What is the best approach for preventing recruitment to terrorism? Findings from ABM experiments in social and situational prevention

Weisburd, David; Wolfowicz, Michael; Hasisi, Badi; Paolucci, Mario; Andrighetto, Giulia

DOI: 10.1111/1745-9133.12579

CRIMINOLOGY & Public Policy

ORIGINAL ARTICLE

What is the best approach for preventing recruitment to terrorism? Findings from ABM experiments in social and situational prevention

David Weisburd[1,2] | **Michael Wolfowicz**[2] | **Badi Hasisi**[2] | **Mario Paolucci**[3] | **Giulia Andrighetto**[3,4]

[1] Department of Criminology, Law, and Society, George Mason University, Fairfax, Virginia, USA

[2] Institute of Criminology, Hebrew University, Jerusalem, Israel

[3] Laboratory of Agent Based Social Simulation, Institute of Cognitive Sciences and Technologies, National Research Council of Italy, Rome, Italy

[4] Institute for Future Studies, Stockholm, Sweden

Correspondence
David Weisburd, Department of Criminology, Law, and Society, George Mason University, 4400 University Drive, MS 6D12, Fairfax, VA 22030, USA.
Email: dweisbur@gmu.edu

Abstract

Research Summary: This study uses agent-based models (ABMs) to compare the impacts of three different types of interventions targeting recruitment to terrorism—community workers at community centers; community-oriented policing; and an employment program for high-risk agents. The first two programs are social interventions that focus on de-radicalization and changing the dispositions of agents in the model, whereas the employment program focuses on "deflection" and represents a situational/opportunity reducing approach to prevention. The results show significant impacts of the community worker and community policing interventions on radicalization but no significant impact on recruitment. In contrast, the employment intervention had a strong and significant impact on recruitment, but little impact on radicalization.

Policy Implications: Our ABM simulations challenge the reliance of existing programs to reduce recruitment to terrorism on counter and de-radicalization approaches. Instead they suggest that policy makers should focus more attention on deflection and opportunity reduction. At the same time, our ABMs point to the salience of social interventions focusing on risk and protective factors for reducing radicalization in society.

KEYWORDS
agent-based modeling, radicalization, recruitment, terrorism

Programs that aim to reduce recruitment to terrorist groups have been based primarily on the logic that society should focus on tackling the risk and protective factors that underpin radicalization (National Academy of Science, Engineering, and Medicine, 2017). The assumption is that if government can reduce radicalization, it will also reduce recruitment. In this context, social programs that focus on counter and de-radicalization have become the predominant approach in preventing recruitment to terrorism (Koehler, 2019). Although reducing radicalization is clearly a positive outcome for democratic societies, it may not necessarily be the most efficient or effective way to reduce recruitment. More than 40 years ago, Clarke (1980) argued that there was a "dispositional" bias in prevention programs in which criminologists and crime prevention experts were primarily interested in changing criminals' attitudes toward crime as a means to reducing crime. Clarke (1980) suggested that rather than trying to change dispositions themselves, changing situational factors related to crime may achieve better results. Analogously, countering radicalization may not even be necessary for preventing recruitment, and situational approaches may be appropriate for preventing recruitment to terrorism as well (Bjørgo, 2013, 2016).

Although there is a strong research literature that examines the relationship between risk factors and radicalization (see Wolfowicz et al., 2020, 2021), we have little solid evidence regarding whether counter-radicalization programs will actually reduce radical attitudes or recruitment to terrorist groups (Gielen, 2019; Koehler & Fiebig, 2019; Pisoui & Ahmed, 2016). There are few evaluations of counter-radicalization programs, and they are generally of low methodological quality (see Jugl et al., 2020). In turn, we are not aware of any quantitative evaluations of programs that seek to reduce recruitment. Importantly, a key problem in developing studies of this type is the low base rates of recruitment to terrorism, making it difficult to develop statistically powerful outcome evaluations.

In this study, we rely on agent-based models (ABMs) to examine how different programmatic approaches can be expected to impact upon radicalization and recruitment to terrorism. Although ABMs cannot replace field experiments, they can give policy makers a good indication as to which initiatives are more likely to be successful in the real world, and whether logic models for interventions operate as envisioned (Eck & Liu, 2008; Groff & Mazerolle, 2008; Weisburd et al., 2017). In our case, ABMs allow for the examination of the impacts of different types of interventions on radicalization and recruitment to terrorism with large populations of affected individuals in a context in which the base characteristics of agents exposed to treatment, and their environmental and social contexts, are the same for each experiment.

Our ABM experiments are enacted in a European context both because the European Union has taken a leadership role in the development of programs to reduce recruitment to terrorism (European Commission, 2014, 2016) and because funding for the development of our ABM was provided by the Horizon 2020 grant program of the European Union. At the same time, research on radicalization and terrorism more generally suggests that similar risk and protective factors are found in Europe and North America (Ozer et al., 2020; Vergani et al., 2020; Wolfowicz et al., 2021a). In line with current approaches being undertaken in major European cities, we test the effects of three different interventions for reducing radicalization and recruitment in a prototypical European city borough. One intervention is based on increasing contacts with pro-social actors through increasing the number of community workers in centers spread out across a city. The second focuses on increasing the legitimacy of police, through training community police officers. These are examples of social interventions meant to decrease the risk of radicalization by focusing on changing the dispositions of vulnerable populations. Our final intervention provides employment to vulnerable young people. It is focused on deflection as a mechanism for situational prevention, and does not directly seek to impact radicalization.

1 | WHAT INCREASES RISK FOR RADICALIZATION?

Although there are certainly many definitions of radicalization, there is a general consensus about the need to differentiate between the cognitive and behavioral outcomes of radicalization. Cognitively, radicalization refers to the support or justification of, or a sense of personal moral obligation toward, the use of violence in the name of an ideology or cause. Although in any population there may be a sizeable portion of individuals who fall into this broad category, an exceptionally small percentage (less than 1%) will ever go on to engage in such radical behaviors (e.g., Bartlett et al., 2010; Borum, 2014; Hafez & Mullins, 2015; Khalil, 2017; McCauley & Moskalenko, 2017; Moskalenko & McCauley, 2020; Neumann, 2013).

Like risk and protective factors for other criminal and criminal-analogous outcomes, risk factors for radicalization can generally be split into categories of static and dynamic factors (Lösel et al., 2018; Wolfowicz et al., 2020). Static risk factors are the stable, often immutable factors that are distributed among individuals in a population, manifested as background characteristics or propensities usually ingrained in individual psychological or personality-related traits (Wikström & Bouhana, 2017). These factors determine an individual's risk status. Dynamic factors are malleable and often change over time. Among dynamic factors, attitudinal risk factors are often seen as providing the greatest opportunity for targeting by interventions. This is because such factors are open to formation and change through the individual's experiences and exposures (Akers, 1998; Sampson & Bartusch, 1998). Taken together, "risk status" and dynamic factors determine an individual's vulnerability to actual recruitment at a given point in time (Douglas & Skeem, 2005).

In constructing our ABM (see below), we sought to identify a small group of static and dynamic risk factors that have consistently been found to be key correlates of radicalization. In this context, authoritarian and fundamentalist personality are generally considered key risk factors or propensities related to radicalization (Pisoiu et al., 2020). Other static risk factors that have been consistently found to influence likelihood of radicalization are gender and age (Wolfowicz et al., 2020). Although criminal record (Wolfowicz et al., 2020) and unemployment (Sageman, 2004) will vary across the life course, they represent key background factors influencing radicalization at the initiation of our ABM.

Turning to dynamic factors, the most important correlates in terms of the relative magnitude of their effects are institutional trust and legitimacy, relative deprivation, and integration. Attitudes pertaining to trust and legitimacy (Fagan & Tyler, 2005; Wolfe et al., 2017), subjective deprivation (Burchardt, 2005; Folger & Kass, 2000), as well as belonging and integration (Thorlindsson & Bernburg, 2004) are defined in our model below as key attitudes that influence risk for recruitment. Institutional trust relates to the degree to which individuals view the state and its institutions as having the authority to govern them (Coromina & Peral, 2016). Relative or subjective forms of deprivation refer to the individual's view that their in-group is less well off than a reference group, often as the result of systematic discrimination (Gurr, 1970; King & Taylor, 2011). Integration, or acculturation, relates to the degree to which an individual feels a part of their society (Lyons-Padilla et al., 2015). These factors are also among those most commonly targeted by counter-radicalization programs (Wolfowicz et al., 2020).

2 | FROM RADICALIZATION TO RECRUITMENT

The European Commission defines recruitment as the solicitation of an individual to "commit or participate in the commission of a terrorist offence, or to join an association or group, for the purpose of contributing to the commission of one or more terrorist offences by the association or the group" (Council of Europe, 2005). Although radicalization is often a precondition for recruitment, this is not always the case. In fact, cognitive radicalization and recruitment can take place simultaneously, with mutually reinforcing effects (McCauley & Moskalenko, 2017; Moghaddam, 2005; Wiktorowicz, 2005). Additionally, as we noted above, a very small proportion of radicalized individuals will ever become recruited.[1]

Just as radicalization is insufficient for explaining recruitment, so too are individual propensity and risk unlikely to be fully predictive of who will or will not be recruited. This is because an individual must also be exposed to radicalizing or recruiting elements, which are to be found in specific settings, and not all high-risk individuals have equal opportunities for such exposure. Such risk may be impacted by the differential likelihood of exposure to radicalizing agents and settings (Akers & Jennings, 2016; Akers & Silverman, 2004; Akins & Winfree, 2016; Pauwels & Schils, 2016; Wolfowicz et al., 2021b). Situational Action Theory (SAT), for example, argues that the likelihood that individuals with a given propensity will come to be exposed to situations conducive to radicalization and recruitment is a function of both social and self-selection (Wikström & Bouhana, 2017).

Recruitment can occur in a number of different ways. Most commonly, recruitment occurs when a recruiter identifies a suitable recruit and convinces them to join the cause. Recruiters may recognize the need for additional attitudinal shifts to occur before recruitment can be successful, and as such they focus their attention on incremental changes in the potential recruit(s) over a period of sustained interactions (Bouhana, 2013; Yayla, 2020). In other cases, recruiters may recognize that most individuals in a population simply lack the propensity for recruitment. To overcome this, they may embed themselves within the population and tailor their "pitches" to each individual, focusing on those whom they feel have the greatest propensity (Bouhana, 2013). In other cases, the recruits come to the recruiters themselves, either by chance or because they are specifically interested in being recruited. In all cases, recruitment is dependent on the convergence of recruiting forces and potential recruits in time and space. There are multiple different settings where vulnerable individuals can come into contact with recruiters, such as cafes, parks, religious institutions, and the Internet. Recognizing that there are certain settings in which recruitment is more likely to be successful, recruiters may station themselves in such places, which in turn can become transformed into "recruitment magnets" (Bouhana, 2013).

In line with these perspectives, the likelihood of recruitment is a function of the interaction between the individual's characteristics and environment, processes of social and self-selection, and the differential opportunities for being in settings where one can be exposed to recruiting forces (Wikström & Bouhana, 2017). This suggests the importance not only of social interventions that seek to influence radicalization, but also situational prevention approaches focused on opportunities for recruitment.

3 | IS THERE EVALUATION EVIDENCE THAT INTERVENTIONS REDUCE RECRUITMENT TO TERRORISM?

Despite the strong interest in recruitment to terrorism, and the large number of counter-radicalization programs that have been developed to reduce recruitment, there is little knowledge about whether such programs actually have the desired impact. In a review of counter-radicalization programs, Jugl et al. (2020) identify six evaluations of programs that focus primarily on efforts to reduce radicalization. These programs generally focus on targeting attitudinally oriented factors, with the goal of reducing radicalization. Overall, the programs were found to be effective, though the methodological quality of the evaluations was generally weak, with five of the nine evaluations scoring the lowest rater level on the Maryland Scientific Methods scale (Farrington et al., 2002). Only two of the studies had a control condition compared to the intervention. None of these studies examined recruitment to terrorism (Jugl et al., 2020). A recent qualitative synthesis of evidence on risk of radicalization also examined diversionary programs, including employment programs, and concluded that such programs demonstrated mostly positive outcomes, including reducing vulnerability to recruitment (Hassan et al., 2021).

As we noted earlier, one of the key problems in developing rigorous outcome evaluations of recruitment programs is the small number of individuals who become recruited to terrorist groups. ABM overcomes this limitation in realistic simulations and in this context allows us to critically assess the assumptions underlying the dominant counter and de-radicalization paradigm, as well as the potential for success of situational prevention interventions.

4 | INTERVENTIONS EXAMINED IN THE CURRENT STUDY

As in any experimental program, we were limited in the number of interventions we could examine. Although ABMs are simulations, and do not require real-world resources and implementation, they are resource intensive in terms of programming and computer time needed.[2] We opted for three "realistic" interventions that were representative of key themes in the efforts of policy makers to reduce recruitment. Two represent social interventions that focus on changing the dispositions of potential recruits: increasing community workers in community centers, and training the police in community-oriented policing (OSCE, 2014). The third intervention, an employment program, emphasizes deflection as a mechanism for reducing recruitment. As we note below, we apply these interventions at high dosages and in this sense our study, like other applications of ABM, is an "efficacy" study that examines the interventions under ideal conditions (e.g., Eck & Liu, 2008; Weisburd et al., 2017).

4.1 | Community workers in community centers

Community centers and their staff are often conceived as being central to prevention efforts through their position to identify and report at-risk individuals. However, their role in counter-radicalization is more nuanced. Community centers are seen to reduce radicalization through their promotion of conventional social norms and social ties (Slocum et al., 2013). But the mere existence of centers is unlikely to have an effect on radicalization. It is only when they are staffed by highly trained and motivated community workers that they have the potential to be effective in increasing social cohesion and integration, and combatting radicalization (Mucha, 2017). The development of ties between community workers and agents increases the likelihood of self-selection, in which citizens will be more likely to come to the centers. In turn, increased numbers of community workers are likely to increase community center activities, which provide opportunities for structured, pro-social activities (Zimmerman et al., 2015).

Rather than testing the effects of community workers reporting on high-risk individuals or introducing new community centers into the communities, we simulate a policy that increases the number of community workers operating at community centers from one (the present average in the community that is the basis for our model, see later) to four workers per community center. In our experiment, all community center workers are well trained to communicate positive counter-radicalization values to people who visit these centers. This is reflective of the investments currently being made in many European countries to train and hire more community workers in order to combat radicalization but for which no current evidence exists concerning the efficacy of this approach.

4.2 | Community policing

Police are also well positioned to build positive relationships in communities that may help to combat radicalization (Bayley & Weisburd, 2011; Weisburd et al., 2009). However, encounters with the police also run the risk of contributing to radicalization, by weakening legitimacy and trust, and increasing feelings of discrimination or injustice (see Donohue, 2008; Tankebe, 2020). In order to capitalize on the many advantages that police have in the fight against radicalization and recruitment, and reduce the potential negative backlash of policing on radicalization, many scholars have suggested that community policing strategies are a potentially effective counter-radicalization approach (Hasisi et al., 2020; Innes et al., 2017; LaFree & Bersani, 2014). Indeed, Western countries such as Australia (Dunn et al., 2016), the Netherlands (van de Weert & Eijkman, 2021), and the United Kingdom (Spalek, 2010, 2012) place community policing as a central component of their counter-radicalization policies.

In this regard, it is important to distinguish between community policing's potential counter-terrorism and counter-radicalization functions. Although community policing may improve citizens' willingness to cooperate and thereby improve the abilities of police to prevent terrorism (Hasisi et al., 2020), our community policing intervention focuses on promoting trust and legitimacy, and reducing the negative impacts of traditional police/citizen contacts (Bayley & Weisburd, 2011; Innes et al., 2017; LaFree & Bersani, 2014). To test the effects of a community policing policy on radicalization and recruitment to terrorism, we model a scenario in which 50% of police officers in our simulated community are trained in community policing. These police officers are programmed to communicate legitimacy values to people they have contact with.

4.3 | Employment of high-risk individuals

Key to the mechanism of employment's potential impacts on recruitment is "deflection" and changes to routine activities (Sampson & Laub, 2005). Time at work is time that is not likely to be spent in communication with radicalized individuals, and especially those who have taken on the role of recruiters (Bouhana & Wikström, 2011; Wikström & Bouhana, 2017). Its primary impact can be seen as resulting from its serving as a potential diversionary path or "off ramp" from recruitment (National Academy of Science, Engineering, and Medicine, 2017; Windisch et al., 2016).

Employment has also been seen as a mechanism for increasing positive social values and ties through differential associations (Sampson & Laub, 2005) thus also contributing to reducing the likelihood for radicalization (LaFree & Miller, 2008). Of course, this assumes that interactions at work are with individuals who are not themselves radicalized. Examples of employment programs to reduce recruitment can be found in the United Kingdom (Thornton & Bouhana, 2019), Belgium (De Waele, 2019), and Australia (Cherney & Belton, 2019). Our experiment considers the effects of an intervention that increases employment among "high-risk" individuals (see later) to achieve a rate of 75% employed. We also assess whether the employment intervention impacts recruitment through the mechanism of de-radicalization or deflection.

5 | USING ABM TO DEVELOP EXPERIMENTS SEEKING TO REDUCE RECRUITMENT TO TERRORISM

ABMs incorporate heterogeneous agents who make decisions in an environment with dynamic situational characteristics. This combination allows us to identify simulated radicalization and recruitment outcomes that emerge dynamically from the interactions of individuals in the model. In this way, ABM represents a bottom-up approach that more closely approximates how attitudes and behaviors emerge from interpersonal interactions in the real world (Conte & Paolucci, 2014; Epstein & Axtell, 1996). Crucially, ABMs comprise a theoretically informed approach to ask the question: "If this process is a reasonable reflection of reality, then what is the expected outcome?" (Eck & Liu, 2008, p. 416).

In recent years, there has been several attempts to apply ABM to assess radicalization (e.g., Galam & Javarone, 2016; Genkin & Gutfraind, 2011; Pruyt & Kwakkel, 2014). However, these studies have been limited in specific ways. First, with few exceptions, they have failed to use real-world data to initialize and validate the models. Second, they have often not made use of theoretically informed models and mechanisms. Third, they have been limited to examining the cognitive elements of radicalization and have not modeled recruitment. Importantly, ABMs have been limited to exploring dynamics and have not yet examined interventions (Thornton, 2015). In contrast, the ABM we develop here is initialized with real-world data, leans on explicit theoretical assumptions, and compares well-defined interventions against a validated baseline. We describe in more detail each element of the model below (see also Appendix S1: ODD Protocol).

5.1 | The ABM landscape

We implemented our model in NetLogo (Wilensky, 1999), a platform that includes turtles (henceforth "agents"), patches (places), and links (relationships). Individual agents are a heterogeneous set of agents who move around and behave within the model. Patches are square cells that are superimposed on a two-dimensional plane. Patches represent different types of places, such as community centers or parks. Links represent the relationships generated between agents

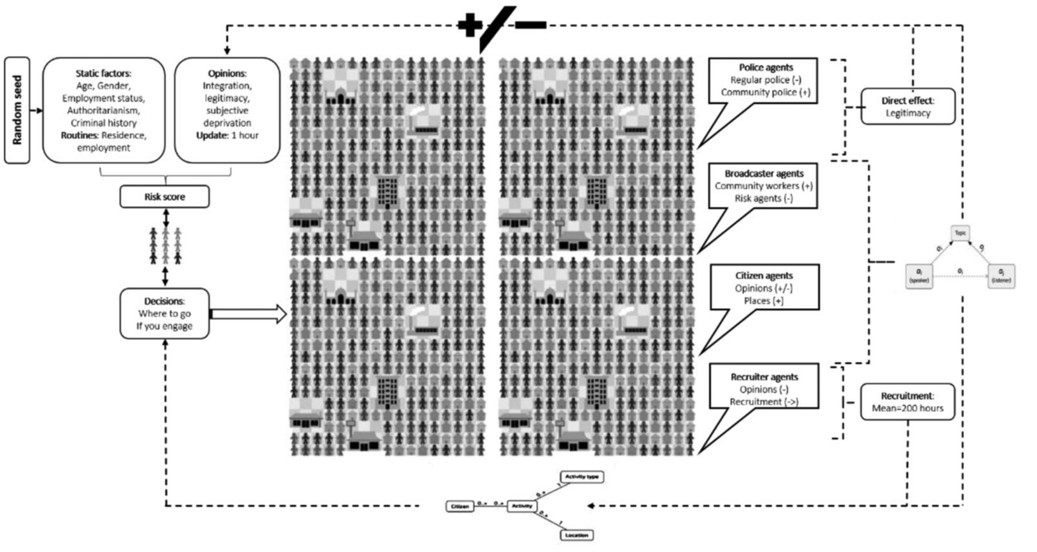

FIGURE 1 Model depiction

and activities, which are connected to the places in which agents successfully engage in activities. In the model, agents traverse the landscape, visit different patches, and interact with other agents in different ways that impact their opinions, risk scores, preferences, routine activities, and recruitment, which all interact with each other dynamically. Figure 1 illustrates our model, which is described in more detail below.

5.2 | The characteristics of the landscape and population of the model

We sought to identify a borough, or section of a city, whose landscape and population of vulnerable individuals was similar to other communities in Europe or elsewhere facing problems of radicalization and recruitment. Having considered a number of possible locations from which to model our ABM, and consulting with local experts, we identified Neukölln, Berlin, Germany. Neukölln, one of Berlin's largest districts, is home to a diverse population of about 350,000. Since 2011, the borough has also absorbed a large number of immigrants from the Middle East, increasing its immigrant population to over 20%. Neukölln has unfortunately seen its fair share of extremism from all sides of the spectrum, suffering from violent attacks from right-wing (e.g., Vorreiter, 2017), left-wing (e.g., Deutsche Welle, 2016), and Islamist extremists (Deutsche Welle, 2003; Knight, 2014).

Neukölln has four neighborhoods: Neukölln, Britz/Buckow, Gropiusstadt, and Buckow Nord/Rudow. Each of these areas differ in terms of their characteristics providing a diverse set of communities for our model. The number and types of places (e.g., community centers, parks, public spaces, workplaces, cafes, etc.) for each community was determined based on data obtained from Google Maps. We identified the number of places that could be characterized as normative or "risky" meeting places, and their locations, as they pertained to Islamic (Becker, 2017, 2019), right-wing (Lewek, 2016), and left-wing forms of radicalism.[3] Given the focus of our inquiry, we followed previous applications of ABM and implemented an abstract landscape (Groff et al., 2019).

TABLE 1 Population level data derived from the census

Factor	Area 1 (Neukölln)	Area 2 (Britz/Buckow)	Area 3 (Gropiusstadt)	Area 4 (Buckow Nord/Rudow)
Population size	155,950	35,751	38,219	29,029
Population density	13,000	13,000	6000	3000
% of males	51.2	47.3	48.1	49.1
% 0–17	16.0	16.0	15.0	16.0
% 18–64	74.0	55.0	58.0	63.0
% 65+	10.0	28.0	27.0	21.0
% Unemployment males	12.0	12.0	7.5	6.5
% Poverty rates	30.0	35.0	15.0	13.0
Collective relative deprivation rating (range: 1–7)	5	5.5	3	1.5

5.3 | The ABM population

Agent characteristics were initialized using data from the Berlin Central Bureau of Statistics (CBS) for each of Neukölln's four neighborhoods (Table 1). Following prior research, for computational purposes we scaled down our simulated borough to 40,000 agents (Groff et al., 2019; Weisburd et al., 2017). In order to generate and assign opinion scores to agents, we resampled the 2008 European Values Survey (EVS) for Germany, cross-tabulated the factors, and then distributed the shared set of characteristics to each individual agent in the population based on their characteristics derived from the census data.[4] The result of this approach was that each citizen agent represents a (re-sampled) survey respondent (Williams et al., 2017).

The equation for assigning propensity to radicalization is represented by Equation (1). Following previous studies using the EVS data (Feldman, 2003; Tillman, 2013), the authoritarian personality variable was derived from 30 items ($M = 5.012$, $SD = 0.918$, $\alpha = 0.85$) made up of three sets of items in the EVS (see Appendix S2 for a listing of the specific items) that related to child-rearing attitudes, religious-political attitudes, and deviant-normative behavior tolerance. Because the EVS data did not include a measure of prior criminality, we used the 2017 Neukölln Criminality Report and assigned it as a binary characteristic based on its correlation with age, gender, employment status, and place of residence.[5] The weightings (w) for each factor, standardized as Cohen's d, were derived from the results of a meta-analysis (Table 2; see Wolfowicz et al., 2020).

$$\text{Propensity } = w_{\text{Age}} + w_{\text{Gender}} + w_{\text{(Un)employed}} + w_{\text{Criminalhistory}} + w_{\text{Authoritarianism}}. \tag{1}$$

Risk of radicalization is calculated as the individual agent's propensity plus three key dynamic factors: trust/legitimacy of authorities, integration/non-integration, and subjective deprivation (Equation 2). These factors were selected on the basis of (a) their relative importance to radicalization among dynamic factors, (b) their classification as attitudinal factors, and (c) their being common targets of counter-radicalization interventions (Wolfowicz et al., 2021). In our model, these factors vary and change according to the experiences of the agents over time. Trust/legitimacy is made up of eight items from the EVS ($M = 2.71$, $SD = 0.526$, $\alpha = 0.85$) assessing respondents' confidence in social and governmental bodies, including the justice system (Yucel & Ekici, 2014). Integration is based on six items from the EVS ($M = 1.85$, $SD = 0.503$, $\alpha = 0.69$) assessing

TABLE 2 Risk and protective effects (in Cohen's *d* units)[a]

Factor	Risk effect	Protective effect
Propensity score		
Age (Under 25)	0.10	
Male	9.11	–0.07
Unemployed	0.17	–0.18
Criminal history	0.68	
Authoritarianism	0.86	
Risk score		
Integration	0.38	–0.36
Trust/legitimacy	0.55	–0.68
Subjective deprivation	0.29	

[a]Drawn from Wolfowicz et al. (2020).

respondents' attachment to their society (Voicu & Ramia, 2021). Subjective deprivation is based on five items ($M = 5.316$, $SD = 0.998$, $\alpha = 0.69$) that measured relative satisfaction with life conditions (Lepianka et al., 2010).[6] As above, weighting (w) was based on a meta-analysis (Wolfowicz et al., 2020).[7] With separate risk and protective weights, the scale ranged from –1 to +1 standard deviations from the mean. For subjective deprivation, for which there are no protective effects, the scale was from of 0 to +1 standard deviations from the mean.

$$\text{Risk (radicalization)} = \text{Propensity} + w_{\text{Integration}} + w_{\text{Trust}} + w_{\text{Subjective deprivation}}. \tag{2}$$

5.4 | Activities of citizen agents

Citizen agents are similar in that they all engage in routine activities, moving around the landscape and visiting different "places." The likelihood that an individual will visit a given place is a function of social and self-selection processes. In our model, relevant factors include (1) place of residence, (2) employment status and place off employment, (3) activity history, (4) personal preferences, and (5) randomness. All agents are assigned with a mandatory 8-h period for sleeping at home each day. As nothing occurs during this period, we do not model it explicitly.[8] Employed agents spend 8-h per day at work. Outside of these hours, agents can decide to (1) stay at home, (2) visit different patches, or (3) spend time on the internet. In line with the dynamics of routine activities, activities are modeled to be more likely to occur in an individual's immediate activity space or radius, and the majority of their activities take place in relative proximity to each other. In order to capture this element of routine activities, the activity radius is set at five patches. Given that the role of routine activities in our model is to facilitate opportunities for social encounters, we implement an abstract representation of space in which agents "teleport" between patches rather than travelling on a street or other type of geographic network (Groff et al., 2019).

The primary activity that we model is inter-agent interaction, of which there are three categories: (1) speaking, (2) listening, and (3) experiencing. It is through these interactions that opinion-related dynamic factors are changed, and through which an individual agent can come to be recruited. We model the process using an opinion dynamics model (see Deffuant et al., 2000, 2002; Flache et al., 2017; Hegselmann & Krause, 2002). In this model, when two agents converge

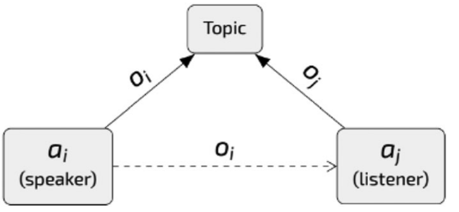

FIGURE 2 Opinion dynamics model

at a location at the same time, they are given the opportunity to interact about one or more topics. We model three topics that agents can choose to discuss when they interact and that pertain to the dynamic risk factors described earlier: (i) trust in/legitimacy of institutions, (ii) integration, and (iii) subjective deprivation. Agents may also communicate about their experiences at specific places. And we include a potential for agents to discuss "other" topics that do not have impact on either radicalization or recruitment.

The decision to interact and the subsequent effects of the interaction are governed by the assumption of bounded confidence in which opinion exchange can only occur when the opinions of two agents are close enough to each other, with a tolerance based on the inverse distance from the extremes of the agents' opinions. This feature of opinion dynamics is akin to the "intensity" conditioner of social learning, which refers to the relative magnitude of the effect that an individual has in influencing another (Akers, 1998). For example, someone with extreme left-wing opinions is unlikely to successfully change the opinions of someone with extreme right-wing opinions and vice versa. In each opinion dynamic exchange, there is one speaker that initiates the exchange, and one listener that is selected by a stochastic factor. The exchange is governed by the level of tolerance of the listener agent, which is calculated as: $t_j = 1 - \alpha|o_j|$ with a conservative convergence level of $\alpha = 0.1$. Interactions are classed as "successful" when the initial difference in opinions is below the level of tolerance, as indicated by: $|o_j - o_i| < t_j$. In this successful interaction, o_j's opinion is updated in the direction of o_i's to a degree dependent upon t_j as defined by: $\Delta o_j = t_j \times \frac{o_i - o_j}{2}$ (see Figure 2).

Reflecting the different ways in which interactions take place in the real world, agents are also able to interact via online communications. In line with the average amount of time Germans spend on social media, agents can spend up to 25% of their leisure time using the internet (Global Web Index, 2018). Through the internet, agents are given the option of communicating with one of 10 randomly selected agents, reflecting a variety of opinions. Given that internet users prefer to connect with similar people, the agent will select the agent with whom they have the highest degree of convergence. Although the same opinion dynamics model was applied, the effects of online communication are half the size of in-person interaction.[9]

5.5 | Activity links

In our model, we use "activity links" to account for the development of preferences (Akers, 1998) and self-selection over time (Wikström & Bouhana, 2017), which in turn impact routine activities (Birks et al., 2008; Brantingham et al., 2008). Activity links are created between an agent and an activity, linked to the place where it occurred, following a "successful" interaction between two agents (an opinion exchange), or when a speaker agent informs a listener agent about a place

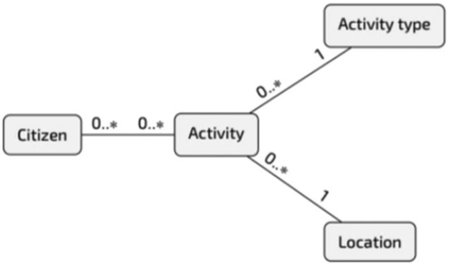

FIGURE 3 Activity links

that the latter has yet to visit. As per Figure 3, an agent can have an unlimited number of activity links, which vary in strength. Subsequent successful interactions at already linked places further increase the weight of that link, and failed interactions decrease the weight.

Activity links also serve as a proxy for modeling the emergence of social networks as generated by the microlevel behaviors of agents, rather than through an imposed network structure (e.g., random networks). That is, the social networks that develop are the result of random encounters, interactions, and preferences. Through the development of links with places in which agents have mutually successful interactions, agents will therefore be implicitly linked to each other. Although these networks are not explicitly modeled nor do they have any direct effects on opinions, they do impact routine activities through future decision making. As such, the role of these networks, characterized by the differential links between agents and places, determine the likelihood of future interactions (by conditioning of priority) and in turn effects of these interactions. In this way, social networks are endogenous to the model (Elsenbroich & Gilbert, 2014).

5.6 | Noncitizen agents

In addition to citizen agents, the model includes two types of agents who are key to the social interventions we examine: community workers (at community centers) and police officers. Unlike citizen agents, community workers can speak to multiple agents simultaneously. Community workers opinion values are set at 1.5 *SD* from the mean, in the direction of normative or positive values. Although these agents maintain their own routine activities, they work at a particular place. Police agents engage in routine patrols and random stops. Although the nature of citizen–police interactions is complex, we model it as being either positive or negative in nature, with stops by regular police having negative effects, and stops by community policing officers being positive. Following data on police stops in Neukölln, we calibrated a probability of 23% for a citizen to have an encounter with police in one year.

The other type of agents included in the model are recruiter agents. These agents can influence the opinions of citizen agents through the opinion-dynamics function—their opinions are set as 1.5 *SD* from the mean in the negative direction from normative values. In addition, they share characteristics with police agents in that there is an exposure component to their interactions with citizen agents, where exposure impacts recruitment (see below). Recruiter agents also maintain normative routine activities and only spend part of their time actively or passively engaged in recruiting activities (6 h). The European Commission (2005) has already identified the existence of "recruitment hotspots," places where recruitment is most concentrated and successful (Vidino, Marone, et al., 2017). As such, similar to community workers, recruiter agents will spend time at specific places. Although recruitment usually occurs at such places, it can also occur through chance encounters during routine activities (Bouhana, 2013; Sageman, 2004).

An additional feature of recruiter agents is that although they can interact with any agent in the model, they "target" high-risk agents, or otherwise "go out of their way" to interact with them specifically (Bouhana, 2013; Hegghammer, 2013). This is accomplished by the recruiter agent "perceiving" the risk status (radicalization) of citizen agents upon coming into contact with them. Recruiter agents also develop a memory and preference for places in which they have successfully interacted with high-risk agents, and form activity links with such places, increasing the likelihood that they will repeatedly come into contact with agents with whom they have previously had successful interactions.

5.7 | Recruitment

In the 2008 European Values Survey for Germany, 5.6% of respondents affirmatively answered that terrorism could be justified, an item commonly used as a proxy for radicalization (Schmid, 2017; Wolfowicz et al., 2021). In line with this statistic, we set a cutoff for "high-risk" agents susceptible to recruitment as those agents in the top 5.6% of risk (radicalization) scores in the population at any step in the model. As a result of the dynamic nature of agents' risk, agents could fall in and out of being high risk at different time periods.

In order for high-risk agents to become recruited, they have to interact with a recruiter agent. The relationship that develops over time between a recruiter and a recruit has been described as being a strong "friendship," which "constitutes the essential foundation of terrorist recruitment" (Yayla, 2020, p. 426). In this regard, although there is a lack of data concerning how many hours of interaction may be needed for recruitment to occur, recent research shows that around 200 hours of interaction are needed for a new association to become a good friend, or for a friend to become a best friend (Hall, 2019). We therefore created a normal distribution with a stochastic factor and a mean of 200 hours of interactions between a recruiter and high-risk agent as being needed for recruitment to occur.

Although it is difficult to know exactly how many individuals are actively engaged in recruitment activities, we relied on available statistics to develop a suitable estimate. First, official statistics show that there are 88 known Jihadists (already recruited and who engage in some recruiting activities) who reside in Neukölln (Senate Department for Home Affairs & Sport, 2017). We assume similar numbers exist for both right- and left-wing and other ideologies. Based on research estimating hidden terrorist populations of around 50% (Asal & Rethemeyer, 2008; Benmelech & Klor, 2020; Warner & Hulme, 2018), and in scaling these numbers to our population of 40,000 civilian agents (and rounding the estimate), we estimated 60 recruiter agents.

6 | THE BASE MODEL

We used the rules described above to implement an ABM model in NetLogo.[10] After extensive calibration, we ran two separate sets of experiments, one for a 6-month intervention period and one for a 12-month period. We conducted 40 runs of the base model and each of the intervention models (for each intervention period) using a random seed. We note that both the selected time frame and the number of runs fall well within the upper bands of what is commonly used in ABM applications in criminology (Groff et al., 2019). The parameters of the base model are displayed in Table 3.

6.1 | Model validation

In order to validate the base model, we ran a series of sensitivity tests that assess whether the model is operating in a realistic manner for the 6-month intervention. First, we followed the approach of manipulating key factors in the model to see whether they led to expected and consistent changes in outcomes (Gerritsen, 2015; Gilbert, 2008). Extreme manipulations of these variables should result in extreme changes to the model's outcomes—which was the case in our models. For example, we increased the proportion of males in the model by increments of 5%, and the proportion of unemployed agents by increments of 10%. The proportion of agents with criminal history was also increased to 5%, 10%, and 20%. In all cases, relevant outcomes increased in a relatively linear fashion commensurate to these manipulations (see Appendix S3).

External validation was also conducted by comparing outputs in the model to real-world data. One key outcome in our study is radicalization, which as noted above is commonly assessed by measures of justification of terrorism. We expected that in running the ABM without any interventions, there would be little impact on overall radicalization (risk) for the citizen agents—because there is little change in survey outcomes over short time periods.[11] In fact, the average change in radicalization across 40 runs of the ABM was only 0.8%.

With regard to recruitment, validating whether the base model produced a realistic numbers of recruited individuals was more challenging, as it is difficult to estimate the scope and size of membership in terrorist organizations, networks, and groups (Davies & Dawson, 2014; Kellett et al., 1991). Estimates for membership in terrorist organizations and the number of foreign fighters from Western countries have often been found to represent only half of the actual numbers (Asal & Rethemeyer, 2008; Benmelech & Klor, 2020; Warner & Hulme, 2018). This is similar to issues concerning the size of the hidden population of gangs and their members, who have often been likened to terrorist groups and terrorists (Decker & Pyrooz, 2015). Some have estimated that gang membership may be as much as two, and even three times higher than official estimates (Pyrooz & Sweeten, 2015).

The ABM is intended to provide a portrait of the real level of recruitment and not simply of the level of recruitment indicated by official data. Official statistics on offending therefore provide only an "at least this much" estimate (Flyghed, 2013). According to statistics from the Berlin Police (Polizei Berlin, 2018a, 2018b), the number of politically motivated criminal defendants recorded in Neukölln in the first half of 2017 was 280. Taken as an "at least this much" estimate of recruitment, a conservative dark figure of 50%, and scaling down to our population of 40,000, we estimated 80 recruited individuals at 6 months and 140 at 1 year. Across 40 simulations, our base model produced an average of 77 recruited agents at 6 months and 158 at 1 year. As such we believe that our base model produces a realistic base rate.

7 | OUTCOMES OF THE EXPERIMENTS

The main outcomes of interest for the simulation experiments were radicalization (risk) and recruitment, as well as the three opinion-based dynamic risk/protective factors: integration, trust/legitimacy, and subjective deprivation. To analyze the overall treatment differences, we

TABLE 3 Model parameters

Variable	Description
Borough dimensions = 8100 cells Cell = approximately 60 m^2	Four adjacent neighborhoods with 45 cell long sides[a].
Activity radius = five cells	At any tick of the model an agent has a range of five cells from the cell at which they were located.
Model termination = 360 days	Each simulation terminates after 360 days, or 6120 ticks (the 8 h of sleep are collapsed, so each day = 16 h).
Number of citizens = 40,000	Population size previously identified to be sufficient for identifying intervention effects and simultaneously being computationally feasible.
Recruitment risk rate = 5.6%	Agents with risk scores in the top 5.6% of scores are at risk of recruitment. This proportion is equal to the percentage of the German population who justified terrorism (a proxy for radicalization) in the 2008 European Values Survey.
Number of police = 160	Based on numbers from the Berlin Police. All police engage in regular patrol. Police–citizen interactions have negative effects on trust/legitimacy opinions. In the community policing intervention, 50% of police are community police officers and have positive effects on trust/legitimacy opinions.
Number of community workers	1/community center, increased to 4/community center in the community worker intervention. Opinions set at 1.5 *SD* below the mean (positive opinions).
Number of recruiter agents = 60	Distributed across neutral places. Opinions set at 1.5 *SD* above the mean (negative positive opinions).
Number of community centers = 9	Distributed across the model according to Google Maps.
Number of “risky” places = 16	Distributed across the model according to identification in the literature.
Number of neutral places = 16 open, 140 “coffee” places (public places).	Distributed across the model according to Google Maps. Up to 20 agents can be located at any neutral place simultaneously.
Amount of time to stay at destinations: Work and sleep = 8 h. Leisure activities = 1 h.	After 1 h, an agent can continue with the same activity or move to a new place.
Opinion-dynamics tolerance = (1 – alpha × |opinion of listener|) Convergence rate alpha = 0.1	Inversely proportional to intensity of opinion.
Time to recruitment = U(1,399) Mean = 200	An at-risk citizen agent must spend time with a recruiter in order to be recruited. A uniform distribution with a mean of 200 h was set.

Abbreviations: *SD*, standard deviation; U, uniform random number.

[a]These are fuzzy boundaries so agents may travel between adjacent communities.

TABLE 4 Main results

	Recruitment	Radicalization	Integration	Trust	Sub. deprivation
6 months					
Base model	77.2	0.504	−0.109	−0.599	0.332
Employment	26.2***	0.505	−0.109	−0.602	0.330
Community workers	79.88	0.467***	−0.185***	−0.679***	0.237***
Community policing	78.38	0.503	−0.108	−0.617***	0.330
12 months					
Base model	157.63	0.510	−0.104	−0.583	0.340
Employment	50.98***	0.508	−0.108*	−0.589**	0.339
Community workers	156.83	0.470***	−0.185***	−0.669***	0.237***
Community policing	150.98	0.503***	−0.109*	−0.616***	0.336

Note: The above displays the means of the number of recruited individuals and scores on radicalization and the three opinion factors.
Statistical significance based on independent *t*-tests from 40 runs: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

compare the mean scores for each factor and assess statistical significance using *t*-tests. We ran two sets of ABM models—one representing a 6-month intervention period, and a second representing a 12-month intervention period. Table 4 presents results for both of the experimental periods.

7.1 | Intervention 1: Community workers

Community workers, as expected, did significantly impact the dynamic risk factors in the model, producing a 70% improvement relative to the base model in integration in 6 months and a 78% improvement in 12 months; a 13% improvement in trust in 6 months and a 15% improvement in 12 months; and a 29% reduction in subjective deprivation in 6 months and a 30% reduction in 12 months. Following this, there was a significant 7% reduction in radicalization relative to the base model in 6 months and an 8% reduction in 12 months. However, the experimental intervention did not significantly influence recruitment, either at 6 months or at 12 months.

7.2 | Intervention 2: Community police officers

Community police officers had, as expected, produced a significant, although small, relative improvement in trust of 3% in the 6-month ABM, which increased to 6% in the 12-month ABM. In the 12-month ABM, the intervention also had a significant but small impact on integration (a 5% improvement). In the 12-month ABM, the intervention also produced a very small (1.4% relative reduction) but significant impact on radicalization.[12] Overall, there was no significant impact on recruitment found in either the 6-month or 12-month intervention periods.

7.3 | Intervention 3: Increasing employment

In the 6-month ABM employment intervention, there are no significant impacts on any of the three dynamic risk factors or radicalization overall. At the same time, the experiment led to very large and significant relative reductions in recruitment. Although 77 citizens were recruited in the base model after 6 months, only 26 citizens were recruited in the intervention model. In the 12-month ABM, significant but small impacts are found for integration (a 3.7% relative improvement) and trust (a 1% relative improvement), but not on radicalization over all. Again, strong and significant impacts are found for recruitment: although 158 citizens were recruited in the base model after 12 months, only 51 citizens were recruited in the intervention model.

8 | DISCUSSION AND CONCLUSIONS

In these ABM experiments, we examined three key policy interventions (community policing, increasing community workers, and increasing employment). Two of the interventions focused primarily on dispositional elements of recruitment. They sought to reduce recruitment to terrorism primarily through de-radicalization. Our ABMs were programmed to target dynamic risk factors that would impact radicalization, and the outcomes of our ABMs suggest that the interventions had the desired impact in the ABM experiments. Increasing community workers at community centers impacted integration, trust and subjective deprivation, and had a strong and significant impact on radicalization. Deploying community police officers had significant, although small, impacts on trust and integration and radicalization (at 12 months) and as expected (given the specification of the model) had little impact on subjective deprivation. Importantly, neither of these interventions showed significant impact on recruitment. These outcomes have important policy implications, because existing programs often assume that successful counter-radicalization programs will invariably lead to reductions in recruitment to terrorist groups.

Particularly in the case of the community workers experiment, where the impact on radicalization was so strong, why did we not observe improvements in recruitment? Importantly, we found little difference in recruitment outcomes both between 6 and 12 months as contrasted with the base model suggesting that the explanation cannot be found simply in the length of the observed outcome period.

We think that a key reason for this outcome relates to the relatively large number of susceptible agents and the limited number of recruiter agents in our model. Following the EVS, we estimated that 5.6% of the population of Neukölln were at high risk for recruitment. This means that there were 2240 individuals who could be recruited at the initiation of our models. Even with a significant 8% reduction in radicalized individuals as a result of the community workers intervention, there were still over 2000 agents who were at high risk. On the other hand, there were a limited number of recruiter agents (60 based on available data, see earlier). Given the time necessary to recruit any particular individual, the ABMs suggest that massive reductions in radicalization would be required for counter-radicalization programs of this type to reduce recruitment. Simply stated, there is an almost endless stream of potential people to recruit in these models, but a limited number of recruiters to do so. Such a situation exists in many European and North American cities, where levels of radicalization are around the 5% level.[13]

What this implies is that there may be a threshold of the proportion of the population susceptible to recruitment, which when reached makes focusing on social prevention through counter-radicalization a poor strategy for developing short-term achievements in combatting recruitment. That is, when radicalization is sufficiently prevalent in the population, focusing on counter and de-radicalization in vulnerable populations may not in itself prevent recruitment.

Does this mean that counter and de-radicalization programs should not be pursued? We think that is a wrong conclusion to draw from our ABM experiments. Irrespective of the impacts on recruitment to terrorism, in a democracy reducing radicalization is a positive and desirable outcome. Our findings suggest that both the community worker and community police officer interventions can be expected to have positive impacts on dispositions of citizens and reduce risk. Although the effects of community workers are broader, and they also had a greater impact on radicalization per se, both interventions suggest promise in advancing positive societal values.

Although our ABMs indicate caution in relying on counter-radicalization programs to reduce recruitment to terrorism, they suggest that situational prevention programs have promising potential. The employment intervention produced extremely large impacts on the number of individuals recruited both in the 6-month intervention and the 12-month intervention. And it does not appear that this impact is due primarily to the positive social interactions that might occur in normative work environments. In the 6-month intervention, we did not find significant impacts on any of three dynamic risk factors. In the 12-month experiment, we began to observe significant but small impacts on integration and trust, but not a significant impact on radicalization. What is interesting in our experiments is that despite the lack of meaningful impacts on dispositions, the employment intervention does have a large impact on recruitment. This suggests that the influence of the prevention program occurred primarily through the mechanism of deflection. Participants in the program no longer had the necessary time to spend with recruiters to be converted to terrorists. Put simply, more time spent at work reduced the amount of available time to move toward recruitment (Simi & Windisch, 2020).

Of course, it must be remembered that our findings are based on a simulation and caution should be exercised in drawing conclusions regarding the impacts of these interventions in the real world (Gilbert & Troitzsch, 2005; Groff, 2007; Groff et al., 2019; Weisburd et al., 2017). We built our simulation on real data from a typical community that has high risk for radicalization and recruitment. But were the characteristics of the agents different, and especially if radicalization levels were lower, we might have observed different results. Accordingly, it is important to test our model in other simulated settings, something which we encourage others to do based on the open source code for our models.[14]

We have also implemented our interventions in essentially ideal conditions, or in what is at least highly controlled conditions. In the real world, there are numerous, additional complications. For example, although employment can be given to a high-risk individual, how to ensure that they actually show up may be complicated and is not guaranteed.

Finally, our models analyzed recruitment in the short term, and they do not provide information on very long-term effects. Indeed, counter-radicalization policies are often implemented as part of a long-term strategy (Vidino, 2010; Vidino, Seamus, et al., 2017). It is quite possible that over time, a significant enough reduction in the number of radicalized individuals, especially if coupled with the targeting of recruiters, could reach a threshold where recruitment in our ABM begins to decline (Bjørgo, 2013). While the lack of substantive changes in recruitment between the 6-month and 12-month intervention periods does not suggest improvement over time, such improvement may require specific thresholds of time. Similarly, in environments in which the number of radicalized individuals at baseline is much smaller social interventions might have stronger impacts. Identifying these thresholds was beyond the scope of our study but is certainly a worthwhile goal for future ABMs.

With these limitations in mind, our ABMs suggest that social programs that rely on impacting radical attitudes are not likely to reduce recruitment to terrorism. In contrast, our employment experiment, which focused primarily on using deflection to reduce opportunities for recruitment, shows promising outcomes. Taken together, our ABM experiments suggest that the logic of public policies that rely on counter-radicalization programs to reduce recruitment is flawed. At the same time, outcomes of our ABM experiments point to the promise of situational prevention approaches in reducing terrorist recruitment in communities.

CONFLICT OF INTEREST

The authors confirm that they have no conflict of interest to declare.

ORCID

David Weisburd https://orcid.org/0000-0003-3778-5190
Michael Wolfowicz https://orcid.org/0000-0001-6268-4151
Badi Hasisi https://orcid.org/0000-0003-4506-5636
Mario Paolucci https://orcid.org/0000-0002-8276-1086
Giulia Andrighetto https://orcid.org/0000-0002-3896-1363

ENDNOTES

[1] There are certainly cases in which recruits are not necessarily strongly radicalized or even the most radicalized. There has also been recent theorizing of ways in which recruitment, or involvement in radical behaviors, gives rise to cognitive radicalization. Although we acknowledge these alternative approaches, we adopt the approach that underpins the prevailing wisdom and most of counter-radicalization policy (Moskalenko & McCauley, 2020).

[2] Each simulation in our study needed about 8 days to be completed, for a total of 1280 computation hours on a super computer at the Hebrew University. For each intervention and the base model, we ran 40 trials leading to a total of over 200,000 simulated hours. In addition to this, many additional hours were needed for building, testing, calibrating, and validating the models.

[3] Normative or risky meeting places were created by having at least one agent at the place with unusually high or low values on dynamic risk factors (1.5 *SD* from the mean). These agents were also given the ability to interact with multiple agents at the same time. Due to a lack of studies of known meeting places for left wing radicalization, we relied on media reports that detailed known “squatting” places of anarchists who have been raided by police, as well as other places associated with left-wing extremism and recruitment.

[4] The European Values Survey is a nationally representative survey. The 2008 survey for Germany included 2018 respondents.

[5] Because there were multiple agents with similar characteristics, a stochastic factor was used to distribute criminal history among them at random each run of the model.

[6] See Appendix S2 for a listing of the items included in the scales.

[7] Importantly, the systematic review suggested that the risk and protective factors influencing radicalization and recruitment did not significantly differ across ideology, and accordingly our model does not distinguish between different types of ideologies (e.g., right-wing, left-wing, religious, etc.).

[8] The model includes 6120 steps, with each step representing a 1-h time frame, representing a 12-month period minus the 8 h per day in which agents sleep.

[9] This decision was based on the magnitude of the effect sizes for differential associations and online communications identified in a systematic review and meta-analysis (Wolfowicz et al., 2020). In general, it has been found that face-to-face interactions have a greater effect than mediated interactions on a wide range of cognitive and behavioral outcomes (see Sprecher, 2014).

[10] The code for the model is available online at https://github.com/LABSS/PROTON-T; see also Appendix S1: ODD Protocol.

[11] Research has found that although there are some annual changes in the proportion of “radicalized” individuals in a population, as assessed by justification of terrorism, the average mean is relatively stable over long periods (Schumann, Rottweiler, & Gill, 2020). The 2017 EVS survey ($N = 2132$) replaced the 2008 survey’s item on justification of terrorism with a new item measuring justification of politically motivated violence, using a 1–10 Likert scale. Combined, responses in the range of 4–10 are equal to 6.1%, a 0.5% difference from the 5.6% justifiers of terrorism in the 2008 EVS survey.

[12] It is important to remember that outcomes in each experiment are based on average scores across a large number of agents. In this context, the standard errors for outcomes calculated across agents are very small leading to even very modest outcomes being statistically significant.

[13] As per the above, the average rate of justification of terrorism according to the 2008 European Values Survey was 5.6%. This number is similar to what has been found in Western European countries in the 2006 PEW Global Values Survey, according to which the combined response for suicide bombings being rarely, sometimes and often justified, was 4.3% (e.g., Berger, 2016; Zhirkov et al., 2014). The responses for U.S. samples have been somewhat similar. For example, the 2007 PEW survey for the United States found that 6% of respondents felt that suicide bombings could sometimes be justified, and a further 2% that they could often be justified (McCauley, 2012).

[14] We did develop a beta version for examining impacts under different population conditions (reflecting a range of other cities in Europe). This effort suggested that the main findings here can be replicated when the model is populated using data from other contexts. See http://193.142.112.115:8020/.

REFERENCES

Akers, R. L. (1998). *Social learning and social structure: A general theory of crime and deviance*. Transaction Publishers.

Akers, R. L., & Jennings, W. G. (2016). Social learning theory. In A. R. Piquero (Ed.), *Wiley handbooks in criminology and criminal justice* (pp. 230–240). John Wiley & Sons.

Akers, R. L., & Silverman, A. (2004). Toward a social learning model of violence and terrorism. In M. A. Zahn, H. H. Brownstein, & S. L. Jackson (Eds.), *Violence: From theory to research* (pp. 19–35). Routledge.

Akins, J. K., & Winfree, L. T., Jr. (2016). Social learning theory and becoming a terrorist: New challenges for a general theory. In G. LaFree & J. D. Freilich (Eds.), *The handbook of the criminology of terrorism* (pp. 133–149). Wiley-Blackwell.

Asal, V., & Rethemeyer, R. K., & (2008). The nature of the beast: Organizational structures and the lethality of terrorist attacks. *The Journal of Politics*, *70*(2), 437–449. https://doi.org/10.1017/S0022381608080419

Bartlett, J., Birdwell, J., & King, M. (2010). *The edge of violence: A radical approach to extremism*. Demos.

Bayley, D. H., & Weisburd, D. (2011). Cops and spooks: The role of police in counterterrorism. In D. Weisburd, T. Feucht, I. Hakimi, L. Mock, & S. Perry (Eds.), *To protect and to serve: Policing in an age of terrorism* (pp. 81–99). Springer. https://doi.org/10.1007/978-0-387-73685-3_4

Becker, E. (2017). Good mosque, bad mosque: Boundaries to belonging in contemporary Germany. *Journal of the American Academy of Religion*, *85*(4), 1050–1088. https://doi.org/10.1093/jaarel/lfx005

Becker, E. (2019). Reconstructing the Muslim self in diaspora: Socio-spatial practices in urban European mosques. *International Journal of Islamic Architecture*, *8*(2), 389–414. https://doi.org/10.1386/ijia.8.2.389_1

Benmelech, E., & Klor, E. F. (2020). What explains the flow of foreign fighters to ISIS? *Terrorism and Political Violence*, *32*(7), 1458–1481. https://doi.org/10.1080/09546553.2018.1482214

Berger, L. (2016). Local, national and global Islam: Religious guidance and European Muslim public opinion on political radicalism and social conservatism. *West European Politics*, *39*(2), 205–228.

Birks, D. J., Donkin, S., & Wellsmith, M. (2008). Synthesis over analysis: Towards an ontology for volume crime simulation. In L. Liu & J. Eck (Eds.), *Artificial crime analysis systems: Using computer simulations and geographic information systems* (pp. 160–192). IGI Global.

Bjørgo, T. (2013). *Strategies for preventing terrorism*. Springer.

Bjørgo, T. (2016). *Preventing crime: A holistic approach*. Springer.

Borum, R. (2014). Psychological vulnerabilities and propensities for involvement in violent extremism. *Behavioral Sciences & the Law*, *32*(3), 286–305.

Bouhana, N. (2013). Recruitment of terrorists. In U. Gürbuz (Ed.), *Capacity building in the fight against terrorism* (pp. 70–73). IOS Press.

Bouhana, N., & Wikström, P. O. (2011). *Al Qai'da-influenced radicalisation: A rapid evidence assessment guided by Situational Action Theory*. Home Office.

Brantingham, P. L., Glasser, U., Jackson, P., Kinney, B., & Vajihollahi, M. (2008). Mastermind: Computational modeling and simulation of spatiotemporal aspects of crime in urban environments. In L. Liu & J. Eck (Eds.), *Artificial crime analysis systems: Using computer simulations and geographic information systems* (pp. 252–280). IGI Global.

Burchardt, T. (2005). Are one man's rags another man's riches? Identifying adaptive expectations using panel data. *Social Indicators Research*, *74*(1), 57–102.
Cherney, A., & Belton, E. (2019). Evaluating case-managed approaches to counter radicalization and violent extremism: An example of the Proactive Integrated Support Model (PRISM) intervention. *Studies in Conflict & Terrorism*, *44*(8), 625–645.
Clarke, R. V. (1980). Situational crime prevention: Theory and practice. *British Journal of Criminology*, *20*, 136–147.
Conte, R., & Paolucci, M. (2014). On agent-based modeling and computational social science. *Frontiers in Psychology*, *5*, 668–668.
Coromina, L., & Peral, E. B. (2016). Trust in political institutions: Stability of measurement model in Europe. In M. Voicu, I. C. Mochmann, & H. Dülmer (Eds.), *Values, economic crisis and democracy* (pp. 50–71). Routledge.
Council of Europe. (2005). Additional protocol to the Council of Europe Convention on the Prevention of Terrorism. Council of Europe Treaty Series-No. 217.
Davies, G., & Dawson, S. (2014). *A framework for estimating the number of extremists in Canada* (Working Paper Series No. 14–08). TSAS (Canadian Network for Research on Terrorism, Security and Society). http://www.tsas.ca/wp-content/uploads/2018/03/TSASWP14-08_Davies-Dawson.pdf
Decker, S. H., & Pyrooz, D. C. (2015). I'm down for a jihad": How 100 years of gang research can inform the study of terrorism, radicalization and extremism. *Perspectives on Terrorism*, *9*(1), 104–112. http://www.terrorismanalysts.com/pt/index.php/pot/article/view/405
Deffuant, G., Neau, D., Amblard, F., & Weisbuch, G. (2000). Mixing beliefs among interacting agents. *Advances in Complex Systems*, *03*(01n04), 87–98. https://doi.org/10.1142/S0219525900000078
Deffuant, G., Amblard, F., & Weisbuch, G. Ã. (2002). How can extremism prevail? A study based on the relative agreement interaction model. *Journal of Artificial Societies and Social Simulation*, *5*(4). http://jasss.soc.surrey.ac.uk/5/4/1.html
Deutsche Welle. (2003). *Germans detain five people in possible terror plot*. https://p.dw.com/p/3Pij
Deutsche Welle. (2016). *Berlin plagued by radical left-wing violence for second night in a row*. https://p.dw.com/p/1HrCO
De Waele, M. (2019). Belgium: Preventing radicalisation on a local level and working for an inclusive society. In S. Jayakumar (Ed.), *Terrorism, radicalisation & countering violent extremism: Practical considerations & concerns* (pp. 69–78). Palgrave MacMillan.
Donohue, W. A. (2008). Terrorism and conflict resolution. In J. Bercovitch, V. Kremenyuk, & I. W. Zartman (Eds.), *The SAGE handbook of conflict resolution* (pp. 437–454). Sage Publications Ltd.
Douglas, K. S., & Skeem, J. L. (2005). Violence risk assessment: Getting specific about being dynamic. *Psychology, Public Policy, and Law*, *11*(3), 347–383.
Dunn, K. M., Atie, R., Kennedy, M., Ali, J. A., O'Reilly, J., & Rogerson, L. (2016). Can you use community policing for counter terrorism? Evidence from NSW, Australia. *Police Practice and Research*, *17*(3), 196–211.
Eck, J. E., & Liu, L. (2008). Contrasting simulated and empirical experiments in crime prevention. *Journal of Experimental Criminology*, *4*(3), 195–213.
Elsenbroich, C., & Gilbert, N. (2014). *Modelling norms*. Springer.
Epstein, J., & Axtell, R. (1996). *Growing artificial societies: Social science from the bottom up*. MIT Press.
European Commission. (2005). *Communication from the Commission to the European Parliament and the Council concerning terrorist recruitment: Addressing the factors contributing to violent radicalisation* (No. COM (2005) 313 final). https://eur-lex.europa.eu/legal-content/GA/TXT/?uri=CELEX:52005DC0313
European Commission. (2014). *Communication on Preventing radicalisation to terrorism and violent extremism: Strengthening the EU's response*. Author.
European Commission. (2016). *Communication on Supporting the prevention of radicalisation leading to violent extremism*. Author.
Fagan, J., & Tyler, T. R. (2005). Legal socialization of children and adolescents. *Social Justice Research*, *18*(3), 217–241.
Farrington, D. P., Gottfredson, D. C., Sherman, L. W., & Welsh, B. C. (2002). The Maryland scientific methods scale. In D. P. Farrington, D. Layton MacKenzie, L.W. Sherman, & B. C. Welsh (Eds.) *Evidence-based crime prevention* (pp. 13–21). Routledge.
Feldman, S. (2003). Enforcing social conformity: A theory of authoritarianism. *Political Psychology*, *24*(1), 41–74. https://doi.org/10.1111/0162-895X.00316

Flache, A., Mäs, M., Feliciani, T., Chattoe-Brown, E., Deffuant, G., Huet, S., & Lorenz, J. (2017). Models of social influence: Towards the next frontiers. *Journal of Artificial Societies and Social Simulation*, *20*(4), 1–2. https://doi.org/10.18564/jasss.3521

Flyghed, J. (2013). Policing of political protest. The security police's control of the extra-parliamentary opposition in Sweden during and after the Cold War. *Journal of Scandinavian Studies in Criminology and Crime Prevention*, *14*(sup1), 81–99. https://doi.org/10.1080/14043858.2013.771912

Folger, R., & Kass, E. E. (2000). Social comparison and fairness. In J. Suls & L. Wheeler (Eds.), *Handbook of social comparison* (pp. 423–441). Springer.

Galam, S., & Javarone, M. A. (2016). Modeling radicalization phenomena in heterogeneous populations. *PLoS ONE*, *11*(5), e0155407.

Genkin, M., & Gutfraind, A. (2011). *How do terrorist cells self-assemble: Insights from an agent-based model of radicalization* (SSRN Scholarly Paper No. ID 1031521). https://papers.ssrn.com/abstract=1031521

Gerritsen, C. (2015). Agent-based modelling as a research tool for criminological research. *Crime Science*, *4*(1), 2. https://doi.org/10.1186/s40163-014-0014-1

Gielen, A. J. (2019). Countering violent extremism: A realist review for assessing what works, for whom, in what circumstances, and how? *Terrorism and Political Violence*, *31*(6), 1149–1167.

Gilbert, N. (2008). *Agent-based models*. SAGE Publications. https://doi.org/10.4135/9781412983259

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the social scientist*. Berkshire: McGraw-Hill Education.

Global Web Index (2018). *Social: Global Web Index's flagship report on the latest trends in social media*. Author.

Groff, E. R. (2007). 'Situating' simulation to model human spatio-temporal interactions: An example using crime events. *Transactions in GIS*, *11*(4), 507–530. https://doi.org/10.1111/j.1467-9671.2007.01058.x

Groff, E., & Mazerolle, L. (2008). Simulated experiments and their potential role in criminology and criminal justice. *Journal of Experimental Criminology*, *4*(3), 187–193.

Groff, E. R., Johnson, S. D., & Thornton, A. (2019). State of the art in agent-based modeling of urban crime: An overview. *Journal of Quantitative Criminology*, *35*(1), 155–193.

Gurr, T. R. (1970). *Why men rebel*. Princeton University Press.

Hafez, M., & Mullins, C. (2015). The radicalization puzzle: A theoretical synthesis of empirical approaches to homegrown extremism. *Studies in Conflict & Terrorism*, *38*(11), 958–975.

Hall, J. A. (2019). How many hours does it take to make a friend? *Journal of Social and Personal Relationships*, *36*(4), 1278–1296.

Hasisi, B., Perry, S., & Wolfowicz, M. (2020). Proactive policing and terrorism. In H. N. Pontell (Ed.), *Oxford research encyclopedia of criminology* (pp. 1–35). Oxford University Press.

Hassan, G., Brouillette-Alarie, S., Ousman, S., Kilinc, D., Varela, W., Lavoie, L., & Venkatesh, V. (2021). *A systematic review on the outcomes of primary and secondary prevention programs in the field of violent radicalization*. Canadian Practitioners Network for the Prevention of Radicalization and Extremist Violence.

Hegghammer, T. (2013). Should I stay or should I go? Explaining variation in western jihadists' choice between domestic and foreign fighting. *The American Political Science Review*, *107*(1), 1–15. https://doi.org/10.1017/S0003055412000615

Hegselmann, R., & Krause, U. (2002). Opinion dynamics and bounded confidence models, analysis and simulation. *Journal of Artificial Societies and Social Simulation*, *5*(3), 1–33.

Innes, M., Roberts, C., & Lowe, T. (2017). A disruptive influence? "Preventing" problems and countering violent extremism policy in practice. *Law & Society Review*, *51*(2), 252–281.

Jugl, I., Lösel, F., Bender, D., & King, S. (2020). Psychosocial prevention programs against radicalization and extremism: A meta-analysis of outcome evaluations. *European Journal of Psychology Applied to Legal Context*, *13*(1), 37–46.

Kellett, A., Beanlands, D. B., & Deacon, J. P. (1991). *Terrorism in Canada, 1960-1989*. Solicitor General Canada, Ministry Secretariat.

Khalil, J. (2017). The Three Pathways (3P) model of violent extremism: A framework to guide policymakers to the right questions about their preventive countermeasures. *The RUSI Journal*, *162*(4), 40–48.

King, M., & Taylor, D. M. (2011). The radicalization of homegrown jihadists: A review of theoretical models and social psychological evidence. *Terrorism and Political Violence*, *23*(4), 602–622.

Knight, B. (2014). *Searching for radicals*. https://www.exberliner.com/features/zeitgeist/searching-for-radicals/

Koehler, D. (2019). Are there 'best practices' in deradicalisation? Experiences from frontline intervention and comparative research. In S. Jayakumar (Ed.), *Terrorism, radicalisation & countering violent extremism* (pp. 59–68). Palgrave Pivot.

Koehler, D., & Fiebig, V. (2019). Knowing what to do. *Perspectives on Terrorism*, *13*(3), 44–62.

LaFree, G., & Bersani, B. E. (2014). County-level correlates of terrorist attacks in the United States. *Criminology & Public Policy*, *13*(3), 455–481.

LaFree, G., & Miller, E. (2008). Desistance from terrorism: What can we learn from criminology? *Dynamics of Asymmetric Conflict*, *1*(3), 203–230.

Lepianka, D., Gelissen, J., & van Oorschot, W. (2010). Popular explanations of poverty in Europe: Effects of contextual and individual characteristics across 28 European countries. *Acta Sociologica*, *53*(1), 53–72. https://doi.org/10.1177/0001699309357842

Lewek, M. (2016). Spaces of fear and their exclusionary consequences: Narratives and everyday routines of Sub-Saharan immigrants in Berlin. In T. Blokland, C. Giustozzi, & D. Krüger & H. Schilling (Eds.), *Creating the unequal city: The exclusionary consequences of everyday routines in Berlin* (pp. 31–52). Routledge. https://doi.org/10.4324/9781315574639-11

Lösel, F., King, S., Bender, D., & Jugl, I. (2018). Protective factors against extremism and violent radicalization: A systematic review of research. *International Journal of Developmental Science*, *12*(1-2), 89–102.

Lyons-Padilla, S., Gelfand, M. J., Mirahmadi, H., Farooq, M., & Van Egmond, M. (2015). Belonging nowhere: Marginalization & radicalization risk among Muslim immigrants. *Behavioral Science & Policy*, *1*(2), 1–12.

McCauley, C. (2012). Testing theories of radicalization in polls of US Muslims. *Analyses of Social Issues and Public Policy*, *12*(1), 296–311.

McCauley, C., & Moskalenko, S. (2017). Understanding political radicalization: The two-pyramids model. *American Psychologist*, *72*(3), 205–216. https://doi.org/10.1037/amp0000062

Moghaddam, F. M. (2005). The staircase to terrorism: A psychological exploration. *American Psychologist*, *60*(2), 1039–1041. https://doi.org/10.1037/0003-066X.60.2.161

Moskalenko, S., & McCauley, C. (2020). *Radicalization to terrorism: What everyone needs to know*. Oxford University Press.

Mucha, W. (2017). Polarization, stigmatization, radicalization. Counterterrorism and homeland security in France and Germany. *Journal for Deradicalization*, *10*, 230–254.

National Academies of Sciences, Engineering, and Medicine. (2017). *Countering violent extremism through public health practice: Proceedings of a workshop*. National Academies Press.

Neumann, P. R. (2013). The trouble with radicalization. *International Affairs*, *89*(4), 873–893.

Organization for Security and Co-operation in Europe (OSCE). (2014). *Preventing terrorism and countering violent extremism and radicalization that lead to terrorism: A community-policing approach*. OSCE/Office for Democratic Institutions and Human Rights (ODIHR).

Ozer, S., Obaidi, M., & Pfattheicher, S. (2020). Group membership and radicalization: A cross-national investigation of collective self-esteem underlying extremism. *Group Processes & Intergroup Relations*, *23*(8), 1230–1248.

Pauwels, L., & Schils, N. (2016). Differential online exposure to extremist content and political violence: Testing the relative strength of social learning and competing perspectives. *Terrorism and Political Violence*, *28*(1), 1–29.

Pisoui, D., & Ahmed, R. (2016). *Radicalisation research: Gap analysis*. RAN [Radicalisation Awareness Network] Research Paper.

Pisoiu, D., Zick, A., Srowig, F., Roth, V., & Seewald, K. (2020). Factors of individual radicalization into extremism, violence and terror—The German contribution in a context. *International Journal of Conflict and Violence (IJCV)*, *14*(2), 1–13.

Polizei Berlin [Berlin Police]. (2018a). *Ausgewählte Fallzahlen der Politisch motivierten Kriminalität in Berlin 1. Halbjahr 2018*. Author.

Polizei Berlin [Berlin Police]. (2018b). *Lagedarstellung politisch motivierte kriminalität in Berlin 2017* (Data set). Der Polizeipräsident in Berlin.

Pruyt, E., & Kwakkel, J. H. (2014). Radicalization under deep uncertainty: A multi-model exploration of activism, extremism, and terrorism. *System Dynamics Review*, *30*(1-2), 1–28.

Pyrooz, D. C., & Sweeten, G. (2015). Gang membership between ages 5 and 17 years in the United States. *Journal of Adolescent Health*, *56*(4), 414–419. https://doi.org/10.1016/j.jadohealth.2014.11.018

Sageman, M. (2004). *Understanding terror networks*. University of Pennsylvania Press.

Sampson, R. J., & Bartusch, D. J. (1998). Legal cynicism and (subcultural?) tolerance of deviance: The neighborhood context of racial differences. *Law and Society Review*, *32*(4), 777–804.
Sampson, R. J., & Laub, J. H. (2005). A life-course view of the development of crime. *The Annals of the American Academy of Political and Social Science*, *602*(1), 12–45.
Schmid, A. (2017). *Public opinion survey. Data to measure sympathy and support for Islamist terrorism*. International Centre for Counter-Terrorism.
Senatsverwaltung für Inneres und Sport [Senate Department for Home Affairs and Sport]. (2017). *Hintergründe zu den angehörigen des salafistischen spektrums in Berlin*. https://www.verfassungsschutz.de/de/oeffentlichkeitsarbeit/publikationen/pb-islamismus/publikationen-landesbehoerden-islamismus/broschuere-be-2017-12-lageanalyse-salafistisches-spektrum-berlin
Simi, P., & Windisch, S. (2020). Why radicalization fails: Barriers to mass casualty terrorism. *Terrorism and Political Violence*, *32*(4), 831–850.
Slocum, L. A., Rengifo, A. F., Choi, T., & Herrmann, C. R. (2013). The elusive relationship between community organizations and crime: An assessment across disadvantaged areas of the South Bronx. *Criminology*, *51*(1), 167–216.
Spalek, B. (2010). Community policing, trust, and Muslim communities in relation to "New Terrorism". *Politics & Policy*, *38*(4), 789–815.
Spalek, B. (2012). Community-based approaches to counter-terrorism. In B. Spalek (Ed.), *Counter-terrorism: Community-based approaches to preventing terror crime* (pp. 27–49). Palgrave Macmillan.
Sprecher, S. (2014). Initial interactions online-text, online-audio, online-video, or face-to-face: Effects of modality on liking, closeness, and other interpersonal outcomes. *Computers in Human Behavior*, *31*, 190–197.
Schumann, Sandy, Rottweiler, Bettina & Gill, Paul(2020) Assessing Public Support for Terrorism Over Time. *OSF Preprints*,
Tankebe, J. (2020). Unintended negative outcomes of counter-terrorism policing: Procedural (in) justice and perceived risk of recruitment into terrorism. In D. Weisburd, E. Savona, B. Hasisi, & F. Calderoni (Eds.), *Understanding recruitment to organized crime and terrorism* (pp. 105–119). Springer.
Thorlindsson, T., & Bernburg, J. G. (2004). Durkheim's theory of social order and deviance: A multi-level test. *European Sociological Review*, *20*(4), 271–285.
Thornton, A. E. (2015). *Understanding radicalisation* (Doctoral dissertation). University College London.
Thornton, A. E., & Bouhana, N. (2019). Preventing radicalization in the UK: Expanding the knowledge-base on the Channel programme. *Policing: A Journal of Policy and Practice*, *13*(3), 331–344.
Tillman, E. R. (2013). Authoritarianism and citizen attitudes towards European integration. *European Union Politics*, *14*(4), 566–589. https://doi.org/10.1177/1465116513483182
van de Weert, A., & Eijkman, Q. A. (2021). In every artery of society? How Dutch community police officers perceive their role in early detection of violent extremism among youth. *Policing: A Journal of Policy and Practice*, *15*(2), 1144–1157
Vidino, L. (2010). *Countering radicalization in America: Lessons from Europe* (Special Report No. 262). United States Institute for Peace (USIP). https://www.usip.org/sites/default/files/resources/SR262%20-%20Countering_Radicalization_in_America.pdf
Vidino, L., Seamus, H., & Katerina, P. (2017). Strategies to counter violent extremism. *International Journal of Terrorism & Political Hot Spots*, *12*(2/3), 209–225.
Vidino, L., Marone, F., & Entenmann, E. (2017). *Fear thy neighbor: Radicalization and Jihadist attacks in the West*. Ledizioni.
Voicu, M., & Ramia, I. (2021). European identity: An analysis of measurement equivalence across countries and mode of data collection in the European Values Survey 2017/2018. *Social Indicators Research*, *154*(3), 815–834.
Vorreiter, P. (2017). *Die Angriffe sollen Angst einjagen*. https://www.deutschlandfunkkultur.de/rechtsextreme-anschlaege-in-berlin-neukoelln-die-angriffe.1001.de.html?dram:aRticle_id=388778
Vergani, M., Iqbal, M., Ilbahar, E., & Barton, G. (2020). The three Ps of radicalization: Push, pull and personal. A systematic scoping review of the scientific evidence about radicalization into violent extremism. *Studies in Conflict & Terrorism*, *43*(10), 854–854.
Warner, J., & Hulme, C. (2018). The Islamic State in Africa: Estimating fighter numbers in cells across the continent. *CTC Sentinel*, *11*(7), 21–28.

Weisburd, D., Braga, A. A., Groff, E. R., & Wooditch, A. (2017). Can hot spots policing reduce crime in urban areas? An agent-based simulation. *Criminology*, *55*(1), 137–173.

Weisburd, D., Jonathan, T., & Perry, S. (2009). The Israeli model for policing terrorism: Goals, strategies, and open questions. *Criminal Justice and Behavior*, *36*(12), 1259–1278.

Wikström, P. O. H., & Bouhana, N. (2017). Analyzing radicalization and terrorism: A situational action theory. In G. LaFree & J. D. Freilich (Eds.), *The handbook of the criminology of terrorism* (pp. 175–186). John Wiley & Sons.

Wiktorowicz, Q. (2005). *Radical Islam rising: Muslim extremism in the West*. Rowman & Littlefield Publishers.

Wilensky, U. (1999). *NetLogo (and NetLogo User Manual)*. Center for Connected Learning and Computer-Based Modeling, Northwestern University. http://ccl.northwestern.edu/netlogo/

Williams, N. E., O'Brien, M. L., & Yao, X. (2017). Using survey data for agent-based modeling: Design and challenges in a model of armed conflict and population change. In A. Grow & J. Van Bavel (Eds.), *Agent-based modelling in population studies: Concepts, methods, and applications* (pp. 159–184). Springer. https://doi.org/10.1007/978-3-319-32283-4_6

Windisch, S., Simi, P., Ligon, G. S., & McNeel, H. (2016). Disengagement from ideologically-based and violent organizations: A systematic review of the literature. *Journal for Deradicalization*, *9*, 1–38.

Wolfe, S. E., McLean, K., & Pratt, T. C. (2017). I learned it by watching you: Legal socialization and the intergenerational transmission of legitimacy attitudes. *British Journal of Criminology*, *57*(5), 1123–1143.

Wolfowicz, M., Litmanovitz, Y., Weisburd, D., & Hasisi, B. (2020). A field-wide systematic review and meta-analysis of putative risk and protective factors for radicalization outcomes. *Journal of Quantitative Criminology*, *36*(3), 407–447.

Wolfowicz, M., Litmanovitz, Y., Weisburd, D., & Hasisi, B. (2021). Cognitive and behavioral radicalization: A systematic review of the putative risk and protective factors. *Campbell Systematic Reviews*, *17*(3), e1174.

Wolfowicz, M., Weisburd, D., & Hasisi, B. (2021a). Does context matter? European-specific risk factors for radicalization. *Monatsschrift für Kriminologie und Strafrechtsreform*, *104*(3), 217–230.

Wolfowicz, M., Weisburd, D., & Hasisi, B. (2021b). Examining the interactive effects of the filter bubble and the echo chamber on radicalization. *Journal of Experimental Criminology*, 1–23.

Yayla, A. S. (2020). Prevention of recruitment to terrorism. In A. P. Schmid (Ed.), *Handbook of terrorism prevention and preparedness* (396–441). ICCT.

Yucel, D., & Ekici, T. (2014). Correlates of generalized trust among Turkish and Greek Cypriots: Evidence from the European Values Survey data. *European Review*, *22*(3), 453–468.

Zimmerman, G. M., Welsh, B. C., & Posick, C. (2015). Investigating the role of neighborhood youth organizations in preventing adolescent violent offending: Evidence from Chicago. *Journal of Quantitative Criminology*, *31*(4), 565–593.

Zhirkov, K., Verkuyten, M., & Weesie, J. (2014). Perceptions of world politics and support for terrorism among Muslims: Evidence from Muslim countries and Western Europe. *Conflict Management and Peace Science*, *31*(5), 481–501.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Weisburd, D., Wolfowicz, M., Hasisi, B., Paolucci, M., & Andrighetto, G. (2022). What is the best approach for preventing recruitment to terrorism? Findings from ABM experiments in social and situational prevention. *Criminology & Public Policy*, *21,* 461–485. https://doi.org/10.1111/1745-9133.12579