolent individuals. Baele (2017) notes that this question stems from claims that violence is typically linked to anger, especially in the case of political violence. The second line of inquiry concerns the way in which lone-actor terrorists cognitively function. Some theories suggest that lone-actor terrorists think and process information in a rigid and inflexible way. The theory that cognitive and ideational inflexibility is associated with extremism and violence has been widely considered in the field of terrorism research. It has been argued that terrorists are limited to black-and-white thinking and oversimplified ‘us versus them’ reasoning. Baele (2017) examined the anger and cognitive inflexibility hypotheses by testing lone-actor terrorist writings for LIWC categories related to emotion and cognitive processes. The scores for the lone-actor texts were compared to scores for texts written by non-violent activists (e.g. Martin Luther King, Nelson Mandela) as well as samples of standard control writings and emotional writings (‘baseline’ texts provided by LIWC developers expressing low and high emotionality, respectively).[16] Lone-actor texts contained higher proportions of negative emotion words (resentment and anger) than the non-violent activist texts, standard control texts, and emotional texts. Furthermore, the lone-actor texts showed high cognitive sophistication and low cognitive inflexibility, based on the proportions of LIWC categories for ‘cognitive processes’, ‘causality’, ‘certainty’, ‘tentative’, words with more than six letters, and a separate measure of cognitively complex language.[19] In short, Baele (2017) argued that the psycho-social characteristics of lone-actor terrorist texts support the idea that perpetrators exhibit high levels of anger but are characterized by high cognitive complexity rather than inflexibility.

In a similar vein, Kaati et al. (2016a) found that lone-actor terrorist language samples contain significantly higher levels of negative emotion, power, and anger, but lower levels of positive emotion and friendship-related words than texts from personal blogs. A similar approach was taken to examine possible radicalisation amongst users of an 'incel' (involuntary celibate) forum, where forum texts were found to contain more swear words, negative emotion words, personal pronouns, modal adverbs, and negative adjectives, but fewer positive adjectives than control texts taken from Wikipedia (Jaki et al., 2019). Psychological constructs measured through LIWC have also been used to classify offender and non-offender texts in machine learning tasks, for example to distinguish between lone-actor terrorist texts and postings from a white supremacy forum (Kaati, Shrestha, & Sardella, 2016).

A weight-based approach entails that words in a dictionary are additionally assigned a weight, for example to signify the sentiment (ranging from negative to positive polarity) or affect (e.g. anger, surprise, joy) of a word. Sentiment analysis has for example been used to identify radical users on Islamic web forums as well as right-wing extremist forums (Scrivens et al., 2018a, 2018b). In both studies, negative sentiment was used to compute 'radical scores', consisting of 1) the average sentiment score across all posts from a single author, 2) the volume of negative posts, 3) the severity of negative posts, and 4) the time between the first and last negative post. By doing so, the most 'radical authors' on two Islamic web forums could be identified. The same approach to calculating radical scores was used to examine a Canadian right-wing forum, albeit scores were computed across time and separately for anti-Semitic, anti-black, and anti-LGBTQ posting behaviour. This analysis showed that the forum exhibited a steady increase in radical score over time, suggesting possible polarisation. Further studies have also examined affect on American white supremacist and Middle Eastern Islamic extremist dark web forums, using custom dictionaries to measure violence and hate, weighted for intensity between 1 and 20 (Abbasi & Chen, 2007). In the study, Middle Eastern forums exhibited higher levels of violence words, whereas the two regions did not differ in terms of hate-related words.

As an emerging field, the study of radicalised language is not without its limitations. We briefly evaluate the state of the art and propose potential future pathways. Firstly, language samples from radicalised and terrorist individual are often compared to a sample of control writings, such as personal blog entries (Akrami et al., 2018; Kaati, Shrestha, & Cohen, 2016b; Kaati, Shrestha, & Sardella, 2016) or Wikipedia articles (Jaki et al., 2019). These language samples are often unrelated in topic to the violent or abusive writings of radicalised individuals. This raises the question whether distinguishing linguistic characteristics of radicalisation are indeed measured, or merely a difference in topic. Perhaps the most challenging task in understanding radicalisation through language is acquiring datasets that allow for valid linguistic comparisons between radicalised and non-radicalised, or violent and non-violent populations, where both groups discuss similar matters. This is necessary so that potential future detection systems can make use of true discriminatory linguistic variables rather than differences in topic or text type alone.

The use of dictionaries is also subject to several limitations. Dictionaries are highly constrained, in that they only capture the precise words that are listed. This raises issues with misspellings and the context-dependent meaning of words. Furthermore, the content of dictionaries is highly subject to bias if they are constructed by humans. Lastly, existing dictionaries have not been developed for the specific purpose of detecting radicalisation, thus relevant psychological concepts may not be measured if out-of-the-box dictionaries such as LIWC are used. Future research may focus on discovering linguistically valid markers of radicalisation, followed by the development of a dictionary specifically developed for the purpose of radicalisation detection.

Lastly, radicalisation needs to be treated as a process rather than a static state, and linguistic analysis needs to take this into account. Linguistic measures should be taken at several timepoints to understand the process of radicalisation, for example across several forum- or social media posts. Notable examples include measurements of topics over time on a Tumblr blog of a radicalising woman who travelled to Syria (Windsor, 2018), as well as the development of radical language use on extremist forums over time (Kleinberg et al., 2020; Scrivens et al., 2018b).

Spatial Modelling of Terrorist Events

Terrorists, just like ordinary criminals, are limited by geographical constraints. Numerous patterns of spatial clustering that are evident for traditional crimes are reflected in terrorism (Clarke & Newman, 2006). Collectively, rational choice perspectives, routine activity approaches and crime-pattern theory suggest offenders will actively select areas and targets in a way that minimises effort and risks and maximises rewards (Johnson & Bowers, 2004; Felson, 2006).

The least effort principle (Zipf, 1965) assumes that when considering a 'number of identical alternatives for action, an offender selects the one closest to him in order to minimize the effort involved' (Lundrigan & Czarnomski, 2006:220). An offender's journey to crime typically demonstrates the distance-decay function, whereby chances of offending and frequency of offences decrease as distance from their home increases (Bernasco & Block, 2009; Wiles & Costello, 2000). Likewise, to increase the utility of their attack the terrorist offender would aim to keep the distance travelled minimal, and proximity to the target has been considered a key feature of terrorist target selection (Clarke & Newman, 2006). As well as considering effort, the risk of interception before an attack will also be taken into consideration (Townsley et al., 2008). Travelling to unknown areas may increase risk as strangers 'stand out' more easily in unknown territory (Bernasco and Block, 2009).
The function of distance decay has been empirically supported when examining the activities of PIRA (Gill et al., 2017). Nearly two-thirds of a sample of core active members travelled less than 4 miles to commit their attacks, with 40 per cent of all attacks occurring within 1 mile of the offender's home location (Gill et al., 2017). Complex attacks typically involved greater distances. Younger offenders (those aged 20 or under) travelled significantly shorter distances. This suggests that there may be predictable behaviours amongst subsamples of terrorist offenders.

The distance-decay effect has also been found for lone actors in Western Europe and the US (Marchment et al., 2018). The mean distance of attacks from the actor's home was 90 miles (144 km), however more than half of all the attacks (56.5 per cent) occurred within 10 miles (6 km) of the individual's home location, and 36 percent of all attacks occurred within 2 miles (3 km). In Western Europe, a high concentration of attacks occurred around the actor's home, with more than half (56 per cent) of all the attacks occurring within 2 miles of the home location.

Variations in distances for different target types reflected previous literature on traditional crimes (Hesseling, 1992; Fritzon, 2001; Santilla et al., 2007). The mean trip length for iconic targets was much longer than for symbolic or arbitrary targets. Those attacking arbitrary targets travelled the shortest distance of the three target types. This suggests that a consideration of costs vs. benefits may take place in decision-making regarding target selection, and that there is a trade-off between distance to the target and the representative value of the target, as lone actors are willing to travel further for targets that are more in line with their grievance.

In treating distance as a dependent variable however, these studies are limited. They assume targets are spatially uniformly distributed. They also overlook potential targets that could have been chosen, but were not. Ideally, distance should be treated as an explanatory variable, rather than the dependent variable (Kleemans, 1996) and should be used alongside other choice criteria, such as the connectedness of the area, to determine why the chosen target was selected above other similar targets (Bernaso and Block, 2009).

To overcome similar limitations, Bernasco and Nieuwbeerta (2005) applied McFadden's (1974) discrete choice model to the spatial decision making of urban burglars. Stemming from the field of economics, this approach allows target selection analyses to simultaneously consider multiple factors including the chosen target destination, areas that could have been chosen but were not, the likely origin of offenders and their perceptions that affect decision making. This approach is now well-established in the study of a variety of urban crimes (see Bernasco, 2006; Bernaso and Block, 2009; Bernasco, 2010a; Bernasco, 2010b; Bernasco and Kooistra, 2010; Bernasco et al., 2012; Bernasco et al., 2013; Baudains et al., 2013; Townsley et al., 2015a; Townsley et al., 2015b; Johnson and Summers, 2015; Vandeviver et al., 2015; Menting et al., 2016; Bernasco et al. (2016) Frith et al., 2017; Lammers, 2017).

Marchment and Gill (2019) applied the discrete choice approach to 150 attacks committed by core members of PIRA. The results suggested that terrorists are similar to traditional criminals in their decision making and they are influenced by spatial context, such as the distance from their home location to the attack location, or the presence of a premises relevant to their ideology. An increase in distance from the home location decreased the likelihood that an area would be chosen. The presence of a major road in an area increased the likelihood that it would be selected. The same was true for the presence of a military base or police station.

A common finding in analyses demonstrating spatial and temporal variation in risk of terrorist attacks is that they are spatially clustered (Berrebi & Lakdawalla, 2007; Townsley et al., 2008; Johnson & Braithwaite, 2009; Siebeneck et al., 2009; Medina et al., 2011; Behlendorf et al., 2012; Mohler, 2013; Tench et al., 2016). However, the spatial analyses that have been completed thus far have been unable to identify the causes of these hotspots – just the fact that they exist.

Local infrastructure is an important element to consider as variations offer different opportunities, risks and rewards. However, a consideration of how the environmental backcloth (Brantingham & Brantingham 1981, 1993) of a city shapes the behaviour of terrorists has largely been neglected. Risk-terrain modelling (RTM) was developed in the study of urban crime to quantitatively assess the spatial influence of features of the urban landscape to identify areas where criminal activity is likely to occur or emerge. RTM has been applied to many different urban crimes including burglaries (Gale & Hollernan, 2013;

Moreto et al., 2013), robberies (Kennedy & Gaziarifoglu, 2011; Dugato, 2013), shootings (Caplan et al, 2011; Drawve et al., 2016; Xu & Griffiths, 2017), aggravated assaults (Kennedy et al., 2011; Kennedy et al., 2016; Anyinam, 2015; Kocher & Leitner, 2015), and assaults on police (Drawve & Barnum, 2018).

Onat (2016) identified areas that were at risk of attack from terrorist groups in Istanbul. He found the riskiest factor in the urban environment to be the presence of bakeries. Although this type of building has no symbolic value, bakeries have a social meaning in Turkish culture and are visited frequently by most residents. Thus, bakeries have a role in an individual's daily routine. Because they attract large numbers of people daily, they can be considered an attractor for many available targets. This again highlights the importance of considering an individual's everyday behaviour, and their awareness space, in the selection of targets. Other significant correlates included religious facilities, bars and clubs, and grocery stores.

Onat and Gul (2018) identified differences in terrorist targeting for separatist and leftist groups. Grocery stores, bakeries, bars/clubs, and educational facilities were identified as risk factors for both types. Religious facilities and office blocks were significant correlates of separatist attacks but not for leftist attacks. Government buildings were found to be a risk factor for leftist attacks only. Marchment et al (2019) found that, for violent dissident Republican attacks in Belfast, previous experience of protests and riots, previous experience of punishment attacks and areas dense with pubs and bars were identified as risk factors for bombings. Previous experience of punishment attacks, police stations places dense with shops were identified as risk factors for bomb hoaxes.

Network Based Designs and the Study of The Terrorist

Broadly speaking, there are five ways of categorising such research within terrorism studies. First, are social network based approaches which look at the ties between individual members of a terrorist network. For example, Gill et al (2014) conducted a social network analysis of over 1000 Provisional IRA members. The study investigates why PIRA members had operational relationships with some members of the movement but not others? Using stochastic methods they illustrate that the Provisional Irish Republican Army's network was clustered along three primary dimensions (a) brigade affiliation (b) whether the member participated in violent activities (c) task/role within PIRA. Members who engaged with violent activities were far more likely to connect with each other. Across brigades, those who engage in a particular task and role (IED constructor, IED planter, gunman, robber/kidnapper/drug smuggler/hijacker) are more likely to connect with others who do the same task or play the same role than with other members who fulfill other roles. Standard forms of homophily (i.e. the tendency to make connections with people who are similar in terms of demography or status) played a very weak role in explaining which members interact with one another. Finally, the analysis illustrates clear patterns of relational change that correspond to changes in the formal structures that PIRA's leadership promoted. In a follow up study, Manrique et al (2016) demonstrate that although men numerically dominate both Provisional IRA and online ISIS networks, women have superior network connectivity which in turn feeds the networks' robustness and survival.

Second, are network based approaches that sequentially organize the mobilization to violence across different terrorists. Such approaches combine the rigour of variable-based approaches and the richness of case studies. Traditional inferential statistical techniques typically focus on the relationship between immediate events with no consideration for the importance of the ordering of these events. Human behaviour is more complex than such context-free interactions imply. Within a behavioural sequence, immediate experiences and behaviours are often highly related. However, experiences and behaviours earlier in the sequence also have an effect on the final outcome. It is therefore imperative to capture the indirect experiences and behaviours and examine how they impact the development of the sequence (Taylor & Donald, 2007), whilst also retaining the complex individual direct inter-relationships. For example, Corner et al's (2020) demonstrated the principle of multifinality in a sample of lone-actor terrorists. It demonstrates the differing role particular risk factors may have across the pathway to violence. Similarly Corner & Gill's (2019) sequence analysis highlights the disengagement pathways from terrorism using a sample of first-hand accounts from former terrorists.

Third, are network studies that model the interactions between different risk factors. This is a major move away from traditional multivariate studies. Given, the relatively small sample sizes often afforded to researchers in psychology or criminology, there is often not the statistical power to model the interactions *between* large numbers of factors. For instance, rather than considering the effect of a number of independent variables on the outcome, depression, it may be of interest to model the hypothesised causal relationship between the many symptoms of depression, in order to estimate the underlying causal structure of the phenomenon. Psychometric network modelling is one way to do so. Network modelling is increasingly popular in psychological sciences. One reason why is the ability to uncover and visualise the structure of complex interactions among multiple constructs. Psychological network graphs consist of nodes and edges where nodes represent variables and the edges define the nature of the statistical relationship among these variables. Psychological network graphs have been used extensively in to model complex, multidimensional relationships of a range of psychopathologies (Robinaugh, Hoekstra, Toner, & Borsboom, 2019).

Psychological network analysis differs from other network structures, such as social network analysis, in that the strength of the edge connecting two nodes is a parameter estimated from the data, rather than an observed connection between people or places, for example. To construct a psychological network, first, a model is estimated on the data and parameters are represented as a weighted network between observed variables. Second, the weighted network structure is analysed using measures from network graph theory. This approach is most often applied to psychopathology, where network analysis focusses on individual symptoms of mental disorders and the associations between them. This can provide insights into the patterns in which symptoms co-occur. Moreover, network analysis can reveal how nodes facilitate connections among clusters of related nodes. This can be useful to understand co-morbidity or pathways between different constructs.

Conclusion

The study of violent extremism from a threat/risk assessment and management literature has advanced in the last few years. Conceptually, large parts of the inspiration came from the general violence literature. The purpose of this commentary was to highlight some methodological areas within terrorism studies, which in turn, might feed back into the general study of threat assessment and management.

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