EXPLORING CRIMINOGENIC DIFFERENCES BETWEEN VIOLENT, NONVIOLENT CRIMINAL, AND NONOFFENDING EXTREMISTS

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Criminal Justice – Doctor of Philosophy

2024

ABSTRACT

Existing counterterrorism policy is mostly focused on preventing violent extremism. The problem is violent extremism is rare. Most extremists will never engage in violence. Some extremists will commit nonviolent crimes to advance their cause, such as fraud or vandalism, and others will be involved in legal activities, such as protesting or advocacy. However, little is known about the factors that distinguish violent extremists from their nonviolent and noncriminal counterparts, and prior research in this area has been methodologically limited. To address this gap, this study leverages a multifactor criminological approach by considering how a sample of (n=739) violent, nonviolent criminal, and nonoffending extremists drawn from the Risk and Protective Factors Dataset (RPFD) may differ in the criminogenic risk and protective factors they demonstrate.

Latent class analysis is used to derive distinct classes of criminogenic risk, and the LTB method of distal outcome prediction is employed to estimate the relationship between classes of criminogenic risk and the type of action extremists engaged in. Classes with a high probability of strain-related risk factors were most likely to engage in extremist violence. Alternatively, classes with a high probability of protective factors were most likely to be involved in nonviolent or nonoffending extremism. Broadly, these findings reiterate the equifinality and multifinality of extremist violence.

Findings from this dissertation have numerous theoretical, methodological, and practical implications. Specifically, this dissertation contributes to the development of criminological theory and advances methods of scientific inquiry into this area of study. Further, this dissertation highlights the importance of considering criminogenic factors in ongoing counterterrorism preventative efforts.

I dedicate this manuscript to the three Spartans who lost their lives on February 13th, 2023, and to all the victims of violent extremism and mass violence. Your memory gives me purpose.

ACKNOWLEDGEMENTS

I did not walk alone on my journey to obtain a Ph.D., and I owe tremendous gratitude to those who supported me throughout this experience.

First, I have often bragged that I have the greatest guidance committee a Ph.D. candidate can ask for, and I believe that to be an understatement. Dr. Wolfe, thank you for taking the time to provide thoughtful feedback and heartfelt banter (Go Chiefs). Dr. Holt, thank you for inviting me to collaborate with you on multiple projects and always being a source of wisdom whenever I needed it. Dr. Freilich, thank you for taking me on as a student of your own. Working with you has been one of the greatest joys of my career to-date. Lastly, to my chair, Dr. Steven Chermak. I have no words to express how eternally grateful I am to have been one of your students. I consider myself incredibly blessed to have a mentor who, in addition to being of the most brilliant minds I've ever met, is a remarkably humble, reliable, and kind-hearted person. Thank you for your invaluable guidance and wisdom, and for giving me the space to grow as a scholar and man.

To my past and present mentors who have helped and guided me on this path. Thank you to Jennifer V. Carson, my first mentor, for being the catalyst that initiated my passion for terrorism research and the conduit to my professional career. To Erin Kearns, thank you for taking a chance on me and being a mentor unparalleled in candidness and compassion. To Matt Allen, thank you for bringing me onto the CP3-Eval team with open arms. To my fellow Research Associates at NCITE, who have assured me there is light at the end of the tunnel. And to the rest of my NCITE family, who have taken me in and supported me since my first day in Omaha.

I am indebted to my greatest support system, my friends. To Mark's Angels, Woody, and Rick – my best friends. I have no words for how much you all mean to me. To Brent Klein, Emily Greene-Colozzi, and Jin Lee, thank you for being the best peer mentors and colleagues from day one. To Brenna Helm, thank you for being the perfect balance of an empathetic yet fiery friend these last 5 years. To Travis Carter, my dynamic duo. I could not have done any of this without you on the other side of the cornhole boards. Finally, to Bev – you found me in the most difficult part of this journey, and you've been my rock ever since.

Lastly, I want to thank my family. To my Mom and Dad, you are the reason I am where I am. Thank you for being the best parents any son could ask for. To my brother, Dylan, and sisters, Mikayla, Heather, and Hilary, I don't deserve siblings like you all, but I am eternally grateful to have you. To my Indiana family, thank you for hosting me countless times on my many travels back and forth, and for bringing me joy when I needed it most. Finally, thank you to my beautiful Grandma, for reading all my papers and always being my #1 supporter.

There are so many people that I am not able to thank here who supported me in this journey, but I appreciate every one of you who gave me the strength I needed to achieve this goal.

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CHAPTER 1: INTRODUCTION

1.1. Problem Statement

At a rally in Washington D.C. on the morning of January 6th, 2021, President Donald Trump encouraged his supporters to act against an unfair, rigged, and “stolen” election (Conklin, 2022). Heeding this call to action, several thousand of the rally attendees marched to the United States (U.S.) Capitol Building to protest the certification of the 2020 Presidential Election results. In just a few hours, this protest descended into a violent insurrection. Thousands of Trump supporters stormed and illegally entered the Capitol Building, forcing security officers to evacuate hundreds of congresspeople from the official voting chambers as the certification was taking place (Lucas, 2022). The insurrectionists committed various property crimes, including unauthorized occupation of Capitol Grounds, damaging or destroying Capitol property, and disrupting the conduct of official Capitol business (Select Committee to Investigate the January 6th Attack on the U.S. Capitol, 2022). Further, hundreds were injured as some rioters used their fists and others armed with weapons, including stun guns, pepper spray, baseball bats, flagpoles and fire extinguishers wielded as clubs, firearms, and even explosive devices attempted to breach police barricades and/or attack police officers.

The House Select Committee to Investigate the January 6th attack on the United States Capitol was established several months after the incident to launch an investigation into the attack, including identifying and prosecuting insurrectionists as well as determining the role of former President Trump in inciting the attacks. To date, over 1,100 people have been arrested and charged with crimes related to the January 6th, 2021, insurrection (U.S. Attorney’s Office: District of Columbia, 2022). The committee published its final report on December 22, 2022, asserting former President Trump disseminated false allegations on the legitimacy of the 2020

Presidential Election, which encouraged his supporters to mobilize towards action (Select Committee to Investigate the January 6th Attack on the U.S. Capitol, 2022). Further, the committee found several militia groups such as the Proud Boys, Oath Keepers, and Three Percenters actively engaged in planning and ultimately led the charge on the Capitol Building. To be sure, the Capitol Breach on January 6th, 2021, included acts of domestic terrorism, motivated by a far-right ideology, emboldened by an anti-democratic conspiracy theory, and facilitated by a belief that action was necessary regardless of legality.

A host of political opinions were present at the National Mall on January 6th; many of which would likely be considered "radical." Tens of thousands of devoted Trump supporters travelled from across the nation to lend their voices and play their part in what is now known as the "Stop the Steal" protest. But importantly, the large majority of people attending the protest did not partake in the violence. In fact, unofficial estimates suggest at least 10,000 people were present at the rally that day (Mascaro et al., 2021), with only about an estimated 2,000 to 2,500 entering the Capitol (Lucas, 2022). Of those that did enter the capital, most were charged with misdemeanor property crimes and or illegal entry (U.S. Attorney's Office: D.C., 2022). Only a fraction of the insurrectionists were charged with violent offenses, with 225 people being charged with assaulting, resisting, or impeding officers or employees, and approximately 75 of those were charged with using a deadly weapon to cause bodily injury to an officer (U.S. Attorney's Office: D.C., 2022). But if everyone attending this event shared similar ideological beliefs, then this begs the important question of what distinguishes those who committed ideologically motivated crime and violence from those who elected to abstain from the breach? Further, what distinguishes those who engaged in violence against police officers from those who only engaged in nonviolent property crimes?

The answer to these questions continues to elude extremism researchers and practitioners alike but has substantial pragmatic relevance. In 2021, the Biden administration proposed its National Strategy for Countering Domestic Terrorism (National Security Council, 2021). At the heart of the Strategy is an explicit focus on mitigating risk factors and fostering protective factors for radicalization to violence, an approach anchored in a public health framework for preventing violent extremism (Barry-Walsh et al., 2020). Interventions derived from such an approach are tailored to specific pools of people. Primary level prevention aims to prevent individuals from adopting extremist beliefs, secondary prevention seeks to prevent those who have adopted extremist beliefs from mobilizing to violence, and tertiary prevention involves reducing the risk of recidivism for those who have committed extremist violence (Clemmow et al., 2023). Extensive radicalization research and theory has been directed towards primary prevention, focusing on the factors that cause individuals to adopt radical belief systems (Bouhana, 2019; Borum, 2003; Kruglanski et al., 2014; McCauley & Moskalenko, 2008; Moghaddam, 2005; Precht, 2007; Silber & Bhatt, 2007; Wiktorowicz, 2004). However, to determine why some extremists engage in crime and/or violence and others do not, a more explicit focus on the secondary level of prevention is necessary – thus, this is the focus of this dissertation.

In particular, a better understanding is needed on the criminality of terrorism and violent extremism. Terrorism, at its core, is a crime – a crime driven by ideological goals (Clarke & Newman, 2006). But the overwhelming majority of those who hold extremist beliefs will never act on them (McCauley & Moskalenko, 2014). Further, as demonstrated on January 6th, 2021, some may engage in nonviolent crimes that, while illegal, do not inflict physical harm unto others (Jensen et al., 2016; McCauley & Moskalenko, 2014). Only a fraction of extremists will engage in violence to forward their cause (Atran, 2010; Wolfowicz et al., 2021). Put simply, most extremists do not engage in crime, some extremists engage in nonviolent crimes, and a very small portion of extremists commit violent crimes (McCauley & Moskalenko, 2014). Thus, the empirical challenge is discerning the criminogenic factors and mechanisms that characterize these actors from one another – particularly in differentiating violent extremists from their nonviolent and noncriminal counterparts.

Using a novel dataset on violent, nonviolent, and nonoffending extremists, this dissertation seeks to build on our understanding of the criminology of terrorism and violent extremism. I leverage a multifactor approach for explaining involvement in violent extremism by drawing a slate of micro-level criminogenic risk and protective factors from four leading criminological perspectives; namely, social bond, low self-control, social learning, and strain theories. Grounded in criminological and extremism scholarship, a series of exploratory and explanatory research aims are proposed to guide this dissertation, with the ultimate purpose of contributing to the evidentiary base for preventing violent extremism at the secondary level of prevention.

1.2. Research Aims and Rationale

A burgeoning body of work demonstrates the relevance of criminological explanations in the study of terrorism and violent extremism. Recent reviews indicate terrorism studies are increasingly leveraging theories of crime and criminality (Fisher & Kearns, 2023), and the salience of criminogenic mechanisms in explaining violent extremism has been strongly supported by recent meta-analyses (Wolfowicz et al., 2021).While much research has focused on the macro-level correlates of terrorism (Adamcyzk et al., 2014; Fahey & LaFree, 2015; Freilich et al., 2015; Gladfelter et al., 2017; LaFree & Bersani, 2014; Mills, 2020a; 2020b), advancements in data quality and availability have also facilitated a growth of micro-level examinations on the criminogenic characteristics of individual perpetrators in violent extremist incidents (Fisher & Kearns, 2023). Notably, recent empirical examinations have considered the applicability of social bond theory (Becker, 2021; Holt et al., 2017; LaFree et al., 2018; Pritchett & Moeller, 2022; Thijs et al., 2022), low self-control theory (DeWaele & Pauwels, 2014; Pauwels & Svennson, 2017; Perry et al., 2018; Rottweiler & Gill, 2020; Rottweiler et al., 2022), social learning theory (Becker, 2021; Holt et al., 2017; LaFree et al., 2018; Pritchett & Moeller, 2022), and strain perspectives in explaining violent extremism (De Waele & Pauwels, 2014; Rottweiler et al., 2022).

However, scholars have increasingly recognized the inability for variables from a single criminological paradigm to adequately explain involvement in violent extremism (Becker, 2021; LaFree et al., 2018). Ultimately, this shortcoming has led a number of recent empirical studies to simultaneously assess criminogenic factors from multiple criminological theories. Various combinations have been leveraged, including variables from social learning and social bond theory (Becker, 2021; De Waele & Pauwels, 2014 Holt et al., 2017; LaFree et al., 2018; Pauwels & Schils, 2016; Pritchett & Moeller, 2022; Schils & Pauwels, 2016), social bond theory and strain theory (Skoczylis & Andrews, 2022), and low self-control theory and social learning theory (Perry et al., 2018; Schils & Pauwels, 2014; Turner et al., 2022). Despite these advancements no known study has considered criminogenic factors from all four mainstream criminological perspectives that have been empirically linked to violent extremist outcomes. Accordingly, this dissertation employs a holistic approach, whereby criminogenic risk and protective factors drawn from low self-control, strain, social learning, and social bond models are considered simultaneously to fully assess the criminogenic nature of violent extremism.

Specifically, prior work in this area has been limited by two primary methodological gaps. First, extant research that uses an multifactor approach for studying the criminology of violent extremism at the micro-level has only estimated independent effects of particular criminogenic risk factors that are collectively included in a regression model (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2021; Thijs et al., 2022). This approach is appropriate for discerning which factors may be more or less salient predictors of extremist violence but do little to advance our understanding of how criminogenic factors interact with one another to amplify or mitigate one's risk of engaging in ideologically motivated crime and violence. Indeed, risk and protective factors, or characteristics that condition one's relative risk of criminal offending, do not occur in a vacuum – no single factor alone can explain involvement in violent extremism (Gill, 2015). Rather, as Wolfowicz et al. (2021) puts it, "it is the accumulative and interactive weight of present risk factors, either in the absence or outweighing of protective factors, that increases or decreases the likelihood or risk of offending" (p. 5; Farrington et al., 2016). Thus, static assessments of singular risk factors provide limited insight into the causal mechanisms that underpin the criminality of violent extremism. Caitlin Clemmow and colleagues (2023) describe it best in stating "practice requires knowledge which goes beyond examining the effects of single factors and moves towards understanding how risk factors co-occur and coalesce with one another…" (p. 2). As a result, a multifactor approach to understanding the criminality of violent extremism must consider the interactions between criminogenic risk and protective factors in a complementary capacity as opposed to competitive.

Accordingly, drawing from extant literature on risk and protective factors to violent extremism and grounded in criminological theory, the first research aim of this dissertation is to *explore the extent to which criminogenic risk and protective factors co-occur and covary to form* *distinct classes that characterize one's relative risk for criminality.* Latent class analysis, a form of finite mixture modeling, is used to model the covariation among these factors and estimate classes based on the observed data. This approach enables classes to be empirically derived from data rather than researcher-imposed, allowing for prior theory to explain the observed covariation but not necessitating conformity with an a priori classification schema. In doing so, this dissertation builds on prior research emphasizing the need for multifactor studies by not only assessing different criminogenic factors simultaneously, but also estimating the nature of their interrelationships.

The second major limitation in prior literature concerns the use of appropriate comparison groups. Limited research in this area utilizes samples of individuals who have actually engaged in some form of extremist action. Many studies assessing the relationship between criminogenic factors and violent extremism use proxy measures such as violent extremist intentions or tendencies, but do not actually examine individuals who have committed extremist violence (Perry et al., 2018; Rottweiler & Gill, 2020; Rottweiler et al., 2022). While there is no doubt value in these studies, they are limited in the sense that intentions or attitudes often do not translate to actual behaviors (Rottweiler et al., 2022). Assessing samples of violent extremists who have actually engaged in extremist violence can alleviate this disconnect and bring clarity to discrepant findings.

Those studies that have leveraged samples of violent extremists have not employed a noncriminal comparison group. Most studies have included a nonviolent extremist comparison group, encompassing extremists who engaged in nonviolent crimes or were members of an extremist group (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022; Thijs et al., 2021). However, scholars have consistently advocated for the use of non-criminal extremists as a comparison group (Freilich et al., 2015; Monahan, 2016). Moskalenko et al. (2023) contend doing so would, "…allow researchers to identify, for example, what distinguishes supporters of Nazism and al Qaeda who do not commit crime from those who commit violent acts to further these extreme ideologies" (p. 9). Currently, extant research lacks effective comparisons between criminal extremists, both violent and nonviolent, and extremists who operate within the parameters of the law. The lessons learned from such a comparison could be incredibly useful for risk assessment and understanding the factors that drive some extremists from belief to criminal action.

As a result, this dissertation uses a sample (n=739) of violent, nonviolent criminal, and nonoffending extremists from the Extremist Crime Database's Risk and Protective Factors Dataset to address this knowledge gap. All of the individuals included in this sample engaged in either violent crime, nonviolent crimes, or legal actions to advance their ideological goals. Specifically, the second research aim of this dissertation is to *examine how violent, nonviolent criminal, and nonoffending extremists differ in their criminogenic risk*. A method of distal outcome prediction is used to assess the relationship between estimated classes of criminogenic risk and the types of action extremists engage in; namely, nonoffending, nonviolent criminal, or violent actions (Lanza et al., 2013). Relevant control variables are included to situate the salience of criminogenic factors, and a series of sensitivity analyses are employed to bolster analytic rigor.

1.3. Overview

The remainder of this dissertation will be organized as follows. Chapter 2 begins by conceptualizing violent, nonviolent criminal, and nonoffending extremism, and examines the research drawing empirical distinctions between the three types of extremism. Then, the research exploring the relevance of criminogenic risk and protective factors to the study of violent extremism is reviewed, with a particular focus on factors drawn from social bond, low self-control, strain, and social learning perspectives. The value of an multifactor approach is situated, and findings of empirical studies employing such an approach are assessed. Finally, two methodological gaps in the extant literature are highlighted, and avenues to address these gaps are explored.

Chapter 3 begins by describing the Risk and Protective Factors Dataset (RPFD), the source of data for this dissertation. The process of developing the RPFD is explained in detail, including how the sample was created, how information was gathered, and how variables were coded. Then, the analytic plan is detailed. First, the operationalization of independent variables is provided. Next, the process of conducting latent class analysis is thoroughly explained. Third, the dependent variable is operationalized, and Lanza et al.'s (2013) method for distal outcome prediction is described in a stepwise manner. Chapter 3 concludes with a discussion of the sensitivity analyses that will be conducted to evaluate the robustness of the LCA results.

Chapter 4 examines the results of the LCA with distal outcome prediction. The chapter starts with a descriptive analysis of the independent variables included in the study, highlighting preliminary similarities and differences in the frequency of criminogenic risk and protective factors across violent, nonviolent criminal, and nonoffending extremists. The LCA model is then enumerated to determine the number of classes that will be estimated. Next, the LCA model is estimated and the characteristics of each class of criminogenic risk are described. Distal outcome prediction using the LTB method is then used to investigate the association between class of criminogenic risk and the type of action an extremist engaged in. The chapter ends with sensitivity analyses to address potential limitations in open-source data.

Chapter 5 discusses the findings and implications of this dissertation. The chapter begins with a review of the key findings that emerged from the LCA model with distal outcome prediction. The theoretical, methodological, and practical implications are then explored to situate the importance of the current set of findings. Next, the limitations of this dissertation are reviewed, and directions for future research are presented. Finally, the chapter concludes with a summary of this dissertation.

CHAPTER 2: LITERATURE REVIEW

There is an ongoing discourse on the conceptual distinctions between "terrorism" and "extremism" (Bak et al., 2019; Onursal & Kirkpatrick, 2021). Scholars have defined terrorism as "the threatened or actual use of illegal force and violence to attain a political, economic, religious, or social goal through fear, coercion, or intimidation" (LaFree & Dugan, 2007: 184). Others generally concur that terrorism necessitates the commission or threat of ideologically motivated violence (Hoffman, 2017; Jongman, 2017). Extremism, on the other hand, has been used in a broader context referring to both subscribing to an extreme belief system that deviates from conventional norms, as well as committing actions to realize an ideological goal (Neumann, 2013; Scruton, 2007). But the form these actions take are not unidimensional – in fact, they vary greatly in their nature and legality. It is important to clarify these distinctions and effectively conceptualize the various types of extremist actions that may be committed.

2.1. Distinguishing Violent, Nonviolent Criminal, and Nonoffending Extremists

There are millions of people who hold extremist beliefs, but most never act on them (McCauley & Moskalenko, 2014; 2017). Some, however, will act in legal ways – referred to in this dissertation as *nonoffending extremists*. These individuals may be considered activists, in that they engage in political action that is nonviolent and noncriminal with the purpose of advancing an ideological goal (McCauley & Moskalenko, 2014; 2017). Examples of noncriminal extremist actions may include partaking in peaceful rallies and protests, producing media, or expressing extreme beliefs in online spaces.

However, others will engage in illegal activities to further an extreme cause – though these activities need not be violent. In fact, some extremist groups explicitly take steps to avoid human casualties in their attacks. The Environmental Liberation Front (ELF), an environmental extremist group who carried out hundreds of ideologically motivated crimes in the late 1990s and early 2000s (Jarboe, 2002), directed its members to "take all necessary precautions against harming life" (Ackerman, 2003: 145). Accordingly, their attacks were mostly property crimes such as arson, equipment sabotage, and vandalism (Leader & Probst, 2003). In another vein, far-right extremists often engage in tax fraud or similar financial crimes to advance their cause (Sullivan et al., 2019). Similarly, some ideologues elect to contribute resources to a terrorist group or movement as opposed to engaging in violence themselves, known as material support (Harms, 2017). These crimes include smuggling, money laundering, or illegal trade that are committed in an effort to provide finances, resources, or labor to an extremist or terroristic cause (Harms, 2017). Taken together, n*onviolent criminal extremists* are extremists who engage in nonviolent crimes to advance an ideological cause, such as financial crimes, material support to extremist groups, or involvement in operational plots that were not intended to cause casualties like property destruction or vandalism (Harms, 2017; Jasko et al., 2017; Jensen et al., 2016; Kerodal et al., 2016; Sullivan et al., 2019).

Finally, *violent extremists* are individuals who commit or threaten violence that harms, or intends to harm, other humans to forward an ideological goal (Jasko et al., 2017; Jensen et al., 2016). These individuals comprise the smallest category of extremists, as only a small fraction of those who hold extremist beliefs ascend to extremist violence (Atran, 2010; Khalil et al., 2022; McCauley & Moskalenko, 2014; Wolfowicz et al., 2021). A wealth of research has been dedicated to understanding the phenomenon of violent extremism, ranging from the characteristics of its perpetrators (e.g., Borum, 2014; Gruenewald et al., 2013; Kruglanski et al., 2019; Thijssen et al., 2023) to the strategies for preventing it (e.g., Amit & Kafy, 2022; Stephens et al., 2021). To inform Countering Violent Extremism (CVE) or Preventing Violent Extremism

(PVE) efforts, the important empirical task is determining what differentiates violent extremists from those who abstain from violence and crime.

Recent research has directed its attention towards this differentiation. Jensen et al. (2020) sought to discern unique pathways to violent extremism by examining and comparing life-course narratives of (n=31) violent and (n=25) nonviolent criminal extremists. The authors identified a slate of causal mechanisms linked to radicalization, including personal crisis, community crisis, psychological or physical vulnerability, psychological or material rewards, recruitment into extremist groups, endorsement of group biases or norms, and cognitive realignment with radical beliefs. Using a fuzzy-set/qualitative comparative analysis, Jensen et al. (2020) identified eight discrete pathways characterized by differential combinations of these mechanisms. Their analysis revealed pathways rooted in combinations of personal crisis, community crisis, and psychological vulnerability and rewards often lead to extremist violence, indicating certain configurations of causal mechanisms differentially influence the type of actions an extremist may ultimately engage in (Jensen et al., 2020).

In another study, Keatley et al. (2021) conducted a crime script analysis on (n=24) violent and (n=16) nonviolent extremists. Violent extremists were those involved in plots that killed or intended to kill other people, and nonviolent actions involved providing "nonphysical support from afar" and included activities such as disseminating extremist literature, sending hate mail, online-fundraising, or participating in online internet forums (Keatley et al., 2021: 6). This contrasts with the conceptual distinction between nonoffending and nonviolent criminal extremists posed above by grouping both legal and illicit means of nonviolent support – an important caveat to note when interpreting their findings. The authors found violent extremists were more likely to experience ostracism, isolation, and bullying than nonviolent extremists, and were also more likely to use alcohol and drugs prior to radicalization. The two groups also differed in their pre-operational activities, as violent extremists were more likely to travel abroad and use the internet to gather information on planning attacks.

Nonviolent extremists, alternatively, spent more time connecting with like-minded individuals and disseminating their ideology both in-person and online. These findings are in line with recent work suggesting nonviolent extremists are generally more active on extremist forums, posting more frequently than their violent counterparts (Scrivens et al., 2022). Using the same sample as Keatley et al. (2021), Knight et al. (2022) assessed subtypes of extremists based on the actions they engaged in (violent versus nonviolent) and their level of group affiliation (lone actor vs. group-affiliated). Their findings indicate that, compared to nonviolent extremists, violent extremists more frequently experienced rejection from others, felt a personal obligation to act, expressed a sense of underachievement, and perceived themselves as of a superior being.

At the group-level, Chermak et al. (2013) compared the characteristics of far-right groups in the U.S. that differentially engaged in violent crime. Groups that had existed for longer, had a charismatic leader, operated through a leaderless resistance structure, and were based in the West or Northeast U.S. were more likely to engage in violent crime. Alternatively, groups who disseminated ideological literature were less likely to be violent, owing perhaps to the use of alternative means for expressing their beliefs besides violent crime. Group behavior is especially relevant when considering violent, nonviolent criminal, and noncriminal extremists have been found to demonstrate similar levels of connectedness with other extremists, albeit they most often affiliate with extremists engaged in comparable types of action (Sawyer & Hienz, 2015).

Another point to consider is the issue of mental illness. Several studies have found that violent extremists are more likely than nonviolent extremists to be mentally ill (Becker, 2021;

LaFree et al., 2018). This relationship may be explained as a function of impaired decision-making, as scholars contend that mental illness inhibits one's cognitive ability to cope with external stress or pressures (Bouhana, 2019). Lone-actor terrorists are particularly more likely to have a mental illness as opposed to group-affiliated actors (Corner & Gill, 2015; Gruenewald et al., 2009). Finally, a consistent finding in the literature is the influence of ideology. Actors subscribing to jihadist and far-right ideologies are more likely to commit extremist violence than far-left ideologues, such as aforementioned environmental extremists (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022).

Taken together, extant empirical research indicates clear differences between the characteristics of violent extremists and their nonviolent and noncriminal counterparts. However, given the primary element that distinguishes these types of extremists is the *criminality* of their actions and the *severity of their crimes*, it is pertinent to consider the criminogenic differences between the subgroups. Indeed, an emerging body of literature has demonstrated the relevance of criminological variables in differentiating violent and nonviolent extremists. Accordingly, the next section explores the scholarship on the criminology of violent extremism, with a specific focus on the utility of criminogenic risk and protective factors and the theoretical explanations that underpin their connection to extremist violence.

2.2. The Relevance of Criminology and Criminogenic Risk and Protective Factors

Criminology has an important part to play in understanding the etiology of violent extremism as a criminal act. This is demonstrated in the growing body of research indicating the applicability of criminological theory to the study of violent extremism (Fisher & Dugan, 2019; Fisher & Kearns, 2023; Freilich et al., 2015) and the salient associations between criminogenic risk factors and radical outcomes (Wolfowicz et al., 2021). In particular, scholars argue that an exclusive approach, where variables from a single criminological paradigm are assessed, is insufficient in explaining involvement in violent extremism (Becker, 2021; Khalil & Dawson, 2023; LaFree et al., 2018). Instead, researchers should conduct analyses that identify "a mutually reinforcing set of factors which produce extremist violence" (Becker, 2021: 1117).

Such a sentiment is increasingly relevant when considering the ever-growing quantity of risk and protective factors to violent extremism (Gill, 2015). Risk factors are "individual or social characteristics that predict an enhanced probability of outcomes like the onset of extremism, radicalization towards violent behavior, or (in rare cases) terrorist acts" (Lösel et al., 2020). Protective factors, on the other hand, reduce one's probability of engaging in extremist-related activities by shielding them from radical influence (Losel et al., 2020). Risk and protective factors may serve as observable 'markers' to indicate an individual's proclivity to engage in extremist violence (Clemmow et al., 2022). A growing body of research has explored the prevalence and potency of a range of risk and protectIve factors, with several large-scale datasets facilitating these explorations (Gill et al., 2014; Jensen et al., 2016; Wolfowicz et al., 2021). Importantly, Borum (2015) notes "Because terrorism involvement represents a broad spectrum of behavior, it may be that different risk factors will apply to different roles or categories of activities" (p. 66). This statement is especially relevant when considering the variation of extremist activities described above, as violent, nonviolent criminal, and nonoffending extremism necessitate unique categories of extremist behavior that are defined by their criminality (or lack thereof).

Criminogenic risk and protective factors, which are individual characteristics that influence one's likelihood for criminally offending (Stephenson et al., 2010), are just one type of factor – but they have substantial relevance to the study of violent extremism. These factors are drawn from a range of criminological frameworks, including learning, control, and strain theories, and indicate the underlying causal mechanisms proposed in each of those perspectives (Wolfowicz et al., 2021; Wolfgang & Ferracuti, 1967). In their meta-analyses, Wolfowicz et al. (2021) concluded that "Criminogenic factors are the most important risk factors for cognitive and behavioral radicalization" (p. 2). These factors, like other risk and protective factors, do not occur in a vacuum. A single factor cannot unilaterally explain involvement in extremist violence. Rather, it is a collection or pattern of factors that complement and coalesce with one another to collectively influence one's decision to engage in violent extremism (Clemmow et al., 2022; Gill, 2015; Wolfowicz et al., 2021).

The problem is that most research linking criminogenic factors to violent extremist outcomes considers singular factors or several factors from a single criminological paradigm . While many factors from various perspectives demonstrate salient independent effects across studies, no known research has used a multifactor approach to assess criminogenic factors from multiple criminological perspectives and estimate their collective relationship with violent extremist outcomes. Such approaches give way to further exploration into how theories may be integrated to better explain violent extremism by considering relationships between relevant factors and variables. The notion of theoretical integration is contested by criminologists, with some advocating for its use in forming more comprehensive explanations of crimes and violence (Bernard & Snipes, 1998; Tittle, 1995), and others asserting integration leads to complications that limit its utility (Hirschi, 1979; 1989; Kornhauser, 1978; Krohn & Eassey, 2014). However, scholars are increasingly calling for integrating explanations of violent extremism to unify a fragmented knowledge base (Freilich et al., 2024; Khalil & Dawson, 2023), and leveraging a multifactor approach to explore relationships between factors is an essential step in laying the foundation for such pursuits.

Accordingly, criminological theory can ground a multifactor pursuit in several ways. First, criminological theory provides frameworks for identifying criminogenic risk and protective factors that may be relevant to explaining involvement in violent extremism. By coupling theoretical guidance with extant empirical research, we can discern the factors that are most strongly associated with involvement in violent extremism and consider them simultaneously. Second, criminological theory offers guidance to understanding interrelationships between criminogenic factors from opposing criminological paradigms. A factor from one perspective may frequently co-occur or covary with a factor from another perspective, and exploring theoretical nuances can help understand those relationships. Finally, criminological theory can explain observed patterns of criminogenic risk and protective factors in terms of *why* and *how* they lead to criminal behavior, or in this case, extremist crime and violence.

2.2.1. Level of Focus

Prior to discussing the criminogenic factors of interest, it is important to clarify the level of explanation with which this dissertation concerns; that is, the micro-level. This is not to say macro-level factors are not of importance. In fact, there is a growing body of research examining the relevance of macro-level factor, primarily those drawn from social disorganization and backlash perspectives, in explaining rates of terrorist incidents (Adamczyk et al., 2014; Fahey & LaFree, 2015; Freilich et al., 2015; LaFree & Bersani, 2014) as well as other ideologically motivated offenses like hate crimes (Gladfelter et al., 2017; Mills, 2020a; 2020b). Further, applications of deterrence and rational choice perspectives have mostly been conducted at the macro-level to examine the aggregate effects of counterterrorism policies and strategies aiming to deter potential terrorist attacks (Bejan & Parkin, 2015; Carson, 2014; Carson et al., 2020; Yang & Jen, 2018; Dugan & Chenoweth, 2012; Lum et al., 2006). Other research has also considered the role of opportunity in terrorist attacks, assessing the characteristics of targets and victims of terrorism through routine activity and situational crime prevention approaches (Clarke & Newman, 2006; Gruenewald et al., 2015; Klein et al., 2017; Mandala & Freilich, 2018).

However, the focus of this dissertation is on criminogenic factors drawn from micro-level criminological theories that explain differences in individual characteristics, or those that "use variations in characteristics of individuals to predict the probability that an individual will commit crime" (Bernard & Snipes, 1996: 336). These theories are especially conducive to a risk-protective factor approach, as they explain the relationship between specific individual-level factors and outcomes of interest. Thus, this dissertation draws criminogenic factors from four criminological paradigms that explain crime at the individual-level to discern differences between violent, nonviolent, and nonoffending extremists: social bond/social control theory, low self-control theory, strain theory, and social learning theory.[1] The following sections describe the propositions of each of these perspectives and highlight the empirical research tying their respective criminogenic risk factors to the study of violent extremism. These sections conclude with a review of studies using criminogenic factors from multiple theories to examine violent extremism-related outcomes.

2.2.2. Social Bond/Social Control Theory

Control theories have substantial relevance in distinguishing violent, nonviolent, and nonoffending extremists, as they focus on understanding why some radicalized individuals elect

[1] Many perspectives, including strain, social learning, and social bond/social control, ultimately include contentions related to both macro- and micro-level variation. However, the criminogenic risk factors derived from these theories indicate the characteristics of individuals or the immediate environment in which they operate, qualifying their relevance to this dissertation.

not to engage in extremist crime and violence (Fisher et al., 2023). Scholars have recently advocated for a more holistic focus on both risk *and* protective factors to extremism (Fisher et al., 2023; Gill, 2015), and criminological control theories provide useful frameworks for assessing those protective factors that restrain a potential offender from engaging in crime when an opportunity to do so is presented. These theories are grounded in the assumption that humans are naturally inclined to antisocial behavior, motivated by a self-interest for maximizing pleasure and minimizing pain (Gottfredson, 2011). The socialization process, then, instills mechanisms to regulate this calculus and fortify individual decision-making to resist deviant temptations.

Social control theories contend individuals form bonds with prosocial societal institutions that restrain them from engaging in crime and deviance (Hirschi, 1969; Laub & Sampson, 1993). Social bonds, in this way, are informal social controls that regulate a person's behavior. Crime and deviance incur social costs that may jeopardize the social investments one makes in prosocial institutions and goals (Laub & Sampson, 1993). Individuals who are less bonded to society will be less dissuaded from deviance by these social costs, and thus more likely to engage in antisocial behavior that violates conventional values and norms (Hirschi, 1969). The relevance of social control theory is evident in prior theories on radicalization that position individuals who are alienated and detached from conventional society, seeking refuge and belonging in a set of extremist beliefs, as especially vulnerable to radicalization (Kruglanski et al., 2014; Silber & Bhatt, 2007; Precht, 2007; Wiktorowicz, 2004). Additionally, scholars argue that of those individuals who do radicalize, those who hold prosocial bonds are more restrained in the actions they are willing and able to engage in and thus less likely to engage in violence (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022).

One of the first social bond/social control models was proposed by Travis Hirschi (1969), which aims to explain why individuals conform to normative laws and norms rather than deviate. four dimensions of social bonds: attachment, commitment, involvement, and belief. *Attachment* refers to the extent to which a person is bonded to other people who endorse prosocial behavior (Hirschi, 1969). To commit a crime is to act in contrast to the expectations of prosocial people and the agreed upon social norms of society. A person who is not bonded to prosocial people will care little about how their behaviors are perceived, thus unrestrained from deviating from social norms (Hirschi, 1969). A primary criminogenic factor in this vein is marital status, as prior studies indicate violent extremists and suicide terrorists are more likely to be unmarried than other terrorists (Gill & Young, 2011; Pedahzur et al., 2003; Perliger et al., 2018). Relatedly, Horgan et al., (2016) found lone-actor extremists were more likely to be single and without children than group-affiliated extremists, suggesting this category of individuals are especially weakly bonded. Attachment bonds are particularly interesting in relation to extremism, as bonds to family or friends involved in extremism may often motivate an individual to engage in extremism themselves (Hafez & Mullins, 2014; Khalil et al., 2022), a possibility reflective of a social learning argument (see *Section 2.2.5*).

Commitment, on the other hand, relates to the rational component of offending, whereby a person considers the potential costs of deviance in terms of the goals and achievements they risk by engaging in crime. Commitment conceptually overlaps with Hirschi's (1969) third dimension, *Involvement*, which captures the temporal impact of bonding in terms of the amount of time one spends engaged in prosocial activities. Individuals who are more involved in conventional activities, such as school, work, or community organizations, may have less time to engage in deviance than others (Hirschi, 1969). Likewise, those who are more committed to prosocial goals are more likely to be involved in prosocial activities, such as getting an education or gaining employment (Hirschi, 1969). Scholars argue empirically separating between two dimensions is difficult, and thus advocate for combined measures of commitment/involvement where factors tied to involvement in prosocial activities are necessarily indicative of one's commitment to prosocial goals (Conger, 1976; Krohn & Massey, 1980; Longshore et al., 2005).

In the context of terrorism and extremism, there are discrepant empirical findings on criminogenic factors related to commitment/involvement social bonds. Contrary to the predictions of social bond theory, studies indicate that perpetrators of violent extremism are more likely to attain higher levels of education compared to the general population (Saeed & Syed, 2018) or regular homicide offenders (Liem et al., 2018), suggesting greater commitment/involvement in the conventional order. However, other studies suggest nonviolent criminal extremists have significantly higher levels of education than violent extremists (Harms, 2017). Additionally, other studies have also found violent jihadi extremists are more likely to be unemployed than other Muslims (Altunbas & Thorton, 2011) and other members of extremist groups who did not perpetrate violence (Perliger et al., 2018), suggesting some degree of weakened social bonds.

Within samples of extremists, research indicates jihadist extremists are more likely to be unemployed and withdraw from social activity than far-right extremists, though they are less likely to live alone (Gill et al., 2022). Similarly, prior work suggests suicide terrorists are more likely to be less educated than other terrorists (Gill & Young, 2011). Military experience may also indicate one's commitment to and involvement in conventional activities. Gruenewald et al. (2013) found loner far-right extremists were more likely to have a military background than non-loner far-rightists, but Chermak and Gruenewald (2014) found far-right homicide offenders were less likely to have military experience than those affiliated with al-Qaeda and associated movements. Overall, these findings illustrate the variation in criminogenic differences across distinct types of extremists.

Finally, Hirschi's (1969) dimension of *belief* relates to the strength of an individual's ties to conventional order, specifically the legitimacy of established laws and norms and the extent to which they ought to be followed. Hirschi (1969) suggests there is variation in the strength of moral belief systems, and the less a person believes that the rules of society should be obeyed, the more likely they are to deviate. The social bond of belief in conventional order becomes especially relevant when considering the variation in extremist belief systems. Some extremists merely sympathize with extremist movements, but do not legitimize violence on their behalf (McCauley & Moskalenko, 2014; 2017; Khalil et al., 2022). Others not only justify the use of violence as morally and ideologically sanctioned but believe they themselves have a personal obligation to take up arms (McCauley & Moskalenko, 2014; 2017). Accordingly, those extremists more deeply engrained into an ideological belief system may possess especially weakened bonds to belief in the conventional order.

Hirschi eventually moved away from social bond theory to collaborate with Michael Gottfredson on *The General Theory of Crime* (see *Section 2.2.3.*). However, his social bond theory remains a popular and relevant framework to explain crime and deviance, and empirical studies continue to test the variables in Hirschi's (1969) model in relation to various types of criminal or delinquent behaviors (Costello & Laub, 2020). Researchers in terrorism and violent extremism testify to its importance for studying protective factors in particular (Fisher et al., 2023), with several studies using Hirschi's (1969) theory, along with other models of social control, to organize protective factors and explain why some extremists engage in violence and others do not (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022; Thijs et al., 2022).

Subsequent social control frameworks have also been deemed relevant to the study of violent extremism. Scholars argue that Sampson and Laub's (1993) age-graded developmental model is particularly well-suited for understanding how social control factors may encourage desistance from violent extremism (Fisher et al., 2023). Sampson and Laub (1993) extend Hirschi's (1969) social bond theory by considering the impact of social bonds over the life-course, and how social bonds may mediate the effects of socio-structural background factors (i.e. poverty, disadvantage). In their model, significant life events, such as marriage or employment, are situated as "turning points" that alter an individual's trajectory of behavior. Positive life events, such as getting married, gaining employment, or having children may establish strong prosocial bonds that facilitate desistance from criminal behavior. Scholars studying 'resilience' indicate positive life events bolster individuals' ability to resist extremist beliefs, significantly reducing the likelihood they adopt attitudes supportive of violent extremism (Skoczylis & Andrews, 2022). Alternatively, negative life events, such as divorce, estrangement from family, or loss of job/employment sever prosocial bonds and may heighten an individual's risk for crime and deviance. While such events constitute a weakening of social bonds in Laub and Sampson's (1993) model, others argue these events are forms of strain (Agnew, 1992; 2010). These perspectives are explored in *Section 2.2.4*.

Importantly, Sampson and Laub's (1993) theory does not challenge the core predictions of Hirschi's (1969) model (Costello & Laub, 1993). Rather Sampson and Laub (1993) expand Hirschi's theory beyond the cross-sectional and account for the (a) effects of social bonds over the life-course and (b) the extent to which social-structural context (i.e. macro-level factors) impacts the informal social controls (i.e. micro-level factors) that facilitate conformity to the conventional order (Costello & Laub, 1993). Because this dissertation is focused on micro-level differences, the selection of criminogenic protective factors for this dissertation is informed by both Hirschi (1969) and Sampson and Laub (1993), as well as the empirical findings of extant research reviewed above.

2.2.3. Low Self-Control Theory

Another criminological control perspective is that of low self-control theory, or the *General Theory of Crime* (Gottfredson & Hirschi, 1990). The central construct of this framework is self-control, which refers to an individual's ability to regulate their own behavior and resist engaging in deviant activities when opportunities to do so are presented. It is predicted that those with low self-control are more likely to engage in crime than those with high self-control. Gottfredson and Hirschi (1990) posit that self-control is primarily developed through a process of child-rearing, where parents monitor a child's behavior, recognize deviant behavior, and provide appropriate punishments for such behavior. Through this socialization process, one's level of self-control is theorized to be established by ages 8 to 10 and remain relatively stable throughout their life-course, although empirical research has offered only mixed support for this postulate (Arneklev et al., 1998; Hay & Forrest, 2006; Turner & Piquero, 2002).

Nonetheless, Gottfredson and Hirschi (1990) provide a slate of behavioral tendencies that characterize individuals with low self-control. Foremost, those with low self-control are impulsive and short-sighted – they desire immediate gratification for their actions and hardly consider potential long-term consequences. Those with high self-control are able to adequately regulate their impulses and evaluate the potential ramifications of an action prior to engaging in it. Because of their desire for immediate pleasure, those with low self-control are also more likely to engage in noncriminal activities that evoke pleasurable stimulus, such as smoking, drinking, drug usage, and gambling. This coincides with their proclivity towards risky activities that provoke feelings of excitement or thrill. Additionally, individuals with low self-control prefer physical activities to cognitive ones, and as a result tend to solve problems through physical means as opposed to verbal. Finally, individuals with low self-control are driven by self-interest, and are thus self-centered and indifferent to the pain and suffering of others afflicted by their behaviors (Gottfredson & Hirschi, 1990).

Empirical research indicates low self-control is a strong predictor of crime and analogous behaviors (de Ridder et al., 2012; Pratt & Cullen, 2000; Vazsonyi et al., 2017). However, some scholars have suggested the relationship between self-control and extremism is actually counterintuitive to Gottfredson and Hirschi's (1990) original predictions. In fact, the original authors themselves later argued that crimes such as terrorism or organized crime may actually necessitate high levels of self-control, due to the coordination and planning these crimes take (Gottfredson & Hirschi, 2000). Recent studies have reiterated this possibility, with Denson et al. (2012) claiming, "many premeditated acts of aggression or terrorism require exceptional self-control to resist the urge to retaliate immediately, to plan an attack years in advance, or to force oneself to enact brutal behaviors" (p. 24; see also, Ravenscroft, 2020).

However, while terrorist events are often meticulously planned and prepared for, attacks are frequently spontaneous and the products of opportunity, particularly those committed by far-right extremists (Freilich & Chermak, 2009; Sweeney & Perliger, 2018) and hate-motivated actors (Iganski, 2008). Additionally, extant research suggests there is a relationship between low self-control and radical beliefs (Perry et al., 2018), as well as violent extremist tendencies and intentions (Perry et al., 2018; Rottweiler et al., 2020). In their meta-analysis, Wolfowicz et al.

(2021) found that low self-control, as well as impulsivity and thrill-seeking behaviors, are of the most salient correlates of radical attitudes and behaviors across the literature on putative risk and protective factors to extremism. Supporting these findings, recent research on 125 lone-actor terrorists in the U.S. and Europe found that about 36% exhibited impulsive behaviors, 30% demonstrated thrill-seeking tendencies, and 39% had issues controlling anger (Corner et al., 2021).

Scholars have also suggested self-control may have a moderating effect on the relationship between certain belief systems and potential for violent extremism. In their study, Rottweiler and Gill (2020) found that low self-control moderates the relationship between individuals subscribing to conspiracy-based belief systems and violent extremist intentions. Specifically, the effects of conspiracy beliefs on violent extremist intentions were significantly stronger when the individual possessed low or average levels of self-control. Alternatively, Pauwels and Svennson (2017) explored the moderating effect of extremist belief systems on the direct relationship between low self-control and self-reported political action, which included violence and property damage. These authors found that, even when the intensity of extremist beliefs was high, those with high self-control were less likely to commit extremist actions than those with weaker beliefs. In contrast, when self-control was low, those with a high degree of extremist beliefs were more likely to offend. This interactive relationship held across various ideologies including nationalist/separatist, left-wing, and religious belief systems. Overall, these findings indicate a clear relationship between low self-control and engaging in extremist actions.

However, as described above, not all extremists commit crimes, and of those that do many engage in nonviolent offenses with only a minute faction ascending to violence (McCauley & Moskalenko, 2014). But the extent to which violent and nonviolent criminal extremists differ in their level of self-control is unclear. Gottfredson and Hirschi (1990) would predict no discrepancy between the two groups, so long as all actors are engaging in some form of crime, violent or nonviolent. As they put it, "the seriousness of crime is, in our view, a nontheoretical criterion" (Gottfredson & Hirschi, 1990: 116). Gottfredson and Hirschi (1990) qualify this assertion by calling into question the ability for outcomes to be measured as more or less serious, stating, "the fact of the matter is that the importance or seriousness of a phenomenon is often hard to assess anyway. Individually, serious crimes may tend to produce more injury or loss, but collectively they may produce much less injury or loss than less serious crimes" (p. 116).

Alternatively, other scholars argue violent crimes are markedly more severe than nonviolent offenses. Cohen (1988) calculated the monetary costs associated with various forms of violent and nonviolent crime, estimated by costs related to direct monetary losses, pain and suffering, and risk of death experienced by the victims. Violent crimes, such as kidnapping and rape, were found to be notably more severe than nonviolent crimes in terms of the monetary costs they produce. Moreover, Cushman et al. (2011) contend violent crimes differ from nonviolent crimes in a moral sense, claiming the human aversion to harming other people is largely rooted in morality and empathy for the potential victim(s). Indeed, while nonviolent crimes are not victimless, previous research suggests violent offenders possess lower levels of empathy than nonviolent offenders (Bock & Hosser, 2014; Owen & Fox, 2011). Given Gottfredson and Hirschi (1990) characterize individuals with low self-control as being self-centered, lacking in compassion, and preferring to solve problems with physical means, it may be that violent offenders demonstrate lower self-control than offenders who do not commit violence.

Few studies have tested the efficacy of Gottfredson and Hirschi's (1990) proposition, with some offering support. In their research on youth delinquency in China, Chan and Chui (2017) found low self-control was significantly related to involvement in both violent and nonviolent delinquency. However, when the low self-control indicators were disaggregated, results showed that, though similar in their impulsivity and risk-taking tendencies, youths with a volatile temper were more likely to engage in violent delinquency and prefer cognitive activities. While the latter finding contrasts Gottfredson and Hirschi's (1990) predictions, Chan and Chui's (2017) findings suggest some variation in self-control across violent and nonviolent delinquency.

In all, despite theoretical debate on the applicability of low self-control to the study of terrorism and extremism, prior studies indicate a relationship between self-control and extremist outcomes (Pauwels & Svennson, 2017; Rottweiler & Gill, 2020; Wolfowicz et al., 2021). However, more research is needed to unpack the nature of this relationship, particularly in how it varies across the type of actions extremists engage in.

2.2.4. Strain Theory

A common theme in the radicalization literature is the role of injustices and grievances in facilitating extreme belief systems. Numerous theories of radicalization assert perceiving a social injustice or developing a personal grievance towards a particular issue are often initiators of radicalization processes (Borum, 2003; Hafez & Mullins, 2014; Hamm & Spaaij, 2017; McCauley & Moskalenko, 2008; Moghaddam, 2005; Sageman, 2008). These frameworks suggest perceived injustices and personal grievances may stem from direct experiences of victimization, identifying with a particular collective that has been victimized, or observing an event or issue that is viewed as unfair, unjust, or morally corrupt. In turn, strain theory is a line of criminological thought that explains criminal behavior as a function of individuals coping with negative events or conditions imposed on them (Agnew, 1992; 2010; Merton, 1938). This is largely congruent with the sentiments advanced in extant radicalization scholarship that individuals gravitate towards extremist causes to rectify the personal grievances they hold and the societal injustices they perceive.

The first strain theory was proposed by Robert Merton in 1938, where he conceptualized strain as the disconnect between the economic goals people want to achieve and the means they are equipped with to achieve them. Merton (1938) argued the "American Dream" idealized the goal of economic wealth and status but placed little emphasis on providing members of society with the tools and resources needed to attain those goals. As a result, individuals would cope with this feeling of strain in different ways, which Merton (1938) coined as "adaptations to strain." Those who rejected the prescribed conventional means for achieving economic wealth, rebelled against them and the goals society sets, or retreated from society as a whole, were most likely to engage in criminal behavior (Merton, 1938). Scholars would later build on Merton's strain theory to explain gang formation (Cloward & Ohlin, 2013; Cohen, 1955), but Mertonian strain was seriously criticized by Kornhauser (1978), which led to the development of new models of strain. No development has been more influential than Robert Agnew's (1992) General Strain Theory (GST).

Unlike earlier models of strain which mostly explained variation in crime at the macro-level (Cloward & Ohlin, 2013; Cohen, 1955; Merton, 1938), GST advances a more micro-level focus by revising the notion of strain to generally refer to negative relationships or conditions that produce a negative emotional response – mostly anger – which places pressure on the aggrieved individual to pursue corrective action (Agnew, 1992). Thus, the scope of strain theory is expanded to include conditions beyond the inability to achieve positively valued goals, although these remain relevant and may relate to any goal important to an individual – not just the pursuit of economic success as proposed by Merton (1938), but any goal valued by the individual. Specifically, Agnew (1992) proposes that, in addition to the failure to achieve positively valued goals, two other types of strain exist: (1) removal of positively valued stimuli and (2) presence of noxious stimuli. All three forms of strain produce negative emotions such as anger, frustration, and disappointment that necessitate a response to cope with these conditions. Of those emotions, Agnew (1992) posits anger is the most potent because it reduces inhibitions, encourages action, and produces a yearning for revenge. Criminal behavior, then, is a type of response that attempts to alleviate feelings of strain or seeks revenge on those who are responsible for imposing it (Agnew, 1992).

Much of the early research on GST was largely centered on explaining traditional crime and criminality (Agnew, 2010). However, Robert Agnew argued that GST could be extended to explain involvement in terrorism and violent extremism, which differs from traditional forms of crime in its motivation and impact, so long as the full scope of potential sources of strain are appropriately considered (Agnew, 2010). Notably, Agnew (2010) claims that terrorism is most likely to be born from "collective strains," which are, "strains experienced by the members of an identifiable group or collectivity, most often a race/ethnic, religious, class, political, and/or territorial group" (p. 136). Collective strains are most likely to lead to violent extremism when they are high in magnitude, in that they have a high degree of harm on the collective experiencing them. Moreover, violent extremism is more likely when these strains are long-lasting, widespread, and anticipated to continue in the future and affect a high number of civilians (Agnew, 2010). Additionally, collective strains are potent when they are viewed as unjust, in that they are perceived as undeserved, not contributive to a greater good, and are intentionally imposed by an external agent willfully committing a violation of social norms or values (Agnew, 2010).

These strains, Agnew (2010) argues, lead to terrorism for a number of reasons. First, drawing from GST, collective strains produce strong emotional reactions that drive individual's desire to pursue corrective action. Second, the disconnect between the strained collective and the source of the strain results in few legal coping mechanisms that may produce a productive response, largely due to the embedded power imbalance between the two. Terrorism is then a mechanism for alleviating feelings of strain (i.e. restoring power to the collective), and seeking revenge on the sources of strain.

Third, social controls may be reduced in the strained collective due to the diminished ties between the collective, the source of their strain, and the extent to which terrorism becomes a morally justified action by members of the collective. The latter may essentially neutralize individuals' concerns of being persecuted for their involvement in terrorism by other members of the collective. This goes hand in hand with Agnew's (2010) fourth reason, that collective strains cultivate beliefs that justify or compel terrorism as necessary. Fifth, collective strains foster strong in-group cohesion and prompt a collective response. Finally, collective strains may draw on individual strains, such as personal grievances or the need for belonging, to facilitate involvement in terrorism. Supporting the latter, scholars contend identity, and individuals' desire to attain or reclaim it, is a salient motivator for joining terrorist groups or movements, explained extensively in Kruglanski et al.'s (2014) "Quest for Significance."

A cursory review of the empirical research on terrorism and violent extremism reveals a multitude of criminogenic risk factors that fit Agnew's (2010) conceptualization of strain, including experiencing discrimination (Ghatak et al., 2017; Lyons-Padilla et al., 2015; Piazza, 2011; Victoroff et al., 2012), perceiving social injustices (Borum, 2003; Moghaddam, 2005; Sageman, 2008), relative deprivation (Coccia, 2018; Freilich et al., 2015; Kunst & Obaidi, 2020), childhood abuse or trauma (Barker & Riley, 2022; Simi et al., 2016), or developing personal grievances (Hafez & Mullins, 2014; Hamm & Spaaij, 2017; McCauley & Moskalenko, 2008) to name a few. More recently, empirical studies have offered mixed support for strain theory and its ability to explain violent extremist outcomes (Nivette et al., 2017; Skoczylis & Andrews, 2022).

Nivette et al. (2017) assess the relationship between collective strain and support for violent extremism using a longitudinal survey of (n=1,214) adolescents in Zurich, Germany. Collective strains were operationalized on a macro-level through Agnew's (2010) argument that strains which are high in magnitude, duration, and that are unjust are most likely to lead to violent extremism. Specifically, the authors used the Fragile State Index to measure collective strain, which uses a series of political, economic, and social indicators to create a score that reflects the extent to which a country's residents are exposed to collective strain(s). Because Agnew (2010) notes that collective strain may draw on individual strains, Nivette et al. (2017) also include a composite score for personal strain, which summarized experiences of negative life events. The authors also include measures for moral neutralizations of deviant behaviors, legal cynicism, generalized trust of other societal members, parental involvement in adolescent's life, and competency in coping with negative conflicts. These measures represent the other criminogenic factors that Agnew (1992; 2010) suggests may condition the effect of strain on criminal behavior, such as social controls as well as moral and legal constraints on one's behavior.

Using ordinary least squares regression models, Nivette et al. (2017) found neither collective nor personal strain was significantly related to one's support for violent extremism when other factors were controlled for. Specifically, males and those who expressed moral neutralizations to justify deviant beliefs or behaviors and legal neutralizations to justify law-violation were most likely to support violent extremism. Additionally, in partial support of Agnew's (2010) theory, individuals who demonstrated poor coping skills were more likely to support violent extremism. Nivette et al. (2017) also explored the extent to which collective strains interacted with moral and legal neutralizations, finding only the latter amplified the impact of collective strain on support for violent extremism. Other works have yielded similarly limited support for the role of strain in explaining involvement in violent extremism (Skoczylis & Andrews, 2022).

2.2.5. Social Learning Theory

Broadly, both control and strain perspectives suggest extremist beliefs and behaviors are born from natural responses to stimuli that are ineffectively regulated, either by legal coping mechanisms, social controls, or the ability to exercise self-restraint. However, other scholars posture that extremism is a learned phenomenon, and individuals who adopt extremist beliefs and engage in extremist behaviors do so by way of direct training or tutelage (Akers & Silverman, 2004; Akins & Winfree, 2016). These contentions are grounded in differential association and social learning theories of crime and criminality, which argue associations with deviant peers facilitate a learning process whereby deviant behaviors are observed, committed, and reinforced (Akers & Silverman, 2004).

Social learning theory is composed of four key concepts: differential association, differential reinforcement, definitions, and imitation (Akers, 2011). Differential association involves the extent to which a person interacts with others who espouse differential definitions for norms, values, and laws (Akers, 2011; Sutherland et al., 1992). Within these associations, individuals learn from peers both (1) the techniques for engaging in deviance and (2) the direction of the definitions. Definitions are the learned motives, drives, and rationalizations for certain behaviors that are either favorable or unfavorable toward law violation (Akers, 2011; Matsueda, 1988; Sutherland et al., 1992). Individuals may learn to define laws as necessary to follow, while others justify law-violation under certain circumstances (Matsueda, 1988).

Definitions learned through differential associations are differentially reinforced through an operant conditioning process, whereby a behavior is encouraged through past or anticipated rewards and discouraged through past or anticipated punishments (Akers, 2011; Burgess & Akers, 1966). Finally, imitation is the modelling of others' behavior. Individuals discern which behaviors to model based on who is engaging in the behavior and the observed consequences they receive from doing so (Akers, 2011). In a meta-analysis of studies testing Akers' social learning model, Pratt et al. (2010) found all four of the core dimensions of the theory were significant predictors of crime and deviance.

Scholars have reiterated the relevance of social learning theory to the study of violent extremism (Akers & Silverman, 2004; Akins & Winfree, 2016), with some work indicating individuals with radical peers and family are more likely to be violent extremists than nonviolent criminal extremists (Jasko et al., 2017). Other research supports the applicability of social learning factors particularly in virtual spaces (Hawdon & Costello, 2020; Wolfowicz & Perry et al., 2021). Hawdon and Costello (2020) assess the dimensions of social learning theory within the context online hate content production, which often serves as one's initial exploration into extreme belief systems (Holt et al., 2017; Turner et al., 2022). Surveying a nationally representative sample of (n=997) adults in the United States, the authors found partial support for the dimensions of social learning theory. Those who held pro-violence and pro-hate definitions were significantly more likely to produce online hate content, as well as those who willfully associate in virtual spaces with others who produce similar content. However, measures for positive reinforcement and imitation were unrelated to the production of online hate content.

In another study, Wolfowicz and Perry et al. (2021) compared Facebook profiles for violent and nonviolent extremists through a social learning framework. The included violent extremists (N=48) were individuals who had carried out lone-actor attacks in Israel between 2014 and 2018 who had public Facebook profiles. Nonviolent extremists (or 'nonviolent radicals') (N=96) were individuals who had at least one radical post but were not known to be involved in a terrorist attack and were matched with the violent extremists based on sex, age, and geographic characteristics.

The authors found all four concepts of social learning theory were significant predictors of violent extremism. Specifically, violent extremists were significantly more likely to post about a terrorist attack that a Facebook friend had committed than nonviolent extremists were, indicating a higher degree of differential association. Further, relating to definitions, violent extremists had a higher ratio of radical posts compared to nonradical posts than nonviolent extremists did. Violent extremists were also more likely to have their posts reinforced by way of likes and shares, and they more frequently made shared posts as opposed to originally authored posts, suggesting a higher degree of imitation. In all, Wolfowicz and Perry et al.'s (2021) findings indicate a differential learning process for violent and nonviolent extremists.

2.2.6. Empirical Research Leveraging Multifactor Approaches to Study Violent Extremism

Taken together, the preceding sections highlight the numerous criminogenic risk and protective factors, drawn from social bond, low self-control, strain, and social learning perspectives, that empirical research has linked to violent extremism. Based on the variation in the theoretical origins of these factors, an exclusive approach that only considers factors from a single criminological paradigm would ultimately be insufficient in explaining involvement in violent extremism (Becker, 2021; De Waele & Pauwels, 2014; Holt et al., 2017; LaFree et al., 2018; Nivette et al., 2017; Pritchett & Moeller, 2022; Pauwels & Schils, 2016; Schils & Pauwels, 2016). Recently, studies have increasingly leveraged multifactor approaches to build a more comprehensive understanding of the criminogenic factors that distinguish extremists who engage in violent crime from those involved in nonviolent crime or no crime at all.

2.2.6.1. Social Learning and Social Bond

Perhaps the most popular combination of factors in this body of work is that of social learning and social bond variables. This makes sense, as Akers (2001) notes that in the process of learning deviant definitions of behaviors, individuals may not necessarily adopt intense definitions that motivate the behavior, but rather hold relatively weak definitions favoring law-abidance. This results in a lack of moral restraint to resist deviating. Criminologists have even proposed integrated models that demonstrate the reciprocal interaction between social learning and social bond variables (Thornberry, 1987). In the context of extremism, Holt et al. (2017) state, "The acceptance of a radical ideology is a learned process where individuals accept increasingly extreme ideas that justify violent behavior. At the same time, individuals with few pro-social bonds may be more likely to be exposed to radical movements at the outset" (p. 129). Thus, scholars have investigated the extent to which social learning and social bond factors work in tandem to condition one's likelihood of engaging in violent extremism.

Qualitatively, Holt et al. (2017) analyzed the case histories of four extremists, two violent and two nonviolent criminal extremists, to explore the role of social control and social learning in facilitating the radicalization process. The authors found that both violent extremists and one nonviolent criminal extremist had challenges forming pro-social ties to others. These weakened pro-social bonds may have facilitated their exposure to radical ideals, as three of the four cases were also radicalized through social ties with other extremists. Alternatively, Holt et al. (2018) found limited support for the relevance of social learning factors. Though differential association and the transference of definitions were observed, imitation and differential reinforcement was less prevalent in the learning process.

Relatedly, multiple studies have leveraged quantitative analyses to distinguish violent and nonviolent extremists on the basis of social learning and social bond variables (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022). These studies use data from the Profiles of Individual Radicalization in the United States (PIRUS) dataset, and thus operationalize violent and nonviolent extremism through Jensen et al.'s (2016) criteria. To be classified as a violent extremist, individuals had to be involved or conspired in a plot that resulted in casualties or intended to result in casualties. Nonviolent extremists, alternatively, may be involved in extremist activities but do not possess the motivation or capacity to commit violence or be involved in a plot that aims to do so (Jensen et al., 2016). Nonviolent activities may include being a member of a known extremist group, receiving training from terrorist organization, or being involved in operational plots that were not intended to cause casualties, such as property destruction or vandalism. Necessarily, these studies collapse nonoffending and nonviolent criminal extremism into a single category to create a nonviolent comparison group – the limitations of which are discussed in Section 2.3.1. Because of the dichotomy between violent and nonviolent extremists, these studies all used binary logistic regression as their analytic model (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022).

Offering limited support for social bonds, LaFree et al. (2018) found that extremists who had a more stable employment history were less likely to be violent, but education, marital status, and military experience were all unrelated to involvement in violent extremism. In contrast, more recent findings suggest violent and nonviolent extremists do not significantly differ in their employment history (Becker, 2021; Pritchett & Moeller, 2022), nor the amount of unstructured time they have (Becker, 2021). Rather, Becker (2021) finds that violent extremists are less likely to be married than nonviolent extremists and more likely to have stronger radical beliefs – indicative of a weakened belief in the conventional order. Pritchett and Moeller (2022) argue a prior criminal history is a relevant indicator for one's belief in conventional laws, as previous violations of the rules may suggest a weak belief in abiding by legal and moral codes. Concordantly, studies indicate violent extremists are more likely to have a violent criminal record than nonviolent extremists (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022; Thijs et al., 2022).

Relating to social learning, these studies have found that extremists with radical peers were more likely to be violent (LaFree et al., 2018; Pritchett & Moeller, 2022). Further Becker (2021) found that those who were involved in a formal or informal extremist group or member of a gang were more likely to be violent. Additionally, while LaFree et al. (2018) did not find the presence of radical family members to be a significant correlate of violent extremism, Pritchett and Moeller (2022) found that extremists with a radical family were more likely to be violent than nonviolent.

2.2.6.2. Low Self-Control and Social Learning

Though low self-control theory and social learning theory differ in their assumptions of human behavior and propositions on the causes of criminality, the notion that they are diametrically opposed frameworks is not theoretically candid. Indeed, Akers (1991) notes that both the *General Theory of Crime* and social learning theory posit self-control as being formed through a process of negative reinforcement and punishment, suggesting a congruency in their proposed socialization processes (Akers, 2011; Gottfredson & Hirschi, 1990). Further, Akers (2001) describes the ability for low self-control to condition social learning processes, noting that behaviors may be self-reinforced through a process of rewarding or punishing personal behavior, thus exercising or alleviating one's self-control.

In their text, Gottfredson and Hirschi (1990) attest that individuals with low self-control will likely associate with one another due to mutual interests in risk-taking activities. Moreover, the authors contend that peer groups may facilitate delinquency in tandem with low self-control by way of increasing opportunities to engage in deviant acts. Theoretically, then, the criminogenic risk and protective factors drawn from both low self-control theory and social learning theory are compatible. Specifically, individuals may demonstrate low self-control and/or associate with deviant peers, but the risk for criminal behavior is highest when both factors are present and potent. A host of studies have found support for the interactive properties of low self-control and deviant peer associations in both off- and online contexts (e.g. Chapple, 2005; Higgins & Makin, 2004; Holt et al., 2012), though some offer more mixed findings, particularly when other social learning factors such as reinforcements or definitions are considered (Nodeland & Morris, 2020; Wolfe & Higgins, 2009).

Adjacent to extremism, Turner et al. (2022) found that low self-control and associating with peers involved in online hate-related activities significantly predicted engagement with online hate content in a sample of (n=989) Australian adolescents. Specifically, results from a series of binary logistic regression models reported youths who associated with deviant peers were more likely to both see and share online hate content. Low self-control, alternatively, was only significantly related to youth's sharing of online hate content when peer associations were accounted for. These findings suggest that having peers involved in online hate enhanced youths' likelihood to be exposed to the content, thus increasing opportunity to engage with the material. Consequently, both low self-control and peer associations simultaneously influenced one's decision to engage with and share the hate content. It is worth noting that these results also accounted for other opportunity factors, such as activeness in online spaces and activities (Turner et al., 2022). Similar studies have offered less supportive results for self-control in the production of online hate content, specifically when measures other social learning factors like differential reinforcement and definitions were included (Bernatsky et al., 2022).

Scholars have also leaned on situational action theory (SAT) as a framework to assess the interaction between self-control and association with deviant peers. While a review of SAT is beyond the scope of this dissertation, a core premise of the model is that crime is a function of an individual's propensity for criminality and exposure to criminogenic settings (Schils & Pauwels, 2014; Wikström, 2017; Wikström & Bouhana, 2017). Propensity for criminality is conditioned by (1) an individual's level of self-control and (2) personal morality, or the extent to which a person views laws as morally acceptable to violate (Schils & Pauwels, 2014; Wikström, 2017). The latter of which may be comparable to the conceptualization of definitions in the social learning framework (Akers, 2001). Criminogenic settings are places or contexts that create opportunities for crime, a function that deviant peers have been postured as facilitating (Gottfredson & Hirschi, 1990; Wikström, 2017). Scholars contend the interaction between these two elements can help explain involvement in violent extremism (Schils & Pauwels, 2014; Perry et al., 2018).

Perry et al. (2018) assessed this interaction by surveying a sample of (n=684) young adults in the United Kingdom. The authors examined how general extremist beliefs and potential for violent extremism were predicted by measures of poor self-control, morality, and exposure to criminogenic settings. General extremist beliefs were captured through participant voting patterns, and potential for violent extremism was measured by considering those who held extreme political beliefs and who had self-reported involvement in violent incidents within the past year as possessing a potential for violent extremism. Results from their multinomial logistic regression model indicated that individuals with low self-control and weak morality were significantly associated with a higher likelihood of demonstrating general political extremism and violent extremist tendencies. The authors then used structural equation modelling to consider the influence of criminogenic settings and the relationships between predictor variables. Exposure to criminogenic settings was significantly related to potential for violent extremism but not general political extremism – this makes sense given holding extremist beliefs is not criminal. However, their findings indicated individuals with weak morality were also more likely to have low self-control and higher exposure to criminogenic settings, suggesting an interaction between criminal propensity and criminogenic settings (Perry et al., 2018).

Schils and Pauwels (2014) similarly examined this interaction in explaining self-reported political violence. Specifically, the authors assessed exposure to extremist settings through a combinative measure of whether individuals directly sought contact with violent extremists online or were passively exposed to extremist content online. Violent extremist propensity was indicated by measures of low self-control and personal morality. Their findings support an interactive relationship between the two concepts, with violent extremist propensity moderating the impact of exposure to violent extremist settings on self-reported political violence. In other words, individuals with a higher violent extremist propensity, thus lower self-control and morality, were significantly more likely to be exposed to violent extremist settings. Additionally, those with a high propensity and exposure demonstrated the highest likelihood of engaging in violent extremism. This relationship held across subgroups defined by gender and immigrant status (Schils & Pauwels, 2014). Ultimately, this body of work indicates a clear connection between the criminogenic factors drawn from both low self-control and social learning perspectives, particularly in the context of violent extremism.

2.2.6.3. Social Bond and Strain

The compatibility of strain and social control perspectives is directly situated in Agnew's GST (1992; 2009). As aforementioned in Agnew's *General Strain Theory of Terrorism*, strains are theorized to reduce social controls that afford legal and peaceful coping strategies (Agnew, 2010). In his words, "[Strains] rob those in the strained collectivity of valued possessions, as well as hope for the future, leaving them with little to lose if they engage in terrorism. They weaken the belief that terrorism is wrong…and they reduce the likelihood that members of the strained collectivity will sanction terrorists…" (p. 141). In this way, feelings of strain reduce social bonds to conventional, prosocial institutions and leave their behavior unrestrained by the normative laws, norms, and values that conventionally regulate one's behavior. Put simply, of those who experience strain, those with salient social bonds will be less inclined to pursue extremist crime or violence as a means of coping because their behavior is being controlled by prosocial forces (Agnew, 2010).

Limited scholarship has explicitly tested the efficacy of this theoretical combination. Skoczylis and Andrews (2022) consider how strain and resilience, or factors that facilitate resistance to extremism, influence support for far-right extremism. Participants of an online survey in the U.K. who reported right-leaning political views (n=1,138) were asked to rate the impact of different life events, with negative life events indicating strain and positive life events indicating resilience. This operationalization of resilience may be congruent to Laub and Sampson's (1993) age-graded social bond model, where positive life events encourage desistance from crime. Estimating binomial logistic regression models, Skoczylis and Andrews (2022) found resilience was a stronger predictor of support for violent extremism than strain, which demonstrated an insignificant relationship. Specifically, individuals who had less positive life events were more likely to support extremism, suggesting "when there is little tying someone to the wider social body, it is then that they begin to develop extremist attitudes" (Skoczylis & Andrews, 2022: 160).

2.2.6.4. Expanded Multifactor Approaches

Albeit few, some studies have utilized a more comprehensive scope of criminogenic risk and protective factors to explain violent extremism (De Waele & Pauwels, 2014; Pauwels & Schils, 2016; Schils & Pauwels, 2016). Using survey data on (n=2,879) adolescents in Belgium, De Waele and Pauwels (2014) draw on measures of strain, low self-control, social bond, and social learning perspectives in one of the first studies to use criminogenic factors from multiple criminological theories to explain politically motivated vandalism and violence. Strain was indicated by whether individuals reported perceived personal discrimination, relating to their own situation, or perceived group discrimination, relating to their respective identity group's situation. Social bond was measured through a social integration scale, which indicated an individual's attachment to parents, parental monitoring, academic orientation, and school integration. It is worth noting that De Waele and Pauwels (2014) also consider measures related to procedural justice and the extent to which respondents trust the police and view their authority as legitimate. While such constructs are drawn from procedural justice theory, they similarly indicate the extent to which social bonds to conventional law and order motivate rule-abidance (Tyler, 2006). Self-control was indicated by two scales drawn from the Grasmick et al. (1993) self-control scale, namely impulsiveness and thrill-seeking tendencies. Finally, peer influence was indicated by measures capturing racist or delinquent behavior of peers.

De Waele and Pauwels (2014) estimate binomial logistic regression models to assess the direct effects between each criminogenic factor and youths' involvement in self-reported political vandalism and violence, which can be respectively interpreted as involvement in nonviolent criminal and violent extremism. Social bond theory was supported in relation to both outcomes of interest, as individuals who were less socially integrated were more likely to self-report acts of politically motivated violence and vandalism. Similarly, while perceptions of police procedural justice demonstrated insignificant effects, those with more favorable perceptions of police legitimacy were less likely to be involved in vandalism or violence, indicating the relevance of salient bonds to conventional law and order.

Strain theory was partially supported, as both perceived personal and group discrimination was significantly related to politically motivated vandalism. Individuals involved in politically motivated violence, however, were only more likely to perceive discrimination among their identity group. The two self-control measures were differentially relevant. Those involved in politically motivated vandalism demonstrated higher levels of thrill-seeking behavior but not impulsivity, and those involved in politically motivated violence scored significantly higher on impulsivity but not thrill-seeking tendencies. Finally, associated with delinquent peers was a significant predictor for both outcomes, but holding attitudes favorable towards racism (i.e.

definitions) was not significantly related to either vandalism or violence, lending partial support for social learning theory.

Using the same data and measures, Pauwels and Schils (2016) conduct a follow-up study to additionally consider how exposure to extremist content on new social media (ENSM) may relate to involvement in politically motivated vandalism and violence. This exposure, they argue, can be functionally understood as facilitating the social learning process. The authors test the key elements of social learning theory and utilize measures for other criminogenic correlates of extremism as control variables, including social bond, low self-control, and strain perspectives, all of which are identically operationalized in De Waele and Pauwels' (2014) study.

Estimating binary logistic regression models, Pauwels and Schils (2016) found that individuals who were actively contacting extremists online, communicating about violent extremism online, and highly exposed to ENSM were more likely to commit politically motivated property crimes. Mirroring De Waele and Pauwels (2014) findings, those who perceived group discrimination demonstrated higher levels of thrill-seeking behavior, and associating with peers involved in delinquency were significantly related to politically motivated property crimes. Alternatively, active contact with other extremists online did not significantly predict involvement in violent extremism, though those who communicated about violent extremism online and were more highly exposed to ENSM were more likely to self-report political violence. Additionally, unfavorable perceptions of police legitimacy, higher levels of impulsivity, and associating with racist or delinquent peers was significantly related to politically motivated violence. Taken together, these studies not only demonstrate the utility of an multifactor approach, and highlight the criminogenic differences between nonviolent criminal and violent extremists (De Waele & Pauwels, 2014; Pauwels & Schils, 2016).

Finally, using the same data and measures as previous studies (De Waele & Pauwels, 2014; Pauwels & Schils, 2016), Schils and Pauwels (2016) propose a fully integrated model of these criminogenic mechanisms through the aforementioned SAT framework. Leveraging a structural equation model, Schils and Pauwels (2016) identify numerous direct and indirect relationships between criminogenic factors and involvement in politically motivated violence. It is important to note that, contrary to prior studies (De Waele & Pauwels, 2014; Pauwels & Schils, 2016), Schils and Pauwels (2016) expanded the outcome to include both politically and religiously motivated crime, and combined property crime and violent crime into a single measure of political/religious violence. This conflation of violent and nonviolent criminal extremism ultimately limits the interpretability of the findings, as these categories are conceptually distinct forms of extremist action (Jensen et al., 2016; McCauley & Moskalenko, 2014; 2017). Nonetheless, findings reveal low self-control mediates the relationship between perceived injustice (strain), perceived alienation (strain), and social integration (social bond) and political/religious violence. Additionally, low self-control held an indirect relationship with political/religious violence through active exposure to violent extremism (social learning), reiterating the complementary properties of those criminogenic factors.

2.2.7. Summary

Two primary takeaways can be derived from the literature reviewed in this section. First, numerous criminogenic risk and protective factors, drawn from social bond, low self-control, strain, and social learning perspectives are empirically supported correlates of violent extremism. Indeed, while findings are relatively inconsistent for some factors, it is evident that criminogenic factors have a salient role to play in explaining extremist crime and violence (Wolfowicz et al., 2021). Second, theorists and researchers alike attest to the complementary properties of these criminogenic factors despite their theoretical distinctions. Concordantly, several empirical studies have demonstrated the potential for multi-factor approaches to explain involvement in violent extremism more holistically. To build on this body of work, the next section highlights two methodological gaps in the research that, if addressed, can help facilitate a more nuanced investigation on the criminology of violent extremism and inform counterefforts at the secondary level of prevention.

2.3. Research Design in Assessing Criminogenic Risk and Protective Factors

The preceding sections highlighted the findings of many empirical studies leveraging multiple criminogenic risk and protective factors to explain involvement in violent extremism (Becker, 2021; De Waele & Pauwels, 2014; LaFree et al., 2018; Pauwels & Schils, 2016; Pritchett & Moeller, 2022; Schils & Pauwels, 2016). However, the research designs previously employed to study the criminogenic differences between violent extremists and other extremists have been limited in two primary ways. First, studies have yet to compare violent extremists and nonviolent criminal extremists – both of which commit criminal acts to advance their cause – to a sample of nonoffending extremists, who hold extremist beliefs but act within the parameters of the law. Second, prior studies have mostly assessed the independent effects of criminogenic risk and protective factors in their relationship to violent extremism. Such approaches are unable to adequately capture the equifinality and multifinality of extremist violence.

The following sections extrapolate these points of improvement. In all, this dissertation asserts that a more complete understanding of violent extremism can be attained by (1) appropriately distinguishing between nonviolent criminal and nonoffending extremist comparison groups and (2) using latent class analysis as an analytic tool to explore distinct configurations of criminogenic factors and their collective relationship with involvement in violent extremism.

2.3.1. Comparison Groups

The literature reviewed in *Section 2.2.* examined numerous studies using a variety of dependent variables to investigate the relationship between criminogenic factors and extremist-related outcomes. Some studies assessed legal behaviors that are ancillary to violent extremism, such as producing or consuming online hate content (Bernatsky et al., 2022; Hawdon & Costello, 2019; Turner et al., 2022), or support for extremist causes (Nivette et al., 2017; Skocyzlis & Andrews, 2022). Other studies have developed proxy measures for violent extremist tendencies (Perry et al., 2018) or intentions (Rottweiler & Gill, 2020; Rottweiler et al., 2022). However, attitudes, beliefs, and intentions often do not materialize into observable behavior (McCauley & Moskalenko, 2014; 2017; Rottweiler et al., 2022). Thus, conclusions from these studies, while important, are limited by this disconnect. More assessments are needed on samples of extremists who actually engaged in ideologically motivated actions to explain the connection between criminogenic factors and extremist behavior.

With that said, comparison and control groups are necessary for advancing causal explanations of violent extremism (Freilich et al., 2015; Victoroff, 2005). Because the goal of secondary prevention efforts is to identify those most at-risk of mobilizing to violence in a larger pool of extremists, it follows that we must be able to discern the factors that uniquely characterize violent extremists and distinguish them from other extremists. Without an appropriate control group to compare violent extremists to, however, no meaningful conclusions can be made on the salience of risk and protective factors in encouraging or inhibiting extremist crime and violence (Fisher et al., 2023; Freilich et al., 2015; Victoroff, 2005).

The question scholars have posed, then, is *who should be included in a comparison group* (Freilich et al., 2015; Freilich & LaFree, 2015; Moskalenko et al., 2023)? The answer to this question is largely tailored to the research objective at hand, as empirical studies have leveraged a number of different approaches (Moskalenko et al., 2023). Some researchers who aim to understand how terrorism differs from other types of crime have opted for comparisons between terrorists and non-political criminals engaged in conventional crimes (i.e., homicide; Gruenewald, 2011; Gruenewald & Pridemore, 2012; Smith & Damphousse, 1996), gang members (Pyrooz et al., 2018), or perpetrators of other acts of targeted violence (Capellan, 2015; Gill et al., 2021; Lankford, 2013; McCauley et al., 2013). Such comparisons are useful for discerning the parallels or divergences between terrorists and other criminal offenders.

Moreover, research has examined self-reported political action (De Waele & Pauwels, 2014; Pauwels & Schils, 2016; Schils & Pauwels, 2014; Schils & Pauwels, 2016) but political action in these studies constitutes both violent and nonviolent actions, and the comparison group – those who did not self-report involvement in political action – includes people who do not have extremist beliefs. This is important, as differentiating violent extremists from other extremists necessarily requires an *extremist* comparison group. To address this line of inquiry, scholars have compared violent extremists to nonviolent criminal extremists, such as those involved in material support or financial crimes (Harms, 2017; Jasko et al., 2017; Kerodal et al., 2016). Importantly, the development of the PIRUS dataset has facilitated a host of comparisons between violent extremists and nonviolent extremists (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022). However, these comparisons are a point of contention, as the structure of the PIRUS violent/nonviolent measure conflates nonviolent criminal extremism and nonoffending extremism. Specifically, Jensen et al. (2016) assert that nonviolent extremists in PIRUS need only meet one of the following criteria (pp. 31-32):

- "Are not charged with any violent criminal act but were known members of an extremist group
- Actively participated in operational actions/plots not intending to result in casualties (e.g. property destruction, vandalism)
- Engaged in only legal/aboveground activism in support of extremism ideology
- Participated in armed standoffs that were defused without injury
- Received "terrorist" training but did not act on it
- Incited others to violence but no direct action themselves
- Threatened but undertook no direct action or operational progress toward a plot
- Involved in a plot targeting a building (arson/explosives) that did not intend to produce any casualties
- Possessed illegal weapons but no operational plans for violence."

Appraising these criteria, it is clear that both nonviolent criminal extremists, who commit illegal actions to advance their cause, and nonoffending extremists, who are involved in only legal actions, are being collectively categorized into a single "nonviolent" classification. As a result, findings from studies that examined the criminogenic differences between violent and nonviolent extremists using PIRUS data are limited by a lack of conceptual clarity in the dependent variable (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022). This is not to say that the findings from these studies are wholly invalid – on the contrary, they provide important insights into the criminogenic factors that are more strongly associated with violent extremism. Rather, it is to say that because secondary prevention efforts are grounded in the premise that some extremists will commit crime and violence to forward their cause and others will not, empirical studies applying criminological theory to explain extremists' differential criminality must leverage valid comparison groups that acutely reflect this distinction.

The remedy for this shortcoming, then, is to distinctly operationalize nonviolent criminal and nonoffending extremists into separate comparison groups. Indeed, while nonviolent criminal extremists have been previously compared to violent extremists (Harms, 2017; Jasko et al., 2017;

Kerodal et al., 2016), scholars have increasingly called for the use of noncriminal extremist comparison groups to study the criminology of violent extremism (Freilich et al., 2015; Monohan, 2012; Moskalenko et al., 2023). Some work has offered preliminary guidance in this area. Barlett and Miller (2012) interviewed 61 “terrorists,” or individuals who were involved in violent jihadist extremist cells or plots in Europe and Canada, as well as 28 “radicals,” which were people who “merely expresses significant dissent from prevailing norms” (p. 3). They also interviewed 70 young Canadian Muslims to understand differences between terrorists, radicals, and the Muslim community more broadly. The authors used an inductive qualitative analysis, finding radicals were involved in political protests more often than terrorists, indicating more frequent use of legal channels to pursue corrective action. Radicals also had slightly higher levels of education and were more likely to be employed. The two groups exhibited similar feelings of discrimination, desires for identity, and religiosity. Additionally, radicals frequently expressed that terrorists wholly lacked critical thinking and analysis of the Qur’an and Muslim faith (Barlett & Miller, 2012).

In another qualitative study, Dornschneider (2016) conducted interviews with formerly violent and nonviolent extremists to construct cognitive maps of individual beliefs and trace chains of beliefs to one’s decision to engage in violence. The violent extremists were (n=7) former members of al-Jama’at al-Islamiyya and al-Jihad in Egypt, or (n=6) members of the Red Army Faction and Bewegung 2. Juni in Germany. The nonviolent extremists were (n=8) members of the Muslim Brotherhood in Egypt or (n=6) members of the Socialist German Student Union and Kommune 1 in Germany. Overall, her analysis indicates that the motivations of violent and nonviolent extremists are similar and both act in perceived self-defense based on negative beliefs about the state – namely that the state is aggressive.

As a whole, these studies demonstrate the utility of leveraging nonoffending extremist comparison groups in the study of violent extremism. Not all extremists will act violently or illegally to advance their cause – but to discern the ones that are most at risk for doing so, we must understand how they differ from those who share their beliefs but do not take the same actions. Importantly, this body of work has yet to compare violent extremists to nonoffending extremists in a U.S. context. Additionally, these studies are primarily qualitative in nature which, while undoubtedly valuable, cannot facilitate evidence-based policy on its own. Rigorous quantitative analyses can build on this literature. Specifically relating to criminogenic risk and protective factors, such analyses will help produce a better understanding of which factors, or patterns of factors, may characterize violent extremists within the larger pool of nonviolent and noncriminal extremists. This dissertation advances the field of research by (a) employing a nonoffending extremist comparison group that only includes individuals involved in extremism in the U.S., and (b) uses a robust open-source dataset to conduct quantitative analyses comparing violent extremists to nonviolent and noncriminal extremists.

2.3.2. The Utility of Latent Class Analysis

There is no single risk or protective factor that can unilaterally explain involvement in violent extremism (Gill, 2015; Wolfowicz et al., 2021), nor is there a uniform profile or pathway that leads to involvement in violent extremism (De Roy van Zujidewijn & Bakker, 2016; Gill et al., 2014; Jensen et al., 2021; McCauley & Moskalenko, 2014). Rather, there are a variety of pathways, characterized by various combinations of risk and protective factors, that may ultimately increase one's risk for engaging in extremist violence. This is the principle of *equifinality*, where "individuals with very different initial states can experience different processes and still end at the same end outcome of violent extremism" (Gill et al., 2021; p. 66)

Likewise, it may be that the same pathways lead to differential outcomes, as some may become involved in violent extremism and others do not despite experiencing similar risk and protective factors – this is *multifinality* (Gill et al., 2021). Essentially, the principles of equifinality and multifinality establish that there are a variety of possible patterns of risk and protective factors that could lead one to engage in extremist crime and violence, but no single pattern will perfectly predict involvement in violent extremism. Analytically, then, studying risk and protective factors necessitates an approach that can capture the equifinality and multifinality of violent extremism.

Prior approaches leveraging multifactor approaches with criminogenic variables are limited in their capacity to account for equifinality and multifinality. Though some scholars have employed advanced quantitative analyses that estimate covariation across independent variables (i.e. structural equation modelling; Schils & Pauwels, 2016), most studies have opted for a 'garbage-can' or 'kitchen-sink' approach (De Waele & Pauwels, 2012; Becker, 2021; LaFree et al., 2018; Nivette et al., 2017; Pauwels & Schils, 2016; Pritchett & Moeller, 2021; Thijs et al., 2022; Turner et al., 2022). This technique involves "throwing a whole bunch of variables into one gigantic regression stew" but has been critiqued for its tendency to lead to model misspecification, where coefficients are biased by the interrelationships among explanatory variables (Achen, 2005; Bernard & Snipes, 1996: 303). Further, multivariate regression models can only speak to the independent net-effects of a specific variable when other variables are accounted for. Independent effects may be useful for determining which single factor is most influential, but these effects do not represent the nature of risk and protective factors. These factors are accumulative, interacting with one another to increase or decrease one's risk for offending (Wolfowicz et al., 2021) – a condition that independent effects alone cannot speak to. Interaction terms may be used to estimate how the effect of an independent variable on a dependent variable may be conditioned by a different independent variable (Ai & Norton, 2003), but interpretation is still limited to the interaction between those two specified independent variables as opposed to a collective relationship between a combination of multiple risk and protective factors and a dependent variable.

Indeed, capturing the equifinal and multifinal nature of extremist violence requires analyses that extend beyond single effects and model how risk and protective factors co-occur with one another to form distinct configurations that collectively influence one's likelihood of engaging in violent extremism (Clemmow et al., 2022). Specifically, Gill (2015) calls for more attention to be directed toward the clustering of factors and the potential multiplicative effects that certain combinations of factors may produce. Researchers have increasingly utilized novel methodological approaches for modeling these interrelationships, including cluster analysis (Clemmow et al., 2020; Clemmow & Gill et al., 2022), multidimensional scaling (Goodwill & Meloy, 2019; Horgan et al., 2018), and psychometric network modelling (Clemmow & Bouhana et al., 2022). However, latent class analysis (hereafter, LCA) has emerged as an especially promising statistical procedure for such an endeavor.

LCA is a form of finite mixture modelling that is used to identify unobserved latent subgroups in observed data (Nylund-Gibson & Choi, 2018; Weller et al., 2020). Unlike traditional cluster analysis, which examines case similarity and assumes the cases with the most similar scores belong to the same cluster, LCA is a model-based, person-centered approach that estimates "classes" of individuals based on individual responses to a set of indicator variables (a.k.a. "manifest" variables) (Nylund-Gibson & Choi, 2018; Weller et al., 2020). These classes are theorized to represent the latent subgroups that underpin the observed data and influence the patterns that emerge. Further, LCA is a probabilistic approach in that it calculates the probability an individual in a given class will demonstrate a particular factor, and also estimates an individual's probability of class membership as opposed to making crude hard-and-fast determinations of class assignment, contrary to cluster analysis (Nylund-Gibson & Choi, 2018; Weller et al., 2020).

Moreover, LCA differs from other nonhierarchical cluster analyses in that it does not assume normality or linearity in the data. As a result, LCA is particularly well-equipped to assess non-normal or discrete distributions, with binary indicator variables being most commonly used (Fox & Escue, 2022; Nylund-Gibson & Choi, 2018). This is especially beneficial in the study of risk and protective factors to extremism, as factors are often assessed based on their presence or absence (Corner et al., 2021; Gill et al., 2014; Wolfowicz et al., 2021) Further, and in contrast to other classification techniques, the model-based approach of LCA permits the use of several model-fit criteria to determine the class solution best fit for the observed data (Fox & Escue, 2022; Nylund-Gibson & Choi, 2018). Finally, the estimated classes can be leveraged as predictor variables for distal outcomes (Bakk et al., 2013; Nylund-Gibson & Choi, 2018). In this way, the relationship between distinct patterns of criminogenic risk and protective factors and types of extremist actions (i.e. violent, nonviolent criminal, nonoffending) can be empirically assessed.

Extant research suggests LCA is superior to cluster analysis and other classification techniques, specifically in its ability to handle crime data (Cleland et al., 2000; DiStefano & Kamphaus, 2006; Fox & Escue, 2022). As Fox and Escue (2022) conclude, “LCA produces the most objective, valid, and reliable results for use in research and practice,” largely based on the robustness of its objective model-fit criteria and capacity to balance parsimony and accuracy in its class solution (p. 54). This claim is substantiated by the growing body of research applying LCA in criminal justice contexts. For example, recent studies have used LCA to estimate distinct classes of mentally ill offenders (Sea et al., 2020), delinquent runaways (Jeanis et al., 2019), rape offenders (Khoshnood et al., 2021a), firearm-related homicide offenders (Khoshnood et al., 2021b), website defacers (Burruss et al., 2021), and mass shooters (Greene-Colozzi, 2022). Moreover, while some recent work has similarly used LCA to identify patterns of factors associated with support for extremism among the general population (Al Baghal, 2014; Clemmow et al., 2023; Schumann et al., 2024), other studies have utilized LCA as a tool for assessing the heterogenous manifestation of risk and protective factors within samples violent extremists (Candilis et al., 2021; Clemmow et al., 2022; Thijssen et al., 2023).

Relating to those studies that examined samples of extremists, Candalis et al. (2021) conducted a survey of 160 convicted terrorists in Baghdad prison in Iraq to assess sociodemographic, familial, motivational, attitudinal, and psychological characteristics. Their LCA revealed three distinct classes of offenders, described as *non-religious nationalists*, *oppressed instrumentalists*, and *aggrieved antisocials*. The three classes were fairly similar in sociodemographic composition, although the *aggrieved antisocials* were more likely to be unmarried than the other two classes. The *non-religious nationalists* demonstrated the lowest probability for the majority of risk factors assessed. Specifically, they reported a low probability of viewing terrorism as an appropriate response to oppression or poverty or justify terrorism against civilians. They were mostly motivated by reverence for their country, had a low probability of experiencing a mental disorder, and scored low on religious commitment.

While the *oppressed instrumentalists* class indicated similarly low probabilities of experiencing a mental disorder, they scored higher on religiosity and were more likely to view terrorism as justified against innocent civilians and an appropriate response to oppression and poverty. *Oppressed instrumentalists* also had a higher probability of being motivated by personal or group causes. Finally, the smallest class was the *aggrieved antisocials*, who reported higher probabilities of having a familial grievance (i.e. family member murdered/charged with terrorism) and having mental disorders. Like the *oppressed instrumentalists*, *aggrieved antisocials* had a high probability of viewing terrorism as a justified response to oppression and poverty and legitimize terrorism against innocent civilians. They were most likely to be motivated by country and group benefit.

In Clemmow et al.'s (2022) study, they use SPSS's Two-Step cluster analysis,[2] an approach similar to LCA in its probabilistic estimation of class solutions and use of model-fit criteria, on a sample of 68 lone-actor terrorists and 115 mass murderers, identifying three clusters of propensity to extremism based on risk and protective factors.[3] Individuals in the *criminal* cluster all had previous criminal convictions, with many being previously imprisoned and arrested as a juvenile. Over half of these individuals experienced chronic stress, and just over 12% had attended university. The *stable* cluster, alternatively, demonstrated fewer criminal tendencies and no chronic stress, with only 10% being unemployed and almost 30% having prior military experience. Finally, the *unstable* cluster rarely had prior criminal convictions, but experienced chronic stress and mental illness much more frequently than the other clusters. Additionally, 25% of individuals in the *unstable* cluster were rejected from the military. In addition to identifying clusters of extremist propensity, Clemmow et al. (2022) compared class membership proportions between lone-actor terrorists and mass murderers. These authors found that nearly half of the lone-actor terrorists in the sample could be classified in the *stable* cluster,

[2] The primary difference between SPSS's Two-Step cluster analysis and LCA is the former uses a distance measure to separate cases into classes instead of calculating a probability of class membership for each case (see Benassi et al. 2020).
[3] The authors define propensity as "the developmental interaction between an individual's differential susceptibility and their exposure to violence-support settings," (Clemmow et al., 2022: 3).

whereas only 19% of mass murderers were classified as such. Alternatively, only 19% of lone-actors were classified as *unstable*, compared to 44% of mass murderers.

Thijssen et al. (2023) surveyed (n=124) male jihadi detainees in the terrorism wings of a Dutch prison. They drew risk and protective factors from the VERA-2R, a risk assessment tool, to serve as indicator variables for the LCA. The authors identified three classes, primarily differentiated on their motivational characteristics. The first class was characterized as *low motivated*, as individuals in this class were less driven to violent extremism by personal motivational factors such as moral imperatives, desire for excitement/adventure, or status-seeking tendencies. The second class, alternatively, was strongly motivated by moral superiority, commitment to a group, and a desire for status and meaning – deemed the *morally driven* class. Lastly, the *hardened ideologically driven* class was largely motivated by a glorification of ideological violence, criminal opportunism, group commitment, thrill-seeking tendencies, and a desire for status. This class also demonstrated substantially lower levels of education and were more likely to have a violent criminal history and suffer from a personality disorder than the other two classes. The *hardened ideologically driven* individuals also demonstrated significantly higher ideological commitment and more violent intentions and preparations than the other two classes, and were more likely to have a peer network involved in violence than the *low motivated* class (Thijssen et al., 2023).

Taken together, it is evident that violent extremists are anything but a homogenous pool of actors, and there are numerous patterns of risk and protective factors that may characterize them. However, several limitations underpin prior studies estimating LCA in a sample of violent extremists. First, most of these studies utilize small samples sizes. There is no fixed threshold on a minimum sample size to conduct an LCA model, but Nylund-Gibson and Choi (2018) recommend a range of N ≈ 300-1000 cases based on their assessment of previous research. Smaller sample sizes may produce unstable class solutions and mask the detection of smaller classes that are theoretically relevant (Nylund-Gibson & Choi, 2018). Further, no studies assessing a sample of violent extremist has leveraged a comparison group of nonviolent or noncriminal extremists. Applying this analytic approach to the criminological study of violent extremism would be particularly advantageous for modelling the equifinality and multifinality of extremist crime and violence by considering the differential outcomes that distinct patterns of criminogenic risk and protective factors may ultimately lead to.

2.4. Current Study

The purpose of this dissertation is to explore how criminogenic risk and protective factors may distinguish violent extremists from their nonviolent and nonoffending counterparts. Prior literature indicates these factors, drawn from social bond, low self-control, social learning, and strain theories of criminality are salient correlates of extremist crime and violence. In particular, multifactor criminological approaches where multiple criminogenic factors are considered in a simultaneous, complementary capacity are important for more fully explaining the complex phenomenon of violent extremism. By improving on two key methodological gaps in previous research, this dissertation advances a nuanced investigation on the criminology of violent extremism. Specifically, this dissertation (1) uses nonviolent criminal and nonoffending extremist comparison groups and (2) estimates an LCA model to capture the equifinal and multifinal nature of extremist crime and violence. To guide the analysis, two hypothesis-free research questions are proposed:

1.) How do criminogenic risk and protective factors, drawn from social bond, low self-control, strain, and social learning theories of crime, co-occur and covary to form distinct classes of criminogenic risk in a sample of violent, nonviolent criminal, and nonoffending extremists?

2.) How do distinct classes of criminogenic risk differentially predict involvement in violent, nonviolent criminal, or nonoffending extremism?

CHAPTER 3: DATA AND METHODS

This chapter will explain the research design of the current dissertation. It will begin with a description of the data and the protocol used to collect it, including the sampling strategy as well as the searching and coding procedure. Then, the analytic plan will be described in detail, particularly the steps of conducting LCA, the variables that will be included, and the approach that will be used to explore how the latent class of criminogenic risk is associated with types of extremist actions. The chapter concludes with a discussion of the sensitivity analyses that will be employed to evaluate the robustness of the estimated results.

3.1. Building the Risk and Protective Factors Dataset

Data for this dissertation is drawn from the newly created open-source database, the Risk and Protective Factors Dataset (hereafter, RPFD). The process of developing the RPFD is discussed in the following sections. Essentially, the RPFD is an expansion on the original Extremist Crime Database (ECDB), which included variables on various facets of a terrorist event, including the incident itself, the perpetrator(s), target(s), victim(s), and affiliated extremist groups (Freilich et al., 2014). The RPFD places a more discrete focus on the perpetrators of extremist events, specifically on the risk and protective factors they exhibited prior to engaging in extremist crime and violence. Because the RPFD draws from the original ECDB database, the following ECDB inclusion criteria is used for the cases involving violent and nonviolent criminal extremists (Freilich et al., 2014):

(1) The individual must have been involved in a terrorist incident within the U.S.

(2) The incident the individual was involved in must have occurred at a specific time and place (vague allegations were not included).

(3) The incident the individual was involved in must have prompted a governmental response.

(4) The incident the individual was involved in must have sought to forward an ideological goal.

Unlike other risk and protective factor datasets that focus on one specific type of actor (Gill et al., 2014), the RPFD includes individuals engaged in various types of actions. Specifically, four distinct types of actors are included: violent extremists, nonviolent criminal extremists, nonoffending extremists, and non-extremist violent offenders. Note that, for the purpose of addressing the research objectives at hand, only the former three categories are included in this dissertation. In its composition, the RPFD improves on existing datasets leveraging nonviolent extremist comparison groups by delineating between nonviolent criminal extremist and nonoffending extremist comparison groups (Jensen et al., 2016). This unique structure makes the RPFD well-suited for exploring the factors that distinguish violent extremists from other types of extremists.

3.1.1. Sampling Violent and Nonviolent Criminal Extremists

The first step to creating the RPFD was to sample violent and nonviolent criminal extremists using a stratified random sampling strategy. These individuals were drawn from the ECDB. The ECDB is a unique dataset in that it contains data on extremists who engage in violent crime to advance their cause as well as nonviolent criminal extremists who commit ideologically motivated financial crime, money laundering schemes, or property crime (Freilich et al., 2014). The purpose of using a sample of cases drawn from the ECDB rather than the entire universe was to maintain feasibility in data collection while ensuring there was adequate representation of each type of case to conduct inferential analyses. Thus, approximately (n=210) violent extremists (hereafter, VEs) and (n=210) nonviolent criminal extremists (hereafter, NVCEs) were randomly sampled from each respective category of offenders to build the initial sample for the RPFD. In some cases, individuals were involved in both violent and nonviolent criminal extremism. If there was evidence that an NVCE had previously engaged in ideologically motivated violence, they were reclassified into the VE category. A total of (n=9) individuals were recoded from NVCEs to VEs because evidence was found that indicated their involvement in a violent extremist plot, producing an initial sample of (n=201) NVCEs and (n=219) VEs.

Importantly, the RPFD sought to include cases that represented the ideological spectrum of extremist beliefs to facilitate meaningful comparisons between ideologues. The RPFD uses the ECDB's classification of ideological beliefs, and Table 1 reports the operational criteria for each of the included ideological categories. The original (n=420) VEs and NCVEs detailed above were randomly sampled from a pool of far-right and jihadist extremists. Specifically, this initial sample of (n=420) VEs and NCVEs included approximately (n=210) far-right extremists and (n=210) jihadist extremists. While this initial sample afforded comparative analysis between far-right and jihadist ideologues, a far-left group was then developed to ensure the scope of extreme ideological beliefs was adequately captured in the dataset. A total of (n=40) far-left NCVEs were randomly sampled from the ECDB's collection of suspects involved in Environmental Liberation Front (ELF) and Animal Liberation Front (ALF) attacks, who primarily committed property crimes to advance their cause (Ackerman, 2003; Leader & Probst, 2003). This completed the (n=241) sample of NCVEs in the RPFD.

Table 1. RPFD Ideological Category Definitions

Ideology	RPFD Definition
Far-right	From ECDB Codebook (p. 3): [4] "The far-right is composed of individuals or groups that subscribe to aspects of the following ideals: • Fiercely nationalistic (as opposed to universal and international in orientation); • Anti-global; • suspicious of centralized federal authority;

[4] The ECDB codebook is available upon request.

Table 1. (cont'd)

	• Reverent of individual liberty (especially their right to own guns, be free of taxes); • Believe in conspiracy theories that involve a grave threat to national sovereignty and/or personal liberty; • Belief that one's personal and/or national "way of life" is under attack and is either already lost or that the threat is imminent (sometimes such beliefs are amorphous and vague, but for some the threat is from a specific ethnic, racial, or religious group); • Belief in the need to be prepared for an attack either by participating in or supporting the need for paramilitary preparations and training or survivalism. NOTE: The mainstream conservative movement and the mainstream Christian right are not included."
Jihadist	From ECDB Codebook (p.3-4): "The Islamic Jihadist movement is composed of individuals or groups that subscribe to aspects of the following ideals: • Only acceptance of the Islamic faith promotes human dignity as well as affirms God's authority; • Rejection of the traditional Muslim respect for "People of the Book," i.e., Christians & Jews; • "Jihad" (defined as to struggle in the path of God in the example of the Prophet Muhammad & his early companions)" is a defining belief in Islam. This belief includes the "lesser Jihad" that endorses violence against a corrupt other; • The Islamic faith and or one's people are oppressed and under attack in both "local and nominally Muslim" Middle-Eastern/North African/Asian governments that are corrupt & authoritarian, as well as in non-Islamic nations (e.g., Israel/Palestine, Russia//Chechnya; India/Kashmir, etc) that occupy indigenous Islamic populations (an argument for political & military mobilization); • The West in general & the U.S. in particular supports the corruption, oppression & humiliation of Islam, and exploits the region's resources; • The people of the West in general and the US in particular are responsible for the actions of their governments and culture (NOTE: this is an important element that distinguishes jihadists from other Muslims critical of Western states because it could justify the killing of innocents);

Table 1. (cont'd)

	• It is a religious obligation is to promote a violent Islamic revolution to combat this assault on Islam, oppression, corruption & the values of the West by targeting nonbelievers (both Muslims and non-Muslims); • Jihad will remain an individual obligation until all lands that were once Muslim (e.g., Andalusia- Southern Spain, Palestine, Philippines, etc) are returned & Islam again reigns supreme in those countries; • Islamic law- Sharia- provides the ideal blueprint for a modern Muslim society and should be implemented in all "Muslim" countries by force."
Far-left	From Duran (2021: 4): "Far-left extremism refers to groups an/or individuals that (1) support violence and/or criminal activity explicitly, or implicitly, to (2) further aspects of one or more of the following ideals: • Marxist and/or Socialist and/or Leninist an/or Stalinist beliefs; • Anarchist beliefs (including individual autonomy and collective equality); • Support for extreme egalitarianism and/or a classless society and/or workers' and ordinary persons' rights; • Opposition of capitalism and/or corporate malfeasance; • Opposition of racism particularly within institutions that historically have suffered from system racism; • A belief that American society in general, and the criminal justice system, especially the police and other law enforcement agencies, in particular are systematically/institutionally racist; • Opposition of militarism and/or American imperialism and/or colonialism both abroad and domestically; • Suspicion of traditional mainstream religions (i.e. Judaism, Christianity); • A belief in Black Separatism/Supremacy and/or militant Black nationalism; • Support for Puerto Rican Independence; • The earth and/or animals are in imminent danger; • Support for biodiversity and bio-centric equality (i.e., that humans are no greater than any other form of life and have no legitimate claim to dominate earth); • The government and /or parts of society such as corporations are responsible for this danger;

Table 1. (cont'd)

	• This danger will ultimately result in the destruction of the modern environment and/or whole species; • The political system is incapable and/or unwilling to fix the crisis by taking actions to preserve American wilderness, protect the environment and support biological diversity; • There is a need to defend the environment and/or animals."

However, the original ECDB did not have an existing collection of violent far-left extremists. As a result, these suspects were identified from another ongoing project that enhanced the ECDB by identifying far-left homicides in the U.S. from 1990-2020 (Duran, 2021). A total of (n=48) violent far-left extremists were identified in this study, constituting the known universe of violent far-left extremists in the U.S. in that time span. Table 1 details the operational criteria indicating far-left extremist belief systems. Approximately (n=38) of these extremists met the inclusion criteria for the RPFD, as (n=10) lacked sufficient evidence of being directly involved in the violent plot. Furthermore, one additional violent environmental extremist was identified in the course of building this sample that met the inclusion criteria for the violent far-left category, completing the sample of (n=39) violent far-left extremists.

In contrast to the other categories of extremists, all of the individuals that met the RPFD inclusion criteria for violent far-left extremists were included to ensure the category had ample sample size for comparative analysis. Accordingly, violent far-left extremists are the only category of VEs which were not randomly sampled into the RPFD. In total, the RPFD contains (n=258) VEs and (n=241) NVCEs.

3.1.2. Sampling Nonoffending Extremists Through a Case-Control Design

As described, the RPFD purposively sampled extremists on the dependent variable of study – the type of action(s) an individual engaged in. Sampling on the dependent variable is key for building a case-control research design (Freilich et al., 2015; Lacy, 1997). The case-control method is a stratified sampling strategy that builds a comparison group based on shared characteristics between a “case,” or a unit that falls into a category of interest in a discrete dependent variable, and a “control”, or a unit that does not fall in the same category of the dependent variable (Freilich et al., 2015; Lacy, 1997). Case-control designs are popular designs for studying risk factors in epidemiological research (e.g. Breslow, 1996; Shetty et al., 2006), and scholars have advocated for their use in the study of rare events and terrorism (Freilich et al., 2015; Lacy, 1997; Monahan, 2016). The merit of the case-control design is the feasibility of estimating predictive effects for variables of interest while controlling for the effects of confounding variables in retrospective examinations of phenomena where true experimental conditions (i.e. random assignment) are not possible (Lacy, 1997). In the RPFD, then, each VE constituted a “case,” and nonoffending extremists, who espoused extreme beliefs but were not known to have ever been convicted of a crime, were matched to each case based on shared attributes, effectively creating a matched “control” group.

The process of matching nonoffending extremists (hereafter, NOEs) to VEs was rigorous. The first step in the process was to determine which attributes the NOE would be matched on. Again, the purpose of matching individuals on shared attributes was to hold those attributes constant while allowing for variation in the risk and protective factor variables of interest. NOEs were matched to VEs on 4 distinct attributes: gender, ideology, geography, and point in time.[5] Table 2 details each of these attributes and their operational parameters. The operational parameters are intended to be specific enough to identify a qualified and conceptually relevant match for each VE but use lenient thresholds to improve the feasibility of identifying potential

[5] Note that efforts were made to match individuals based on age as well, but age information was often unavailable or inconsistent in the open-source reports. As a result, this attribute was not included as a parameter for the matching process.

matches. For example, suppose a white supremacist man carried out an act of extremist violence in Chicago in 2012. This VE would constitute a "case," and the RPFD principal investigators would attempt to identify a NOE who was a man, had similar white supremacist views, lived in Chicago or surrounding areas, and was an active extremist, indicated by active involvement in an extremist group or participation in activities supporting extreme causes (e.g. attending a white supremacist rally), within +/- 3 years of 2012. This identification process involved scouring publicly available information, including newspapers, social media, scholarly articles, and watch group reports to find an individual who was matched on each attribute. In the cases where multiple potential matches were identified, random selection was used to determine which match would be included in the sample.

Table 2. Attributes for Identifying Matched NOE Cases

Attribute	Description	Operational Parameters
Point in Time	Was the individual an active non-offending extremist about the time the matched VE carried out their attack?	Active within +/- 3 years of VE attack
Gender	Was the individual the same gender as the matched VE?	Male VE = Male NOE Female VE = Female NOE
Geography	Did the individual reside in the same geographic region/setting as the matched VE?	Most specific level possible based on iterative process: (1) Neighborhood *If no matches found:* (2) City *If no matches found:* (3) County *If no matches found:* (4) Region of State *If no matches found:* (5) State
Ideology	Did the individual subscribe to extremist beliefs similar to those of the matched VE, based on ECDB ideological categories?	(1) Far-right (2) Jihadist (3) Far-left

There were some caveats in the matching process. First, NOE matches were not identified for VEs who were not living within U.S. borders at the time of committing their attack. Because geography was a core parameter of the matching process, this decision was made to retain focus on extremism in the homeland. Approximately (n=18) VEs did not have a known residence in the U.S. and thus did not have a NOE matched to them. Second, there were some cases where matches simply could not be identified. The identification process is at the mercy of publicly available information, and while it is possible that many qualified matches exist in a specified area, they were not always identifiable in the source material. Matched NOE cases could not be identified for approximately (n=7) cases.

Second, there were several matches who were initially included in the data, but upon further investigation, it was revealed that they had previously been convicted of a crime. If it was uncovered that an identified NOE had been previously convicted of a crime, whether ideological or not, they were excluded from the data and a new match was found in their place. Note that there must have been evidence that the individual was *convicted* of a crime. Arrests were not considered cause for disqualification, as many cases resulted in acquittals or charges being dropped. Additionally, arrests were often related to minor infractions during legal extremist activities such as protests or rallies, which often did not lead to a criminal conviction. This exclusion criteria resulted in a final sample of (n=233) NOEs.

Finally, there are clear measurement and ethical issues when labelling a person a "nonoffending extremist." In some cases, it is easily discernable, as the person was involved in a designated extremist group or even self-identified and claimed the title of an extremist. However, it may be considered a somewhat subjective endeavor to determine which viewpoints are far enough removed from the mainstream to be considered "extreme." The investigators of the

RPFD sought to mitigate the subjectiveness of such a classification by employing an extremism confidence scale to capture the attitudinal and behavioral characteristics that warrant a person's inclusion as a NOE. This scale draws objective indicators from extant scholarship related to the beliefs a person espouses and the activities they engage in (Duran, 2021; Freilich et al., 2014). The scale indicators are listed in Table 3 and are specific to ideological category (i.e. far-right, far-left, jihadist).[6]

[6] Note that most scale indicators require endorsement of violence to support an ideological belief(s). This is because some of the beliefs listed may only be considered extreme when they are used to justify violence (e.g. protection of gun rights, combatting racism). This inclusion differs from the ECDB definitions provided in Table 1 because the ECDB requires an incident to involve a violent or criminal act in order for it to be included in the dataset. Because this behavioral criterion is not applicable to the NOE sample, an attitudinal metric is used in the confidence scale to indicate whether an individual supports violence to advance an ideological belief. This strategy enhances transparency on the comparability between the VE and NVCE samples and the NOE sample in their extreme beliefs.

Table 3. Nonoffending Extremist Confidence Scale

Ideological Category	Indicators	Score
Far-right	(1) Does the individual claim to be a right-wing extremist? (2) Does the individual deny being a right-wing extremist? (3) Does the individual support violence to combat globalism? (4) Does the individual endorse conspiratorial beliefs that involve a grave threat to national sovereignty and/or personal liberty and a belief that one's personal and/or national "way of life" is under attack and is either already lost or that the threat is imminent? (5) Does the individual endorse xenophobic beliefs? (6) Does the individual endorse racist beliefs? (7) Does the individual support violence to protect gun rights? (8) Does the individual support violence to support the right to be free of taxes? (9) Does the individual support violence to combat abortion? (10) Does the individual support beliefs associated with extremist groups/movement such as White Supremacy, Militia, Patriot, Sovereign Citizens, or similar organizations/beliefs? (11) Was the perpetrator known to express political activism/attitudes including political speech like expressing political opinions and organizational behaviors like leafletting, rallying, protesting etc.?	FOR CRITERIA (1), (3) – (15) 1=Evidence of yes 0=No evidence of yes FOR CRITERIA (2) -1 = Evidence of yes 0 = No evidence of yes

Table 3. (cont'd)

	(12) Evidence the suspect had an acknowledged or implied membership in, or association with extremist groups (e.g., individuals declare they are in a Neo-Nazi group on social media, post terrorist symbols—e.g., swastikas). (13) Evidence the suspect participated in online sites or spaces that promote extremist ideals. (14) Did the individual have direct contact (offline/online) with other violent extremists (e.g., perp's fellow group members)? (15) Evidence the suspect produced extremist videos, media, and/or messaging.	
Jihadist	(1) Does the individual claim to a supporter of jihadi extremist groups such as al-Qaeda, ISIS, Hamas, Muslim Brotherhood, or other similar groups? (2) Does the individual deny being a supporter of jihadi extremist groups such as al-Qaeda, ISIS, Hamas, Muslim Brotherhood, or other similar groups ? (3) Does the individual endorse violence to support Sharia law as the blueprint for a modern Muslim society? (4) Does the individual reject the traditional Muslim respect for "People of the Book" (i.e., Christians and Jews) and/or express anti-Jewish or anti-Christian beliefs? (5) Does the individual believe that "Jihad" is a defining belief in Islam, while also endorsing violence against "corrupt" others within the U.S. where Muslim values are negatively affected as a result of American hedonism (i.e., support of gay rights and feminism)?	FOR CRITERIA (1), (3) – (15) 1=Evidence of yes 0=No evidence of yes FOR CRITERIA (2) -1 = Evidence of yes 0 = No evidence of yes

Table 3. (cont'd)

	(6) Does the individual endorse violence versus the American people who are in turn responsible for their government's actions and extremists? (7) Was the perpetrator known to express political activism/attitudes including political speech like expressing political opinions and organizational behaviors like leafletting, rallying, protesting etc.? (8) Evidence the suspect had an acknowledged or implied membership in, or association with extremist groups (e.g., individuals declare they are ISIS on social media, post terrorist symbols—green birds, flags, lions). (9) Evidence the suspect participated in online sites or spaces that promote extremist ideals. (10) Did the individual have direct contact (offline/online) with other violent extremists (e.g., perp's fellow group members)? (11) Evidence the suspect produced extremist videos, media, and/or messaging.	
Far-left	(1) Does the individual claim to be a left-wing (extremist)? (2) Does the individual deny being a left-wing extremist? (3) Does the individual endorse violence to support Marxist and/or Socialist and/or Leninist and/or Stalinist beliefs? (4) Does the individual endorse violence to support anarchist beliefs (including individual autonomy and collective equality)?	FOR CRITERIA (1), (3) – (15) 1=Evidence of yes 0=No evidence of yes FOR CRITERIA (2) -1 = Evidence of yes 0 = No evidence of yes

Table 3. (cont'd)

(5) Does the individual support violence in favor of extreme egalitarianism and/or a classless society and/or workers' and ordinary persons rights?
(6) Does the individual support violence to combat capitalism and/or corporate malfeasance?
(7) Does the individual support violence to combat racism?
(8) Does the individual support violence to combat militarism and/or American imperialism and/or colonialism both abroad and domestically?
(9) Does the individual support Black Separatism/Supremacy and/or militant Black nationalism such as support for Nation of Islam, Black Hebrews, Black Panther, and/or revolutionary groups like the Weathermen and similar organizations beliefs?
(10) Does the individual endorse violence to support for Puerto Rican Independence?
(11) Does the individual endorse violence to support biodiversity and biocentric equality (i.e., that humans are no greater than any other form of life and have no legitimate claim to dominate earth?
(12) Was the perpetrator known to express political activism/attitudes including political speech like expressing political opinions and organizational behaviors like leafletting, rallying, protesting etc.?
(13) Evidence the suspect had an acknowledged or implied membership in, or association with extremist groups (e.g., individuals declare they are a member of Nation of Islam/Black Panther/Black Hebrews on social media, post terrorist symbols).

Table 3. (cont'd)

	(14) Evidence the suspect participated in online sites or spaces that promote extremist ideals. (15) Did the individual have direct contact (offline/online) with other violent extremists (e.g., perp's fellow group members)? (16) Evidence the suspect produced extremist videos, media, and/or messaging.

For each indicator that an individual demonstrates, they are scored a “1,” with no evidence of an indicator resulting in a “0” score. There is one exception for the denial of extremist beliefs indicator, in which they are scored a “-1” if there is evidence the individual denied being an extremist to reflect the extent to which this reduces confidence in their NOE classification. The score is then totaled and averaged to produce a standardized confidence score across the ideological categories. The result is a standardized metric based in observable criteria that indicates the confidence of one’s classification as a NOE. This confidence scale will be discussed again in later sections regarding its use for sensitivity analyses.

3.1.3. Data Collection Process[7]

The coding process for the RPFD is an extension of the ECDB’s searching and coding process (see Freilich et al., 2014). In the original ECDB protocol, student assistants were assigned specific terrorist events that met the ECDB inclusion criteria, and essentially treated each incident as a case study. To build a case file, student assistants used a comprehensive slate of open-source search engines that included news media, social media, scholarly articles, watch-group reports, person-searching websites (i.e. White Pages), court records, police reports, department of corrections websites, and any other publicly available sources they could find.[8] All the information uncovered in this search process was collected and collated into a clean case file.

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[7] The information provided in this section is directly from the ECDB Codebook, which, as stated earlier, is available upon request.

[8] Full list of sources: (1) Lexis-Nexis; (2) ProQuest; (3) Yahoo; (4) Bing; (5) Google; (6) Newsbank; (7) Newslibrary; (8) Newspapers.com; (9) Google Scholar; (10) USA.gov; (11) Google Video; (12) Dogpile; (13) Google News; (14) Google Images; (15) Gun Violence Archive; (16) Every Town Research; (17) Spokeo; (18) Veromi; (19) PeekYou; (20) BRBPub; (21) AnyWho; (22) Legacy.com; (23) National Archives; (24) NNDB; (25) Facebook; (26) Twitter; (27) Instagram; (28) Pinterest; (29) LinkedIn; (30) Blogger; (31) Technorati; (32) White Pages; (33) Local/District Courts Websites; (34) JudyRecords; (35) Court Listener; (36) Local/State Department of Corrections Websites; (37) NCSC; (38) Vinelink; (39) Inmate Locator; (40) Federal BOP; (41) National Sex Offender Public Website; (42) BeenVerified

Case files were then assigned to another student assistant to be coded. These "coders" would vet the information contained in the case file, conduct re-searches to identify any additional information, and then carefully analyze the case file to identify variables of interest. When information pertaining to a variable was found, the coder would then input the correct variable response into the database. If there was conflicting information on a variable, the coder would evaluate the credibility of each contrasting source and determine which information was most reliable. For example, information reported in verified court documents is considered more reliable, as the information is the product of sworn testimony under oath and is often subject to cross examination. Alternatively, personal blogs or websites are considered less reliable due to the potential for opinionated and uncorroborated information to be reported. A more detailed discussion of information reliability is provided later in this section.

The RPFD utilizes the same existing ECDB case files for the individuals selected into its sample. As described above, the ECDB's case files were set at the incident-level, but were used to code for suspect, victim, target, and group-level variables. The same scheme is leveraged here, but only suspect-level variables from a newly developed codebook are coded for. The RPFD codebook includes variables related to nearly 150 risk and protective factors, capturing sociodemographic characteristics, familial ties, community connections, substance use, mental health, ideological beliefs, online activities, criminal history, and warning behaviors.[9] The selection of factors to include in the codebook was based on similar datasets and extant literature (Gill et al., 2014; Jensen et al., 2016; Wolfowicz et al., 2021).

To ensure comprehensiveness, each existing ECDB case file was updated by a student assistant prior to coding. Specifically, student assistants revisited the open-source searching

[9] The RPFD codebook is available upon request.

protocol to identify and collect any outstanding information that the original ECDB case files were unable to include. However, while the RPFD already had existing case files for the far-right and jihadist VEs and NCVEs, as well as the far-left NCVEs, there were no existing case files for the far-left VEs due to them not being included in the original ECDB sample. Accordingly, the principal investigators and student assistants developed new case files for each case, following the same ECDB searching protocol described above. Additionally, case files were developed for the matched sample of NOEs. Just like the ECDB process, completed case files were then assigned to a student assistant to be vetted, re-searched, and coded into the final dataset.

One of the most pervasive issues in open-source data collection, particularly in the presence or absence of risk and protective factors, is the determination of when a variable is considered “Missing” and when it should be coded as “No” (or not present) (Corner et al., 2021; Gill et al., 2014). Corner et al. (2021) describe this limitation: “…it is often difficult to distinguish between missing data and variables that should be coded as a 'no'. Given the nature of newspaper and open-source reporting, it is unrealistic to expect each biographically oriented story to contain lengthy passages that list each variable or behavior the offender did not engage in (e.g., the offender was not a substance abuser, a former convict, recently exposed to new media)” (p. 3). In fact, Corner et al. (2021) report that, in their data collection, definitive “No” answers were present less than 5% of the time, most often the consequence of corrections to false information in earlier media reports. Since definitive "No" answers are so rare, multiple imputation or other methods of handling missing data is infeasible and impractical (Corner et al., 2021). To address this issue the RPFD codes for *evidence* of variables, an approach prior studies have demonstrated the utility of (Gill et al., 2014; Corner et al., 2021). While this could not be done for some variables that were operationalized through multiple categories (e.g.

race/ethnicity, education level, socioeconomic status), most variables in the RPFD codebook related to risk and protective factors are dichotomous, with “1” = evidence the factor was present and “0” = no evidence the factor was present.

By adopting this strategy, the data codified in the RPFD is necessarily dependent on the quality of information reported in the open-source material. Some cases were extensively covered so that the absence of evidence indicating a “No” response could be confidently coded as “No” without definitive evidence stating as such. Other cases, unfortunately, were less reported on, and thus the possibility that a factor was present but was not reported on, and therefore coded as “No,” was more plausible. While it is not possible to control what information is reported on and what is not, the RPFD principal investigators sought to provide a metric that indicated the reliability of the available information. Specifically, each case file was scored on a reliability scale, shown in Table 4, that captured the quality of information available in terms of comprehensiveness and source type.

Table 4. RPFD Reliability Scale

Evidence	Points/Rationale	Notes
Factual police documents (e.g., transcripts of police interviews of witnesses, or participants or other police documents like arrest reports, after action reports, or witness statements, or police press releases or social media posts that contain details about the offender or shooting)	2	All sources weighted at 2 points have high credibility & tend to cover a broader range of info/variables.
Factual court documents (e.g., court opinion outlines facts of the case &/or details about offender)	2	
Documentary (i.e., focused on the offender & the event)	2	

Table 4. (cont'd)

Media coverage	Potential 1.5 points: (NOTE: ".375" points for EACH OF our 4 categories of quotes/paraphrasing. Does the media coverage contain any quotes or paraphrases from each of these sources? Perp/family (.375 if yes) Victim/family (.375) Legal agents (.375) Acquaintances/friends (.375)	
Local media coverage (Does the search file contain any media stories from local news outlets)?	If yes, .5 points	A search file that includes quotes/paraphrases from all 5 sources noted above; AND has local news media also comes to 2 points.
Primary perpetrator document (i.e., diary, manifesto, social media)	Potential 1.5 points: 1.5 points for in-depth substantive manifesto, diary or journal that explains motivation & provides details on their background and/or extremism fantasizing, or violence fantasizing, etc.). OR .5 points for short or redacted document; for e.g., 1-2 page diary, or redacted manifesto, etc.	An in-depth manifesto can also cover a huge range of variables, but since it is the perp themselves it is weighted slightly less than court/police above.
Department of Corrections information about offender race, DOB, photo, etc.	1	All sources weighted at 1 point are l credible, but tend to capture fewer variables
Other factual government information (e.g., Mayor,	1	

Table 4. (cont'd)

Governor, or other government press releases that contain formation about the offender or event).		
Factual watch-group information	1	
Social media (acquaintance, witness) information about the events or the shooter NOTE: Do NOT count if offender, since we have primary perpetrator documents above NOTE: Do NOT count if law enforcement since we have police documents above.	1	
Perpetrator obituary (NOTE: Must be perpetrator OR perp's family since this could get us info about offender &/or their parents, siblings & other family)	1	
Other docs (e.g., Reddit, Columbine Angels, etc.)	.5	These sources have lower credibility
Total possible points	**15 points**	

The RPFD reliability scale is based on an instrument developed for The American School Shooting Study (TASSS; Freilich et al., 2022). The scale includes the various articles of information that may be identified in open sources to capture the quantity of information available, but also places weights on each of those sources to indicate the quality of the available information. Police documents, court documents, and documentaries are weighted the strongest because the information reported in those sources are on-record and validated by official sources. Additionally, testimonies from different agents of information, including perpetrators and their families, victims and their families, legal agents, and friends/acquaintances of the perpetrator are independently weighted to indicate the overall quality of media coverage. Other sources are weighted based on the credibility and utility of the evidence they are capable of providing.

The purpose of this score was to enhance the transparency of the data and provide an objective metric by which to grade the reliability and comprehensiveness of the information that an individual's codified data was based on. In doing so, biases in reporting may be more clearly ascertained by evaluating the relationship between reliability scores and potential attributes of the case that may influence the extent to which it is reported on. Essentially, the reliability score is a tool to enhance the robustness of analyzing RPFD data by providing the opportunity for sensitivity analyses, which are discussed in later sections.

3.2. Analytic Plan

The analyses for this dissertation occur in five steps. The first step involves a basic descriptive examination of the data and selected variables to situate the independent frequencies of each criminogenic factor. Then, bivariate correlations will be estimated to gauge the strength and direction of associations among the variables. The third step is to specify an LCA model to estimate latent classes of criminogenic risk. Once an LCA model is estimated, the Lanza, Tan, and Bray (2013; LTB) approach is used to assess the relationship between the latent classes of criminogenic risk and the type of action extremists engaged in (i.e., violent, nonviolent criminal, nonoffending). Finally, sensitivity analyses are employed to evaluate the robustness of the results. This section explains the process of conducting an LCA in detail, including how an LCA model is specified and estimated, how the LTB approach is used, and how sensitivity analyses will be employed.

3.2.1. Variable Selection/Distribution Specification

The first step in specifying the LCA model is selecting variables to indicate the latent classes. Binary variables are most commonly used in LCA models (Bauer & Steinley, 2021; Nylund-Gibson & Choi, 2018), likely due to their simplicity in interpretation. Thus, the independent variables included in this analysis, also referred to as “indicator” or “manifest” variables, are dichotomized for this reason. The next section operationalizes the independent variables included in the analysis.

3.2.1.1. Independent Variables

A total of 22 independent variables are included in the LCA model, indicating constructs from social bond, low self-control, strain, and social learning criminological perspectives. Table 5 synthesizes the variables’ operationalization and Figure 1, discussed in later sections, provides a diagrammatic representation of the LCA model with these variables included. Prior to discussing the operationalization for each of these variables, however, it is important to describe the temporality of their coding.

Risk and protective factors are precursors to actions, in that they occur prior to and impact one’s likelihood of engaging in a certain action. Logically, a factor occurring 5 years after a violent extremist carries out an attack did not contribute to the individual’s original decision to commit the attack. Thus, it is necessary to properly consider the temporal ordering between factor manifestation and action commitment. To do this, the RPFD establishes an endpoint for each individual that designates the time in which risk and protective factors are coded up to. For VEs, this was easily discernable, as their endpoint was the date of their attack. If an individual committed an act of violent extremism on January 1st, 2020, all risk and protective factors in the RPFD codebook would be coded prior to that date. Additionally, in cases where an individual was involved in multiple acts of violent extremism, the date of their first attack served as their endpoint.

The endpoint was similar for some NCVEs – namely, those engaged in acts of property crime. In those attacks where extremists committed property crimes such as vandalism or equipment sabotage, the point in time of the incident served as the endpoint. However, other NVCEs had slightly more ambiguous endpoints. Specifically, extremists engaged in money laundering and financial crimes may have been involved in these illicit schemes for years. As opposed to coding up until the time they were arrested for their crimes, the endpoint for these extremists was the time at which they began their schemes. The RPFD researchers determined this was most consistent with the endpoint used for VEs, and most representative of how risk and protective factors manifest – as precursors to actions.

Finally, the endpoint for NOEs was based on the matched-sampling strategy. This is because NOEs do not engage in crime, and their legal actions (i.e. protests, rallies, online posting) are far too broad and frequent to establish a definitive point-in-time endpoint. Additionally, the goal of matched sampling was to identify NOE who were active within three years of the time that the VE they were matched to carried out their attack; this time span was described as the *reference point* for a case. Therefore, the endpoint for NOEs was intended to reflect the conditions of this matching parameter. Specifically, the endpoint for NOE cases was three years after the year the VE they are matched to committed their attack. For example, if a violent extremist committed their attack in 2015, risk and protective factors were coded up until the end of 2018 for the NOE matched to them. This cutoff ensured that the variables coded for these cases reflected those demonstrated within the reference period and maintains consistency with the matching process detailed in earlier sections.

Social Bonds. The criminogenic protective factors for this dissertation are drawn from social bond frameworks (Hirschi, 1969; Laub & Sampson, 1993), and prior research (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2021; Skocyliz & Andrews, 2018; Thijs et al., 2022). Based on variables available in the RPFD dataset, eight indicator variables are used to capture distinct social bonds. *Marital status* indicates whether the individual was married or in a serious committed relationship at the time the incident they were involved in occurred, with a "1" code indicating evidence of being married or in committed relationship and "0" indicating no evidence. *Family bonds* relates to an individual's relationship with immediate family members (i.e. parents and siblings), with a "1" code indicating evidence of strong attachment to parents or siblings and "0" indicating no evidence of such bonds. Coders used testimonies in the open-source material from family, friends, and the extremists themselves to code this variable. Strong family bonds were indicated by frequent communication between the extremist and family members, whether the individual expressed a love for family members, and the extent to which family played an important role in their life.

Next, *Aspirations* indicated whether there was evidence the individual expressed prosocial goals and a desire to achieve them (Evidence of Yes="1"). Examples of prosocial aspirations included career goals or personal goals (i.e. wanting to get married, have children). *Education* captured whether an individual furthered their education by attending college, coded as "1"=Evidence of college attendance and "0"=No evidence. *Stable Employment History* indicated whether there was evidence an individual was regularly employed, coded as "1," or sporadically employed/no evidence of regular employment coded as "0." *Community Involvement* related to an individual's participation in community organizations, such as social organizations, recreational groups, religious groups, or other activities. Individuals who were involved in at least one community organization were coded as "1", individuals with no evidence of community involvement were coded as "0". Finally, military service may indicate one's commitment to conventional goals and involvement in conventional activities (Becker, 2021; LaFree et al., 2018). As a result, *Military Experience* was coded as "1" if there was evidence an individual had previously served in the military, with a "0" code reflecting no such evidence.

Reject Democratic Values is the only social bond variable that is coded as a risk rather than protective factor. This is because this variables captures a severed bond to the normative order. *Reject Democratic Values* indicates the extent to which an individual rejected the conventional belief system, specifically the democratic values, norms, and laws that necessitate prosocial behaviors. This inclusion was informed by Hirschi's (1969) emphasis on the importance of belief in the conventional order, and the ramifications of severing this bond. If there was evidence an individual expressed a rejection of democratic values or claimed to live under an alternative set of laws and norms (i.e. Sharia Law, God's Law), *Reject Democratic Values* was coded as a "1," with no evidence resulting in a "0" code.

Low self-control. Prior studies have demonstrated the utility of disaggregating the elements of self-control when distinguishing between violent and nonviolent offending (Chan & Choi, 2017). Accordingly, low self-control was indicated through a slate of three criminogenic risk factors representing discrete behaviors or behavioral patterns that are drawn from prior research on this topic (Clevenger et al., 2016; Piquero et al., 2005). First, *Impulsivity/Thrill-Seeking Behavior* indicates whether there was evidence the individual had previously exhibited impulsive and risk-taking behaviors such as erratic decision-making, reckless driving, engaging in risky sexual behavior, compulsive lying, aggression, hyperactivity, irrational financial spending, or adrenaline-provoking recreational activities. If there was evidence an individual demonstrated impulsive behaviors or sought out thrill-seeking activities prior to their involvement in extremist action(s), *Impulsive/Thrill-Seeking Behavior* was coded as a "1," with no evidence resulting in a "0" code.

Second, *Problems Controlling Anger* captures issues regulating anger/frustration and temper volatility. This variable was coded as "1" if there was evidence the individual had a history of angry outbursts, consisting of yelling, screaming, physical violence or advocating for physical violence. Finally, *Substance Abuse* indicates whether there was evidence the individual previously abused alcohol or drugs. As Gottfredson and Hirschi (1990) claim "people lacking in self-control will also tend to pursue immediate pleasures…they will tend to smoke, drink, and use drugs" (p. 90). Thus, substance use may be used to indicate an individual's need for immediate gratification (Clevenger et al., 2016). If an individual was known to previously abuse alcohol or drugs, they were coded as a "1," with no evidence of such abuse being coded as "0."

Table 5. Variable Operationalizations

Variable Name	Description	Coding Structure
<u>Dependent Variable</u>		
Type of Extremist Action	What type of action did the extremist engage in?	(0) Nonoffending Extremism (1) Nonviolent Criminal Extremism (2) Violent Extremism
<u>Independent Variables</u>		
Social Bonds		
Family Bonds	Was there evidence the individual had strong bonds to immediate family members (i.e. parents or siblings)?	(0) No evidence of familial bonds (1) Average-to-strong familial bonds
Marital Status	Was the individual known to be married or in a serious committed relationship?	(0) No known significant other (1) Married OR in committed relationship
Aspirations	Was there evidence the individual expressed prosocial aspirations and a desire to achieve them?	(0) No evidence of prosocial aspirations (1) Evidence of prosocial aspirations
Employment History	Was there evidence the individual was regularly employed in legitimate occupations?	(0) Sporadic employment/No evidence of a stable employment history (1) Evidence of a stable employment history
Community Involvement	Was there evidence the individual participated in community organizations?	(0) No evidence of community involvement (1) Evidence of community involvement
Military Experience	Was the individual known to be currently or formerly in military service?	(0) No evidence of military service (1) Evidence of military service
Education	Was there evidence the individual attended college?	(0) No evidence of college attendance (1) Evidence of college attendance
Reject Democratic Values	Was there evidence the individual expressed anger/rejection of democratic pluralistic values?	(0) No evidence of rejecting democratic values (1) Evidence of rejecting democratic values

Table 5. (cont'd)

Low Self-Control		
Impulsive/Thrill-Seeking Behavior	Was there evidence the individual previously engaged in impulsive and/or risk-taking behavior?	(0) No evidence of prior impulsive/thrill-seeking behavior (1) Evidence of prior impulsive/thrill-seeking behavior
Problems Controlling Anger	Was there evidence the individual had a history of anger issues including temper volatility or angry outbursts consisting of yelling, screaming, physical violence, or advocating for physical violence?	(0) No evidence of prior angry outbursts (1) Evidence of prior angry outbursts
Substance Abuse	Was there evidence the suspect previously abused alcohol or drugs?	(0) No evidence of prior drug or alcohol abuse (1) Evidence of prior drug or alcohol abuse
Strain		
Perceived Injustice	Was there evidence the individual exhibited strong feelings of being a victim of a societal injustice?	(0) No known expressions of a perceived injustice (1) Known expressions of a perceived injustice
Personal Grievance	Was the individual known to express personal grievances/grudges including hatred towards particular groups or anger towards cultural/political/social issues?	(0) No evidence of a personal grievance (1) Evidence of a personal grievance
Experience Prejudice/Discrimination	Was there evidence the individual previously experienced prejudice or discrimination?	(0) No known experiences of prejudice/discrimination (1) Known experiences of prejudice/discrimination
Negative Life Transitions	Was there evidence the individual experienced a negative life transition(s)?	(0) No known negative life transitions (1) Known negative life transitions

Table 5. (cont'd)

Prior Abuse	Was there evidence the individual was abused either verbally or physically as a child or adult?	(0) No known prior abuse (1) Known prior abuse
Social Learning		
Extremist Network	Was the individual known to have any family or friends involved in the extremist movement or engaged in extremist actions?	(0) No evidence of an extremist social network (1) Evidence of an extremist social network
Criminal Peers	Was the individual known to have prior involvement with non-extremist criminal peers?	(0) No evidence of criminal peers (1) Evidence of criminal peers
Extremist Online Spaces	Was there evidence the individual participated in online sites or spaces that promote extremist ideals?	(0) No evidence of involvement in extremist online spaces (1) Evidence of involvement in extremist online spaces
Contact Infamous Extremist(s)	Was there evidence the individual sought contact with infamous or incarcerated extremists?	(0) No evidence of contacting infamous extremists (1) Evidence of contacting infamous extremists
Justify Extremist Actions	Was there evidence the individual provided moral/ideological reasons for engaging in offending?	(0) No evidence of justifying extremist actions (1) Evidence of justifying extremist actions
Glorify Violence	Was there evidence the individual expressed an acceptance of violence as a necessary means to achieve ideological goals?	(0) No known expressions of glorifying violence (1) Known expressions of glorifying violence
Prior Arrests	Was there evidence the individual was previously arrested?	(0) No known arrest history/contacts with police (1) Arrested at least once

Table 5. (cont'd)

<u>Control Variables</u>		
Mental Illness	Did the individual have a known history of mental illness?	(0) No known mental illness (1) Known mental illness
Ideology	What is the individual's ideological category?	(0) Far-right (1) Jihadist (2) Far-left
Group Affiliation	(0) Acted Alone: These individuals planned, prepared for, and executed the attack by themselves, with no cooperation or support from any other persons. (1) Acting with others with no clear boundaries: These are small groups of like-minded individuals who plan, prepare for, and execute the attack only while work with each other. They do not have any group structure in place, but cooperate with each other to carry out the attack. (2) Part of an informal group: These individuals act on behalf of a group with some of the characteristics of formalized groups, but not all of them. Groups may operate under a certain name, but lack a hierarchical structure, or vice versa. These individuals mostly act under their own direction and dedicate the attack to a specific group or movement.	(0) Lone-actor (1) Acting with others-no clear group boundaries (2) Informal group (3) Formal group

Table 5. (cont'd)

	(3) Part of a formal group: These individuals act under the direction of a group which operates under a specific name, has a hierarchical leadership structure, has recruiting/financing processes in place, and established goals that all group members subscribe to.

Strain. Strain-related risk factors are indicated through five variables. The first two factors are informed by Agnew's (2010) work on strain and terrorism. First, scholars have frequently emphasized the role of perceived injustices in facilitating radicalization (Borum, 2003; Moghaddam, 2005; Sageman, 2008). Agnew (2010) similarly described the salience of perceived injustices to indicate both personal and collective strains. Accordingly, *Perceived Injustice* indicates whether an individual perceived themselves as being the victim of a societal injustice, either directly or through their identity group. Individuals known to express perceived injustice were coded as "1," with no evidence of such expressions being coded as "0." Personal grievances are also postured as expressions of strain that facilitate radicalization (Agnew, 2010). These grievances are mostly grounded in a desire for revenge and are often born from personal experiences of harm to themselves or loved ones (McCauley & Moskalenko, 2017). They evoke emotional responses from individuals, such as anger, that are displaced onto the perceived source of their strain (Agnew, 2010). To account for their influence, *Personal Grievances* indicates whether there was evidence an individual expressed grievances or grudges towards specific groups of people, or anger towards particular cultural, political, or social issues. Evidence of such grievances resulted in a "1" code, with no evidence being coded as "0."

The latter three strain variables capture criminogenic risk factors drawn from GST and relate to negative life experiences that may qualify as noxious stimuli, removal of positively valued stimuli, or failure to achieve positively valued goals (Agnew, 1992). *Experience Prejudice/Discrimination* captures whether an individual was victimized or discriminated against based on their identity. Prior research indicates such experiences may promote in-group/out-group ideals and radicalize personal grievances (see Victoroff et al., 2012). Negative life events may similarly promote exploration into radical ideals, and could constitute noxious stimuli, removal of positive stimuli, or failure to achieve goals, depending on the nature of the transition (Agnew, 1992). *Negative Transitions,* then, captures whether the suspect was known to have experienced any major negative events that impacted their way of life, such as significant losses or failures. Finally, *Abuse* indicates whether there was evidence the individual had experienced physical or verbal abuse, either as a child or as an adult.

Social Learning. Six variables are used to indicate criminogenic risk factors drawn from social learning theory. The first three relate to differential associations. *Extremist Network* was coded as "1" if there was evidence a suspect's family member(s) or peer(s) subscribed to an extreme ideology or involved in extremist movement activities, with no evidence being coded as "0." Alternatively, *Criminal Peers* indicates whether there was evidence the individual associated with peers who engaged in non-extremist criminal activity. Those with known criminal peers were coded as "1," and those with no evidence of criminal peers were coded as "0." In this way, both ideological and criminogenic peer influence can be separately captured by using discrete measures for each. Finally, given the salience of online platforms in facilitating extremism (Holt et al., 2017; Turner et al., 2022), *Online Sites* captures whether a suspect was known to visit extremist websites or forums that promoted radicalized ideals, with evidence of an online presence being coded as "1," and no evidence coded as "0."

Akin to imitation in social learning theory, theorists posit extremists often model their behavior after other, infamous extremists (Hamm & Spaaij, 2017). Such communication may heighten one's criminogenic risk by facilitating imitation/modeling (Akers, 2011; Burgess & Akers, 1966). To capture this possibility and indicate imitation/modelling, a variable is included to indicate whether an individual sought contact with an infamous or incarcerated extremist. Evidence of such contact resulted in a "1" code, and no evidence resulted in a "0" code. Finally, relating to definitions, two variables captured the extent to which an individual held definitions favorable towards law violation. *Justify* indicated the extent to which an extremist recognized the illegality of extremist actions but justified their commission through ideological reasons and rationale (Sykes & Matza, 2017). Justifications may have included statements such as a "they deserved it" or "it was necessary," whereby the action was perceived as beyond the purview of conventional law. If there was evidence a suspect made statements justifying extremist actions, they were coded as "1", with no evidence coded as "0". To indicate one's endorsement of violence more specifically, *Glorify Violence* indicated a suspect's acceptance of violence as a necessary means to achieve ideological goals, with evidence of acceptance being coded as "1" and no evidence "0."

Finally, *Prior Arrests* is included as a criminogenic risk factor to indicate the influence of differential reinforcement. Social learning theory posits that experiences punishment as a result of a particular behavior, they will be dissuading from engaging in that behavior in the future due to the perceived threat of aversive effects (Akers, 2011; Burgess & Akers, 1966; Jeffery, 1965). If there was evidence an individual was arrested at least once, and thus experienced a positive punishment as a result of a specific behavior, *Prior Arrests* was coded as "1", with no evidence of previous arrest being coded as "0."[10] While social learning theory would contends that those who were previously arrested would be less likely to engage in criminal behavior, extant research suggests extremists who have a criminal history are more likely to be violent (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022). Accordingly, inclusion of the *Prior Arrests* variable may bring clarity to these counterintuitive claims.

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[10] It is important to note that because this variable is considered as a risk factor, any prior arrest must have temporally preceded the case endpoint and could not have been related to the extremist incident that warranted their inclusion in the RPFD.

3.2.1.2. Control Variables

Logically, criminogenic factors on their own cannot explain all of the variance in types of action extremists engage in, and prior research has identified a number of exogenous variables that may be influential. Thus, three control variables are included in the LCA model to account for this spuriousness. Like the independent variables described above, control variables were binarized for use in the LCA model (see Table 3).

First, empirical studies consistently indicate individuals with a mental illness are more likely to be violent extremists than nonviolent (Becker, 2021; LaFree et al., 2018). The original RPFD Mental Health variable included eight categories: (0) No known mental illness, (1) Unspecified mental illness, (2) Personality disorders, (3) Learning disabilities, (4) Mood disorders, (5) Anti-social behavior/conduct disorders, (6) Associated stressor/trauma issues, (7) Psychotic disorders, (8) Comorbidity (presence of two or more diagnoses). To create a binary measure for *Mental Illness*, categories 1-8 were collapsed to represent evidence of a known mental illness (“1”), with no evidence of a mental illness resulting in a “0” code.

Second, extant research indicates some ideologies are more violent than others. In particular, far-right and jihadist ideologues are more likely to be violent than far-left extremists (Asal & Rethemeyer, 2008; Asal et al., 2009; Becker, 2021; Carson & Turner, 2022; LaFree et al., 2018; Pritchett & Moeller, 2022). Ideology was included in the analysis to control for this variation and was composed of three categories: (1) Far-right, (2) Jihadist, and (3) Far-left. The descriptions for each of these ideological categories are detailed in Table 3. For analysis, this variable was recoded into two dummy variables, *Jihadist* and *Far-left*, with the Far-right category serving as the reference group.

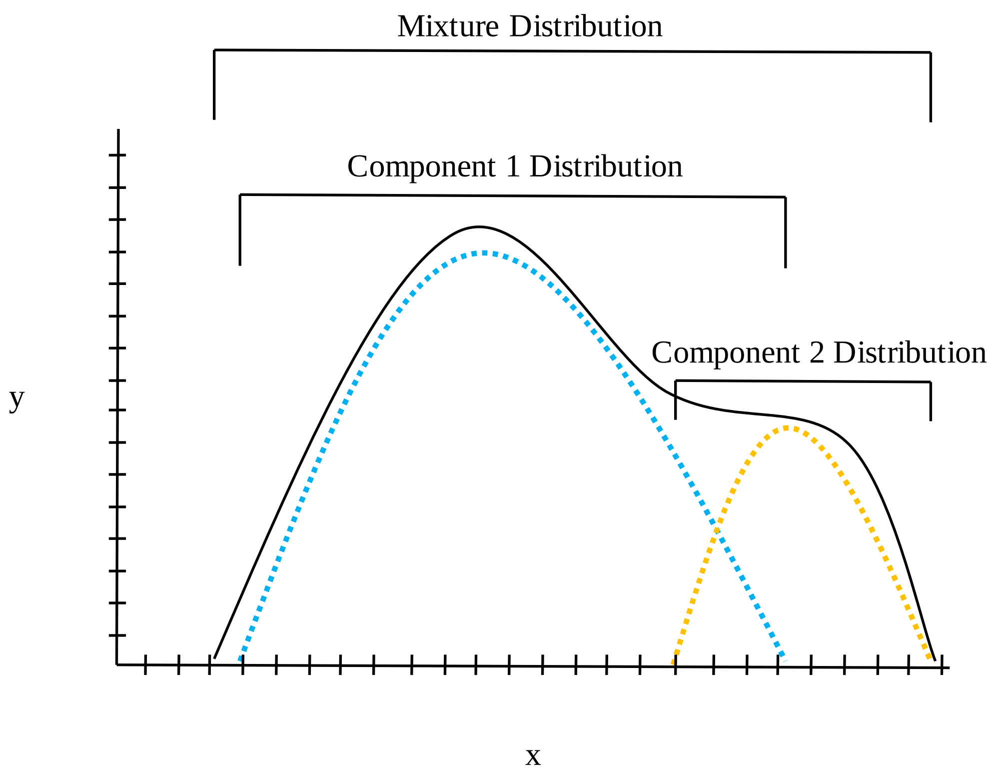
Finally, empirical evidence indicates lone-actors, or individuals who conceive and carry out attacks entirely alone, are more violent than actors who act with others or are members of a formalized terrorist group (Phillips, 2017). Research also suggests lone-actors are more likely to be mentally ill, which may partially explain this finding and warrants the inclusion of both variables as controls. The RPFD's *Group Affiliation* measure is based on the ECDB's original *Lone Wolf or Group* variable (see Turner et al., 2023). The variable includes four categories: (1) Acted alone, (2) Acting with others with no clear group boundaries, (3) Part of informal group, and (4) Part of formal group. The descriptions for each category can be found in Table 5. To binarize this measure, the *Acted Alone* category is used as the reference group to create three dummy variables indicating the latter three categories: *Acting With Others, Informal Group*, and *Formal Group*.

3.2.2. Class Enumeration

Once variables are selected, the second step in specifying an LCA model is class enumeration. The idea behind LCA, and finite mixture modelling in general, is that multiple component distributions make up a larger mixture distribution in data; these are the underlying "latent classes" that are assumed to differentially influence patterns in the observed data (Bauer & Steinley, 2021). Component distributions are the distributions of each class estimated in an LCA model. Figure 1 illustrates this concept, depicting a hypothetical two-component mixture model. However, determining how many components, or classes, are in an LCA model is an intuitive, data-driven process that is accomplished through class enumeration.

Class enumeration is the process of selecting a class solution, or the number of latent classes in a model. Specifically, because LCA is a model-based approach, the optimal class solution is determined using model-fit criteria estimated through maximum likelihood estimation. This is done by estimating multiple models on the same set of data, with a different number of classes specified for each model, and identifying the number of classes that model-fit indices indicate are best fit for the observed data (Nylund-Gibson & Choi, 2018). Indeed, while theory should be used to inform the enumeration process (Nylund-Gibson & Choi, 2018), the iterative, data-driven approach of LCA facilitates robust identification of latent classes through model-fit indices that accurately characterize the subgroups underpinning the data.

Figure 1. Illustration of Component and Mixture Distributions in a Two-Class Model



Overall, there is no scholarly consensus on the *best* model-fit criterion for LCA. However, prior research has identified numerous fit-indices that may be used to identify the optimal class solution, and advocate for a joint approach where multiple criteria are collectively considered (Bauer & Steinley, 2021; Nylund-Gibson & Choi, 2018; Weller et al., 2020). The most popular choice is information criteria (IC), which seek to balance accuracy and parsimony by finding the solution that maximizes the log-likelihood while minimizing the number of parameters in the model. Lower IC values indicate a better fit. Most often, researchers use Akaike information criteria (AIC) and Bayesian information criteria (BIC) to assess fit of LCA models. Scholars assert BIC performs the best for LCA models, particularly when separation between classes is high (Bauer & Steinley, 2021; Nylund-Gibson & Choi, 2018; Nylund-Gibson et al., 2007; Weller et al., 2020). AIC, alternatively, often favors class solutions with too many classes (Bauer & Steinley, 2021). Importantly, scholars argue it is best to consider both ICs together when determining a class solution that is most optimal fit for the data (Kuha, 2004; Nylund-Gibson & Choi, 2018; Weller et al., 2020).

Diagnostic criteria may also be used to evaluate model fit for an LCA. In particular, entropy provides a useful tool for gauging the separation between classes in an LCA model. Entropy is a metric, ranging from 0 to 1, that indicates how well separated the classes in a class solution are. Higher entropy values indicate a higher separation between classes and thus less classification error when assigning individuals to classes (Weller et al., 2020), which is discussed in later sections. While there is no consensus on an appropriate entropy value threshold, Weller et al. (2020) suggest values over .80 are acceptable. Another diagnostic criterion, the average latent class posterior probability, is discussed in *Section 3.2.4*.2. Heeding the guidance of previous scholars (Nylund-Gibson & Choi, 2018; Nylund-Gibson et al., 2007; Weller et al., 2020) the current dissertation uses both AIC and BIC estimates in conjunction with diagnostic criteria to identify the most optimal class solution for the data.

3.2.3. Estimation of Class Parameters

After the variables are selected and classes are enumerated, maximum likelihood estimation is used to estimate the class parameters, or the probability coefficients that define the characteristics of a class, that are most likely to produce the observed data (Bauer & Steinley, 2021; Vermunt & Magidson, 2004). In an LCA model, binary indicator variables are assumed to follow a Bernoulli distribution (Bauer & Steinley, 2021). Use of a Bernoulli distribution allows us to model the probability that a variable will observe a success, or a "1" response (Bauer & Steinley, 2021). The probability mass function (PMF) for the Bernoulli distribution, is as follows (Bauer & Steinley, 2021):

$$(1) \qquad f(y; \mathrm{d}) = \mathrm{d}^{y}(1-\mathrm{d})^{1-y}$$

In Equation 1, *y* equals the possible outcome (0 or 1), and d is the probability of observing a "success" or a "1." Essentially, this equation calculates the probability of observing a "1" for a single binary indicator variable. When $y = 1$, the PMF = d, whereas if $y = 0$, the PMF = 1-d. A higher frequency of y="1" responses will result in a higher probability (d) of observing that variable. Importantly, LCA assumes that all independent variables included in the model are locally independent, in that they are not interdependent on one another. Because of this assumption of local independence, the univariate PMFs for each indicator variable can be multiplied to produce a component distribution, or the distribution of probability values for each indicator variable in a class, for class *k* (Bauer & Steinley, 2021):

$$(2) \qquad g_k(\boldsymbol{y}_i; \boldsymbol{\theta_k}) = \prod_{j-1}^{p} \mathrm{d}_{jk}^{y_{ij}} (1-\mathrm{d}_{jk})^{1-y_{ij}}$$

In Equation 2, *i* indexes the individual, *j* indexes the variable, *k* indexes the class, and *p* indexes the number of variables. Essentially, $\mathrm{d}jk$ equals the probability that y_{ij}, or the response for person *i* in variable *j*, is "1" in class *k*. In other words, Equation 2 indicates the joint probability a person will demonstrate an indicator variable value "1" in a specified class. The result is an estimated component distribution ($\mathbf{y}_i$; $\boldsymbol{\theta}_k$) for class *k*, where $\mathbf{y_i}$ is a vector of outcome responses for *p* variables for person *i*, and $\boldsymbol{\theta}_k$ is a vector of parameters for *k* class. Overall, the primary takeaway from Equation 2 is the ability to multiply univariate PMFs to estimate a component distribution for each latent class (*k*) based on each person's (*i*) responses to each indicator variable (*j*) (Bauer & Steinley, 2021).

With that said, the idea behind a mixture model is that multiple component distributions compose a larger mixture distribution, as discussed above. To obtain a full mixture model, then, the component distributions for each class are simply summed. However, classes are not equal in size – some will be larger, representing a larger proportion of the sample, and others will be smaller. Thus, to produce a full mixture model, mixing probabilities are then added to the equation to weigh the summation of component distributions. Mixing probabilities, also known as class proportion shares, represent the overall probability that a person *i* will be categorized in class *k*, or the relative frequency of a class within the sample (Bauer & Steinley, 2021). Thus, the final LCA estimation Equation (3) where p_k represents the mixing probabilities for *k* classes is expressed as (Bauer & Steinley, 2021):

$$(3) \qquad f(y_i;\psi) = \sum_{k-1}^{K} \pi_k \prod_{j-1}^{p} \mathrm{d}_{jk}^{y_{ij}} \left(1-\mathrm{d}_{jk}\right)^{1-y_{ij}}$$

By summing component distributions for each class as conditioned by mixing probabilities, the class parameters are robust to the relative proportions of each estimated class. This, inherently, is conditional on the number of classes selected in the class enumeration process, as intuitively, fewer classes will result in higher mixing probabilities, and more classes will result in lower mixing probabilities.

In total, the LCA model estimates two class parameters from the final estimation Equation 3: (1) class-specific indicator probabilities, and (2) individual posterior probabilities of class membership. Class-specific indicator probabilities indicate the probability individuals in class *k* will score a “1” for indicator variable *j*. These values necessarily characterize the attributes of a class. Second, individual posterior probabilities of class membership indicate the probability that individual *i* will be in class *k* based on their scores on *p* variables. Posterior probabilities of class membership are an especially important parameter for using estimated classes to predict distal outcomes, which are discussed in the next section.

3.2.4. Using Latent Class Membership to Predict Distal Outcomes

The next step in the analytic plan is assessing the relationship between the estimated latent classes of criminogenic risk and the type of extremist action individuals are engaged in. In this dissertation, the type of extremist action serves as the dependent variable, or the “distal outcome” under study. A distal outcome is a variable which is theorized to be influenced by the latent classes (Bauer & Steinley, 2021). The LTB approach is used for estimating the relationship between latent class membership and categorical distal outcomes (Lanza et al., 2013). This section begins by operationalizing the dependent variable, then explains the LTB approach.

3.2.4.1. Dependent Variable

The dependent variable of study is the type of extremist action the individual was known to engage in. This is a categorical measure with three categories: *nonoffending extremism*, *nonviolent criminal extremism*, and *violent extremism*. Individuals engaged in nonoffending extremism are those who were known to espouse extremist beliefs and participate any legal activities to advance their cause, including partaking in protests/rallies, writing literature, producing media, attending extremist events, or any other noncriminal extremist activities. NOEs may also be individuals who were known members of an extremist group but did not participate in any violent or criminal actions.

In line with prior research, individuals engaged in nonviolent criminal extremism, alternatively, were those who committed ideologically motivated crime that did not or was not intended to physically harm another person(s) (Harms, 2017; Jasko et al., 2017; Kerodal et al., 2016). Nonviolent crimes included offenses such as tax fraud, money laundering, embezzlement, property damage, and vandalism, to name a few (Freilich et al., 2015; Jensen et al., 2016). Finally, individuals involved in violent extremism plotted or participated in criminal action that intended to physically harm or kill another person(s) (Harms, 2017; Jasko et al., 2017; Jensen et al., 2016). Importantly, if an extremist was involved in both violent and nonviolent crimes, they were coded as violent. This was the case for approximately (n=9) individuals who were most often involved in a nonviolent crime, such as providing material support, and were simultaneously mobilizing towards a violent attack.

The dependent variable was a categorical variable where "1" = *Violent Extremist*, "2" = *Nonviolent Criminal Extremist*, and "3" = *Nonoffending Extremist.* As will be explained in the next section, a reference category was not constructed because the LTB approach estimates the probability of observing each outcome in each class of an LCA model. Thus, the dependent variable was considered as a single categorical outcome with three distinct categories representing each type of extremist action.

3.2.4.2. The LTB Approach

Prior to discussing the LTB approach, it is important to first describe the method which it improves upon. Historically, the classify-analyze approach was used to assess the relationship between latent classes and distal outcomes (Nylund-Gibson et al., 2019). In this approach, individuals in the sample are assigned to classes through the principle of modal assignment. Essentially, each individual in the sample has a non-zero probability of being assigned to each estimated latent class. In this way, the sum of one person's posterior probability of membership for each latent class is equal to 1. For example, in a three-class model, an individual may have a .90 posterior probability of being assigned to class 1, .06 posterior probability of being assigned to class 2, and .04 posterior probability of being assigned to class 3. Modal assignment, then, is a technique that assigns each individual in the sample to the class they have the highest posterior probability of being in, which in this example is class 1. In principle, modal assignment facilitates the creation of a latent class variable.

The accuracy of modal assignment can be indicated by the average latent class posterior probability (ALCPP). As a supplemental diagnostic criterion, the ALCPP calculates the mean posterior probability for all the individual cases assigned to a particular class (Weller et al., 2020). ALCPP values closer to 1.00 are preferred, and values over .90 are considered ideal (Weller et al., 2020). For example, an ALCPP value of .95 for a class indicates that the mean posterior probability of class membership for individuals assigned to that class is .95. In this way, the ALCPP brings notable transparency to the process of modal assignment and provides an additional metric with which to gauge the fit of an LCA model. This dissertation consults the ALCPP in conjunction with the aforementioned AIC, BIC, and entropy metrics to select the optimal class solution (see *Section 3.2.2.*)

The use of modal assignment to create a latent class variable intuitively gives way to the naïve classify-analyze approach for estimating the predictive relationship between the variable and a distal outcome. Individuals are assigned to a particular class to create a latent class variable, and the relationship between the categorical latent class variable and a distal outcome is analyzed. However, studies indicate this approach downward biases the estimates of the relationship between the latent class variable and covariates (Bakk et al., 2013; Bolck et al., 2004; Vermunt, 2010). Specifically, the classify-analyze approach is biased by classification error, as it assumes modal assignment is perfectly accurate. This is not the case, as the non-zero probability of class membership precludes such perfection in assignment. For example, while some individuals may have a .98 probability of being assigned to a class 1, others may only have a .70 probability of being assigned to that class. Nonetheless, by rule of modal assignment, both would be classified into the class 1. The classification error, then, is the residual of individuals' latent class posterior probability, or the probability they will be assigned to a latent class which they do not have the highest probability of being assigned to.

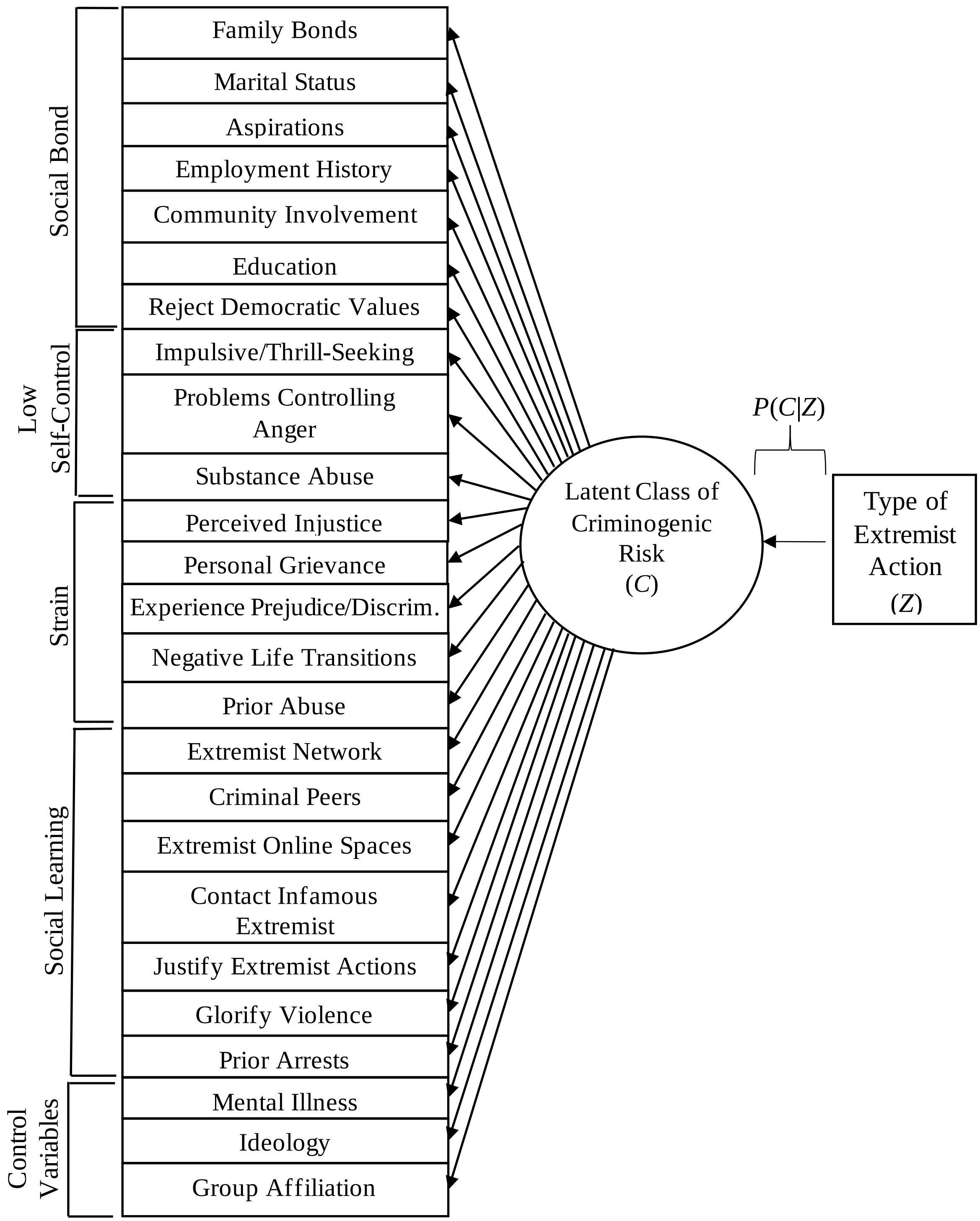
Necessarily, it is the rigidity of the classify-analyze approach that limits its rigor, as classification error is essentially ignored by modal assignment. Thus, scholars have proposed a number of techniques to correct for this issue (Nylund-Gibson et al., 2019). One solution is termed the one-step approach, also known as the distal-as-indicator approach, whereby the distal outcome is simply included in the latent class model as an indicator variable alongside the other indicator variables (Nylund-Gibson et al., 2019). While there are advantages to the one-step approach, its main drawback is that the latent class solution, and the characteristics of the classes therein, are conditioned by the inclusion of the distal outcome in the LCA model (Asparouhov & Muthén, 2014). This is counterintuitive to the logic underpinning many applied research questions; specifically, that the derived latent classes temporally precede and are conceptually distinct from the distal outcomes of interest. Therefore, the one-step approach cannot estimate direct effects between the latent classes and the distal outcome (Nylund-Gibson et al., 2019).

Other scholars advocate for a three-step approach when examining the relationship between latent classes and auxiliary variables (Asparouhov & Muthén, 2021; Nylund-Gibson et al., 2019). Vermunt's (2010) three-step approach was originally proposed to correct for classification error with covariates predicting latent classes; in other words, situating the latent class variable as the outcome rather than the predictor. However, Bakk et al. (2013) found Vermunt's (2010) approach was also applicable for using the latent class variable to predict distal outcomes – termed the BCH approach. While the BCH approach is recommended by scholars for using latent classes to predict distal outcomes, this mostly applies to continuous distal outcomes. Specifically in using the statistical software *MPlus*, the automatic BCH approach can only estimate continuous distal outcomes. Although scholars advocate for a manual BCH approach whereby the class parameters are fixed through a manual input process (Nylund-Gibson & Choi, 2018; Nylund-Gibson et al., 2019), there is no guidance on how such a process is computationally conducted with a categorical distal outcome.

Accordingly, many scholars advocate for the LTB approach when examining the relationship between latent classes and categorical distal outcomes (Asparouhov & Muthén, 2014; Bakk & Kuha, 2020; Bakk & Vermunt, 2016; Collier & Leite, 2017). Lanza et al. (2013) propose a unique technique, described as *inclusive LCA analysis*, that avoids the primary drawback of the one-step approach – the influence of the distal outcome on the latent class solution – while also avoiding the classification error inherent to modal assignment (see also, Bray et al., 2015). The LTB method has been described as a two-step approach (Bakk & Vermunt, 2016), or a variant of the one-step approach (Bakk & Kuha, 2020). Ultimately, the procedure consists of two steps.

The first step is estimating a standard LCA model with the selected indicator variables. In this step, a class solution is selected through the enumeration process based on model-fit and diagnostic criteria. Differing from the aforementioned one-step approach, the distal outcome is included as a covariate in this LCA model as opposed to an indicator variable. In this way, the class-indicator probabilities estimated for the indicator variables are not conditioned by the distal outcome, overcoming this limitation of the one-step approach. Instead, the distal outcome is used as a predictor in a multinomial logistic regression model whereby the derived latent class variable is situated as the outcome. Thus, while Step 1 estimates the parameters of the core LCA model, it also calculates the probability of observing a specific category of the latent class variable (C) given the distal outcome (Z), resulting in the conditional probability of $P(C|Z)$. This step is illustrated in Figure 2 with the current set of variables included.

Figure 2. Step 1 of LTB Approach: LCA Model with Distal Outcome as Covariate



The purpose of Step 2 is to estimate *P(Z|C)*, or the conditional probability of observing the distal outcome (*Z*) given the latent class (*C*). To achieve this, Lanza et al. (2013) propose using Bayes Theorem. Bayes Theorem states the following:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{4}$$

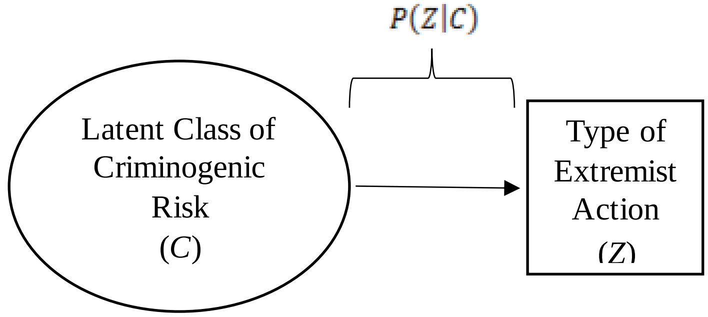
In Equation 4, *P(B|A)* represents the conditional probability of *B* given *A*, *P(A)* represents the marginal distribution of *A*, and *P(B)* represents the marginal distribution of *B*. If all of these values are known, then we can use Bayes Theorem to estimate *P(A|B)*, or the conditional probability of *A* given *B*. Applying Bayes Theorem to the current LCA model, where *C* is the latent class variable and *Z* is the distal outcome, estimating the conditional probability of *Z* given *C* can be expressed as:

$$P(Z|C) = \frac{P(C|Z)P(C)}{P(Z)} \tag{5}$$

In Step 1, the LTB approach estimates the probability of *C* given *Z* (*P(C|Z)*) by including the distal outcome *Z* as a covariate to the latent class model. Thus, by incorporating the marginal distributions of *C* (*P(C)*) and *Z* (*P(Z)*),[11] Step 2 of the LTB approach estimates the conditional probability of *Z* given *C*. In this way, we can estimate the probability that a person in *c* class of criminogenic risk will be involved in *z* type of extremist action. Figure 3 illustrates Step 2 of the LTB approach as it relates to the current set of variables. Computationally, the LTB approach is automated in the *MPlus* software with the option "DCAT" in the "AUXILIARY" command ("DCOT" for continuous outcomes).

[11] Note that to obtain the marginal distribution of *P(Z)*, scholars suggest using the empirical distribution of the distal outcome *Z*. This is the technique that is used in the "DCAT" option in the "Auxiliary" command in *MPlus*.

Figure 3. Step 2 of LTB Approach: Estimating Probability of Distal Outcome Given Latent Class



3.2.5. Sensitivity Analyses

The final step in the analytic plan is to conduct supplemental sensitivity analysis to evaluate the robustness of the results. Specifically, two sensitivity analyses will be conducted, both of which involving sample adjustments based on RPFD metrics. First, the aforementioned variable coding scheme in the RPFD relies on the presence of evidence that a variable occurred. This results in variables relating to the presence or absence of risk and protective factors to actually indicate the presence or absence of *evidence* that indicates the presence of a factor. In other words, the "No." or "0," responses for these variables conflate negative evidence, or evidence that indicates a factor was not present, with missing values, or the absence of evidence for a variable. While it has been established that definitive evidence indicating "No" responses in open-source information is extremely rare and infeasible to appropriately capture (Corner et al., 2021; Gill et al., 2014), the information reflected in the variable responses is inherently biased by the quantity and quality of open-source information available on a particular case. This bias may result in an abundance of "No" responses for cases where especially little information is known about the individual, thus inflating the "0" values for specified variables.

Given LCA is a data-driven approach, such bias may influence the estimated latent classes that are assumed to underly the data. Thus, it is necessary to assess whether the results of the LCA – namely, the estimated classes of criminogenic risk and their relation with the type of extremist action one was involved in – are sensitive to the quantity and quality of information available on a case. The RPFD reliability score offers a useful metric for exploring this possibility, as it not only indicates the number of different sources providing information on a case, it also weights those sources based on the credibility of information they provide (see *Section 3.1.3.*). To conduct this sensitivity analysis using reliability scores, the mean reliability score will be conducted for the sample. Then, any cases that fall below one standard deviation from the mean are dropped from the sample, as these cases represent those with less reliable information and thus less confidence in the “No” responses. The LCA is then re-ran with the adjusted sample to assess whether the latent classes of criminogenic risk that emerge from the data and their relationship with the distal outcome are congruent to the results previously estimated in the full sample.

The second sensitivity analysis mimics the steps taken in the first one, but rather than using the reliability score as the operational metric, the NOE confidence scale is used (see *Section 3.1.2.*). As described above, the matching process for NOEs was rigorous, and the confidence scale sought mitigate the subjectiveness of classifying someone as an extremist based on the beliefs they espouse by employing a slate of objective attitudinal and behavioral criteria prior literature had conceptualized to indicate extremists. However, it may be that individuals who scored lower on the confidence scale are on the fringe of extremism, in that they hold some, maybe even just one belief that would warrant their inclusion as a NOE. These individuals may be conceptually distinct from those who epitomize extremism by endorsing various extreme beliefs and participating in NOE activities, thus scoring higher on the confidence scale.

Accordingly, to account for this potential variation and ensure validity within the comparison group, individuals who score below one standard deviation of the mean confidence score for the NOE sample are omitted. The analysis is then re-ran only with NOEs who score at or above the mean confidence score to determine if the results of the LCA and distal outcome prediction are sensitive to the confidence score of NOEs included in the sample.

Finally, the first and second sensitivity analysis are combined to produce a comprehensive sensitivity analysis. An LCA model will be estimated using a sample adjusted by both reliability score and confidence score. This model will help surmise whether the latent classes estimated in the original LCA model are sensitive to both the reliability of open-source information available on a case and the confidence in the NOE matched sample as a meaningful comparison group.

CHAPTER 4: RESULTS

This section will present the results. The section will be divided into three parts. First, results from the descriptive analysis will be presented and discussed. All descriptive analyses were conducted using the *STATA/BE 17.0* statistical software. Second, the LCA model with distal outcome prediction will be conducted, and the findings from this analysis will be reviewed in detail. The *MPlus 8.10* statistical software with the mixture modelling add-on was used to estimate an LCA model and conduct the LTB method. Specifically, the LTB method was automated by using the "*DCAT*" option in the "AUXILIARY" command. Finally, results from the sensitivity analysis will be explored and discussed. The data sub-setting for the sensitivity analysis was conducted in *STATA/BE 17.0* while the LCA models for the sensitivity analysis were estimated in *MPlus 8.10*.

4.1. Descriptive Analysis

Table 6 displays the frequencies and percentages for each variable in the analysis across the three categories of extremists. In terms of protective factors, VEs, NVCEs, and NOE are similar in many ways. First, a comparable percentage of each group had close familial bonds with either parents or siblings (29% vs. 19% vs. 22%), although VEs counterintuitively held these bonds slightly more frequently. Interestingly, NVCEs had the lowest percentage of individuals who expressed prosocial aspirations (24%), with VEs (30%) and NOEs (36%) demonstrating slightly higher proportions. However, this finding is inconsistent with the activities we see NCVEs being involved in. NVCEs had the highest percentage of individuals who were married or in a committed relationship (48%), followed by NOEs (37%) and VEs (32%), suggesting marital bonds may reduce one's risk of engaging in violence. Both NVCEs (56%) and NOEs (64%) had much higher percentages of individuals with stable employment histories compared to VEs, with just 36% of VEs being regularly employed. These findings are partially consistent with Sampson and Laub's (1992) developmental model that significant life events may result in desistance from crime – only in this case, the aversion is from violence specifically rather than crime in general.

VEs and NVCEs are both involved in their communities less frequently (22% and 23%, respectively) compared to almost 40% of NOEs. Interestingly, all three groups had nearly equal percentages of individuals who had sought a college education (54% vs. 56% vs. 54%). Additionally, though it is a rarity for each group, a higher percentage of VEs had military experience than NVCEs or NOEs (16% vs. 7% vs. 7%). While military experience may be conceptualized as a protective factor in the sense that it promotes involvement in prosocial activities, researchers have linked current or past military service to engagement in radical behaviors, suggesting this category of people may be uniquely exposed to certain extremist-enabling influences (Haugstvedt & Koehler, 2021). Finally, a particularly substantial point of divergence is the extent to which an individual rejects the conventional norms and rules that govern a democratic society. VEs (36%) and NVCEs (48%) are much more likely to reject democratic values than NOEs, which makes sense given that the latter group abides by the conventional order and the former groups actively violate normative laws and morals.

Table 6. Descriptive Statistics for Full Sample (n=731)

Variable	**Violent Extremists (N=258)**	**Nonviolent Criminal Extremists (N=241)**	**Nonoffending Extremists (N=232)**
Social Bond			
Family Bonds			
No	183 (70.93%)	196 (81.33%)	182 (78.45%)
Yes	75 (29.07%)	45 (18.67%)	50 (21.55%)
Marital Status			
No	176 (68.22%)	125 (51.875)	146 (62.93%)
Yes	82 (31.78%)	116 (48.13%)	86 (37.07%)

Table 6. (cont'd)

Aspirations			
No	180 (69.77%)	183 (75.93%)	148 (63.79%)
Yes	78 (30.23%)	58 (24.07%)	84 (36.21%)
Employment History			
No	166 (64.34%)	105 (43.57%)	84 (36.21%)
Yes	92 (35.66%)	136 (56.43%)	148 (63.79%)
Community			
Involvement	202 (78.29%)	186 (77.18%)	142 (61.21%)
No	56 (21.71%)	55 (22.82%)	90 (38.79%)
Yes			
Education			
No	118 (45.74%)	105 (43.57%)	107 (46.12%)
Yes	140 (54.26%)	136 (56.43%)	125 (53.88%)
Military Experience			
No	218 (84.50%)	224 (92.95%)	215 (92.67%)
Yes	40 (15.50%)	17 (7.05%)	17 (7.33%)
Reject Democratic			
Values	164 (63.57%)	125 (51.87%)	209 (90.09%)
No	94 (36.43%)	116 (48.13%)	23 (9.91%)
Yes			
Low Self-Control			
Impulsive/Thrill-			
seeking	183 (63.18%)	212 (87.97%)	211 (90.95%)
No	95 (36.82%)	29 (12.03%)	21 (9.05%)
Yes			
Problems Controlling			
Anger	195 (75.58%)	229 (95.02%)	220 (94.83%)
No	63 (24.42%)	12 (4.98%)	12 (5.17%)
Yes			
Substance Abuse			
No	167 (64.73%)	217 (90.04%)	223 (96.12%)
Yes	91 (35.27%)	24 (9.96%)	23 (9.91%)
Strain			
Perceived Injustice			
No	109 (42.25%)	133 (55.19%)	157 (67.67%)
Yes	149 (57.75%)	108 (44.81%)	75 (32.33%)
Personal Grievance			
No	75 (29.07%)	155 (64.32%)	148 (63.79%)
Yes	183 (70.93%)	86 (35.68%)	84 (36.21%)
Experience			
Prejudice/Discrim.	223 (86.43%)	221 (91.70%)	180 (77.59%)
No	35 (13.57%)	20 (8.30%)	52 (22.41%)
Yes			

Table 6. (cont'd)

Negative Life			
Transitions	41 (15.89%)	88 (36.51%)	140 (60.34%)
No	217 (84.11%)	153 (63.49%)	92 (39.66%)
Yes			
Prior Abuse			
No	199 (77.13%)	222 (92.12%)	227 (97.84%)
Yes	59 (22.87%)	19 (7.88%)	5 (2.16%)
Social Learning			
Extremist Network			
No	90 (34.88%)	83 (24.44%)	82 (35.34%)
Yes	168 (65.12%)	158 (65.56%)	150 (64.66%)
Criminal Peers			
No	168 (65.12%)	210 (87.14%)	219 (94.40%)
Yes	90 (34.88%)	31 (12.86%)	13 (5.60%)
Extremist Online			
Spaces	200 (77.52%)	208 (86.31%)	190 (81.90%)
No	58 (22.48%)	33 (13.69%)	42 (18.10%)
Yes			
Contact Infamous			
Extremists	207 (80.23%)	202 (83.82%)	182 (78.45%)
No	51 (19.77%)	39 (16.18%)	50 (21.55%)
Yes			
Justify Extremist			
Actions	127 (49.22%)	111 (46.06%)	129 (55.60%)
No	131 (50.78%)	130 (53.94%)	103 (44.40%)
Yes			
Glorify Violence			
No	128 (49.61%)	193 (80.08%)	169 (72.84%)
Yes	130 (50.39%)	48 (19.92%)	63 (27.16%)
Prior Arrests			
No	133 (51.55%)	185 (76.76%)	196 (84.48%)
Yes	125 (48.45%)	56 (23.24%)	36 (15.52%)
Control Variables			
Mental Illness			
No	155 (60.08%)	213 (88.38%)	231 (99.57%)
Yes	103 (39.92%)	28 (11.62%)	1 (.43%)
Lone actor			
No	177 (68.60%)	195 (80.91%)	207 (89.22%)
Yes	80 (31.01%)	45 (18.67%)	25 (10.78%)
Missing	1 (.39%)	1 (.41%)	
Far-right ideology			
No	152 (58.91%)	135 (56.02%)	129 (55.60%)
Yes	106 (41.09%)	106 (43.98%)	103 (44.40%)

Turning to criminogenic risk factors, the descriptive findings indicate VEs, as a whole, may have lower self-control than NVCEs or NOEs. Specifically, a much higher percentage of VEs (36%) demonstrated impulsive and thrill-seeking behaviors than NVCEs (12%) or NOEs (9%). Further, VEs had problems controlling their anger more often than NVCEs and NOEs (24% vs. 5% vs. 5%) and abused substances more frequently than NVCEs and NOEs (25% vs. 10% vs. 10%), suggesting a proclivity towards activities that are immediately gratifying. Overall, although NCVEs and NOEs do not differ in their self-control, these findings suggest VEs possess much lower self-control than nonviolent and noncriminal extremists.

The risk factors related to strains also reveal stark differences between VEs, NVCEs and NOEs. First, a higher percentage of VEs perceived some form of social injustice that underpinned their ideology (58%) compared to NVCEs (45%) and NOEs (32%). An even larger difference can be observed in the proportion of individuals who hold a personal grievance connected to their ideology. While 71% of VEs expressed a personal grievance of some form, only 36% of both NVCEs and NOEs held a personal grievance. Additionally, VEs experienced negative life transitions (84% vs. 63% vs. 40%) and were abused (23% vs. 8% vs. 2%), much more often than NVCEs or NOEs. NOEs, however, experienced prejudice or discrimination slightly more frequently than VEs or NVCEs, but the difference is subtle (14% vs. 8% vs. 22%).

Overall, VEs, NVCES, and NOEs were similar in their exposure to risk factors related to the social learning process, but there were some key differences. Specifically, VEs associated with criminal or delinquent peers more often than NVCEs or NOEs (35% vs. 13% vs. 6%), despite all three groups having an almost equal percentage of individuals exposed to other extremists in their social networks (65% vs. 66% vs. 65%). The three groups were also comparable in their presence in online extremist spaces (22% vs. 14% vs. 18%), their contact with infamous extremists (20% vs. 16% vs. 22%), and their justifying of extremist actions (51% vs. 54% vs. 44%). The latter finding is interesting, as this risk factor indicates whether an individual possesses definitions favorable of criminal behavior when driven by ideological goals. However, when those definitions are placed in the context of violence, the differences between the groups are more poignant. While over half of VEs expressed an acceptance or glorification of violence (50%), only 20% of NVCEs and 27% of NOEs made similar expressions. Thus, the possession of pro-violence definitions is more common amongst extremists who actively engage in violence.

Finally, VEs, NVCEs, and NOEs differ in terms of the control variables as well. Consistent with prior research (Becker 2021, LaFree et al., 2018), a much higher percentage of VEs had a mental illness (40%) than NVCEs (11%) or NOEs (.4%). Further, VEs acted alone more often than NVCEs or NOEs (31% vs. 19% vs. 11%), a cause for concern when considering extant research has tied lone actors to more severe attack outcomes (Phillips, 2017; Turner et al., 2023). Finally, an equivalent percentage of each group subscribed to a far-right ideology, confirming the reliability of the RPFD sampling scheme.

4.3. LCA

The descriptive analysis revealed important preliminary differences between VEs and their nonviolent and noncriminal counterparts on numerous criminogenic risk and protective factors. Next, the analytic strategy detailed in *Section 3.2.* is employed to explore interrelationships amongst the criminogenic factors and between the criminogenic factors and the type of extremist action an individual engaged in.

4.3.1. Class Enumeration

As aforementioned, estimating a LCA model begins by enumerating the class solution that best fits the data. The enumeration process is model-based in that it aims to identify the best fitting number of classes by consulting several model-fit and diagnostic criteria. The enumeration process begins by calculating these criteria for a two-class solution, as this is the minimum number of classes an LCA can estimate as a one-class solution would indicate no heterogeneity in the observed data, and then calculating the model-fit and diagnostic criteria for each succeeding class solution until the best fitting model is identified. Table 7 displays the results of the enumeration process for the LCA model using the full, unadjusted sample for this study.

Table 7. Model Fit and Diagnostic Criteria for Class Solutions 2-7

	Model Fit Criteria		Diagnostic Criteria	
Class Solution	**BIC**	**AIC**	**Entropy**	**ALCPP**
2	20495.03	20251.52	.79	**.94**
3	20128.08	19760.52	.79	.90
4	20011.54	19519.93	.81	.89
5	19910.38	19294.73	.85	.91
6	**19856.34**	19116.64	.86	.91
7	19865.53	**19001.78**	**.87**	.89

The process of selecting a class solution, though guided by objective criteria, is slightly based on interpretation. As shown in Table 7, lower IC values indicate a better fitting model, whereas entropy values above .80 and ALCPP values above .90 are preferable and indicate strong separation between classes. While the BIC favors a 6-class solution, the AIC and entropy values favor a 7-class solution, and the ALCPP favors a 2-class solution. It is important to note that diagnostic criteria should not be used to guide the selection of class solutions on their own, but rather only in conjunction with IC (Weller et al., 2020). The BIC has been recognized as the best-performing information criterion for selection class solutions for LCA models with categorical indicator variables (Bauer & Steinley, 2021; Nylund-Gibson & Choi, 2018; Nylund-Gibson et al., 2007; Weller et al., 2020). The AIC, on the other hand, has been shown to overestimate the number of classes in LCA models (Bauer & Steinley, 2021). Additionally, the difference between the 6-class solution's entropy value of .86 and the 7-class solution's value of .87 is marginal, and the 6-class solution has a higher ALCPP value, suggesting the class solutions are comparable in their separation between classes. Taken together, and erring on the side of parsimony, these criteria indicate the 6-class solution is the best fit for the LCA model.

4.3.2. Class Estimation

The next step of LCA is estimating the parameters that characterize the LCA model – specifically the conditional item response probabilities (hereafter, indicator probabilities) and class proportion shares. Table 8 reports the results of the full 6-class LCA model. The class proportion shares, or the estimated proportion of cases attributable to each class, is reported directly under the class number designation. The indicator probabilities, alternatively, are calculated for each indicator variable across each class and range from 0-1, with values closer to 1 indicating a higher probability of observing a "Yes" response for that variable in each class. Nylund-Gibson et al. (2018) posit that indicator probabilities greater than .70 are considered "high" and those less than .30 are considered "low" (p. 13). For the following results, any values in between these two thresholds are deemed "moderate." To help visualize the results, darker shading in Table 8 represents higher indicator probabilities, while lighter shading represents lower probabilities.

Class 1 – Bonded Rebels

Class 1 of the LCA model, constituting the third smallest proportion share of the six classes (.13), are deemed the "Bonded Rebels." This designation is qualified by the high indicator probabilities for the criminogenic protective factors drawn from social bond theory. Specifically, individuals in this class have a moderately high probability of being married or in a committed relationship (*P*=.64), a high probability of having a stable employment history (*P*=.79), and a high probability of attending college (*P*=.74). However, the reason these individuals are deemed "Rebels" is their weak commitment to conventional laws and norms, as they have a high probability (*P*=.71) of rejecting democratic values that govern normative behavior.

Bonded Rebels demonstrate very low indicator probabilities for all risk factors indicative of low self-control and do not report any high probabilities for strain-related risk factors except a moderate probability of experiencing negative life transitions (*P*=.57), which is fairly low compared to other classes. The only other risk factor approaching the high probability threshold is that of justifying extremist actions. Individuals in this class have a *P*=.66 probability of expressing justifications for past extremist actions, including violent or criminal attacks. Across the six classes, this is the second highest indicator probability for this factor, warranting its relevance for characterizing this class. Finally, these individuals have an almost nonexistent probability of being mentally ill (*P*=.00), a low probability of acting alone (*P*=.24), and an exceptionally high probability of subscribing to a far-right ideology (*P*=.98).

Class 2 – Strained Lone Actors

Compared to the *Bonded Rebels*, Class 2 is theoretically at a higher overall criminogenic risk for violent extremism due to the lower probabilities of observing criminogenic protective factors and higher probabilities of observing criminogenic risk factors. While Class 2 is characterized by increased indicator probabilities for several risk factors, the most poignant are the strain-related risk factors. Moreover, of all six classes, this class has the highest probability of being a lone actor (*P*=.95). Thus, Class 2 is designated as the "Strained Lone Actors" class and represents the second smallest proportion of cases in the sample (.12).

Class indicator probabilities for the social bond factors indicate *Strained Lone Actors* are less bonded to social institutions than *Bonded Rebels* but are not unbounded entirely. Individuals in this class have low probabilities of being married (*P*=.13) and having military experience (*P*=.23). Albeit the latter value is the highest across all six classes, suggesting that while it is a rarity for extremists to have served in the military, *Strained Lone Actors* have the highest probability of doing so. Additionally, the *Strained Lone Actors* class reported moderate probabilities for having close familial bonds (*P*=.31), expressing prosocial aspirations (*P*=.47), being regularly employed (*P*=.48), and being involved in their community (*P*=.31). However, individuals in this class only had a .40 probability of rejecting democratic values and norms, much lower than that of the *Bonded Rebels*.

While the value does not reach Nylund-Gibson et al.'s (2018) threshold of .70, individuals in Class 2 had the highest probability of demonstrating impulsive or thrill-seeking behavior (*P*=.55) across all six classes. This, coupled with the moderate probabilities of having problems controlling their anger (*P*=.37) and substance abuse (*P*=.38), suggests *Strained Lone Actors* have relatively low self-control compared to the other classes.

As aforementioned, *Strained Lone Actors* are characterized by high probabilities of observing strain-related risk factors. Individuals in this class are likely to perceive an injustice in society (*P*=.77), hold a personal grievance related to their ideology (*P*=.76), and experience a negative life transition (*P*=.95). The other strain factors report low indicator probabilities, but collectively the indicator probabilities suggest *Strained Lone Actors* are strained by both negative life experiences and connections to perceived social injustices.

Table 8. 6-Class LCA Model with Full Sample (n=731)

Variable	Class 1 (Bonded Rebels) .13	Class 2 (Strained Lone Actors) .12	Class 3 (Strained Learners) .20	Class 4 (Pro-Socially Bonded) .22	Class 5 (Unbound and Low-Risk) .23	Class 6 (Unbound Transitioners) .09
Social Bonds						
Family Bonds	0.12	0.31	0.31	0.30	0.13	0.21
Marital Status	0.64	0.13	0.53	0.55	0.15	0.26
Aspirations	0.33	0.47	0.36	0.51	0.02	0.11
Employment History	0.79	0.48	0.53	0.85	0.19	0.16
Community Involvement	0.13	0.31	0.37	0.60	0.06	0.00
Education	0.74	0.65	0.72	0.85	0.10	0.20
Military Experience	0.10	0.23	0.19	0.05	0.03	0.03
Reject Democratic Values	0.71	0.40	0.54	0.04	0.18	0.19
Low Self-Control						
Impulsive/Thrill-seeking	0.02	0.55	0.35	0.06	0.07	0.31
Problems Controlling Anger	0.00	0.37	0.22	0.01	0.00	0.30
Substance Abuse	0.05	0.38	0.23	0.02	0.02	0.65
Strain						
Perceived Injustice	0.31	0.77	0.87	0.36	0.18	0.22
Personal Grievance	0.21	0.76	0.88	0.26	0.30	0.64
Experience Prejudice/Discrim.	0.00	0.24	0.19	0.32	0.02	0.01
Negative Life Transitions	0.57	0.95	0.87	0.61	0.19	0.95
Prior Abuse	0.01	0.24	0.21	0.04	0.02	0.27
Social Learning						
Extremist Network	0.57	0.12	0.90	0.73	0.63	0.78
Criminal Peers	0.02	0.23	0.33	0.10	0.06	0.52
Extremist Online Spaces	0.04	0.37	0.38	0.08	0.15	0.02
Contact Infamous Extremists	0.06	0.11	0.41	0.27	0.09	0.06

Table 8. (cont'd)

Justify Extremist Actions	0.66	0.62	0.73	0.31	0.40	0.30
Glorify Violence	0.00	0.58	0.80	0.17	0.18	0.16
Prior Arrests	0.15	0.50	0.40	0.19	0.10	0.76
Control Variables						
Mental Illness	0.00	0.70	0.22	0.05	0.02	0.37
Lone actor	0.24	0.95	0.05	0.14	0.05	0.08
Far-right ideology	0.98	0.24	0.28	0.01	0.57	0.88

Overall, the criminogenic risk factors related to the social learning process are fairly low in the *Strained Lone Actors* class. Individuals in this class have low probability of being exposed to extremists in their social network (*P*=.12) or criminal peers (*P*=.23) and are unlikely to reach out and contact infamous extremists (*P*=.11). These findings make sense given the high probability of being a lone actor in this class. They also have a moderately low probability of being active in extremist online spaces (*P*=.37). However, *Strained Lone Actors* report moderate probabilities of justifying prior extremist attacks (*P*=.62) and accepting or glorifying violence to advance their ideological goals (*P*=.58), indicating individuals in this class may hold pro-crime and pro-violence definitions for extremist actions. Additionally, while this class also has a moderate probability of having been previously arrested (*P*=.50) indicating some exposure to forms of differential reinforcement, this value may also represent the presence of a criminal history, a risk factor other studies have linked to an increased risk for violent extremism (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022).

In addition to being overwhelmingly likely to act alone, individuals in the *Strained Lone Actors* class have the highest probability of all six classes of having a mental illness (*P*=.70). In contrast to the *Bonded Rebels* class, *Strained Lone Actors* were not likely to subscribe to a far-right ideology (*P*=.24). This finding indicates individuals in this class are more likely to subscribe to jihadist or far-left ideologies. Overall, the combination of factors in this class presents a profile of an individual who is not strongly bound to social institutions, experiencing direct and vicarious strains in their lives, and mobilizing to extremism action alone.

Class 3 – Strained Learners

Similar to the *Strained Lone Actors* in Class 2, Class 3 is characterized by high probabilities of strain-related risk factors. However, a key difference between the two classes is the prevalence of social learning risk factors in Class 3. Thus, Class 3, estimated to constitute approximately 20% of the sample, is labelled the “Strained Learners” class. Also mirroring the *Strained Lone Actors*, the *Strained Learners* have some social bonding, demonstrating a moderate probability of having strong familial bonds (*P*=.31), be married (*P*=.53), express prosocial aspirations (*P*=.36), be regularly employed (*P*=.53), be involved in their community (*P*=.37), and to reject democratic values and norms (*P*=.54). They have a high probability of attending college (*P*=.72), but a low probability of serving in the military (*P*=.19) which is consistent with the other classes.

Strained Learners have moderate-to-low probabilities of demonstrating low self-control risk factors, including having a history of impulsive behavior (*P*=.35), having problems controlling anger (*P*=.22), and abusing substances (*P*=.23). In contrast, and as aforementioned, the high probability of strain-related risk factors characterizes this class. Specifically, individuals deemed Strained Learners have a high probability of perceiving an injustice in society (*P*=.87), hold a personal grievance against a person or collective (*P*=.88), and experience a negative life transition (*P*=.87). Mirroring the *Strained Lone Actors, Strained Learners* were unlikely to experience prejudice or discrimination (*P*=.19) or be abused (*P*=.21).

In assessing the social learning indicator probabilities, the social learning process is most observable amongst the *Strained Learners*. Individuals in this class have the highest probability across all six classes to be associated with other extremists in their social networks (*P*=.90), suggesting differential association is an important element in their involvement in extremist activities. Additionally, *Strained Learners* have a moderate probability of associating with criminal or delinquent peers (*P*=.33) and of engaging in extremist online spaces (*P*=.38). They also have the highest probability of all six classes to contact infamous extremists (*P*=.41), indicating imitation may play a role in the social learning process for these individuals. Furthermore, *Strained Learners* are the most likely to have pro-crime and pro-violence definitions, demonstrating the highest probability of justifying extremist actions (*P*=.73) and glorifying violence (*P*=.80) of all six classes. Finally, they are moderately exposed to differential reinforcements (*P*=.40), which, again, may also indicate their involvement in past criminal behavior. In terms of the control variables, individuals in this class were unlikely to have a mental illness (*P*=.22), act alone (*P*=.05), or subscribe to a far-right ideology (*P*=.28).

The relationship between the *Strained Learners* class and the distal outcome is much more contested than that of other classes. As shown in Table 8, there is an equal probability that a *Strained Learner* would engage in any of the three types of extremist action. The highest probability is engagement in violent extremism (*P*=.38), but the difference is marginal from those engaging in nonviolent criminal extremism (*P*=.33) or nonoffending extremism (*P*=.29). Thus, the *Strained Learners* class marks a unique combination of criminogenic risk and protective factors that demonstrate the equifinality of violent extremism; that is, the same pathway may lead to multiple different outcomes for everyone involved.

Class 4 – Pro-Socially Bonded

The fourth class is characterized by a high salience of criminogenic protective factors and limited criminogenic risk factors. Thus, Class 4 is the "Pro-Socially Bonded" class, as these individuals have strong prosocial bonds that may shield them from engaging in crime and deviance. Specifically, those who are *Pro-Socially Bonded* have a high probability of being gainfully employed (*P*=.85) and attending college (*P*=.85) and are moderately likely to be married (*P*=.55), have prosocial aspirations (*P*=.51), and be involved in their community (*P*=.60). In addition, and in stark contrast to the three classes previously discussed, *Pro-Socially*

Bonded individuals are unlikely to reject conventional democratic laws and norms, indicating a stronger bond to normative rules (*P*=.04).

For most of the criminogenic risk factors, those who are in the *Pro-Socially Bonded* class demonstrate low probabilities, particularly on the low self-control factors. These individuals do have a moderate probability of perceiving a societal injustice (*P*=.36), experiencing prejudice or discrimination (*P*=.32), and going through a negative life transition (*P*=.61), suggesting some degree of level of strain may be present. Additionally, they have a high probability of associating with other extremists socially (*P*=.73). Regarding the control variables, *Pro-Socially Bonded* individuals are unlikely to have a mental illness (*P*=.05), act alone (*P*=.14), or subscribe to a far-right ideology (*P*=.01). Taken together, this class may be considered the least at-risk for criminal or violent behavior due to the high prevalence of criminogenic protective factors and limited presence of criminogenic risk factors.

Class 5 – Unbound and Low-Risk

The fifth class of the LCA model is characterized by low indicator probabilities across all criminogenic factors, both risk and protective. In this way, individuals in Class 5, which constitutes the largest proportion share of the sample (.23), both lack bonds to social institutions but are at low risk for engaging in crime in deviance. Because of this, Class 5 is labeled "Unbound and Low-Risk."

Individuals deemed *Unbound and Low-Risk* are unlikely to be bonded to any social institution. They have a low probability of being close with their family (*P*=.13), being married (*P*=.15), having prosocial aspirations (*P*=.02), being regularly employed (*P*=.19), being involved in their community (*P*=.06), having attended college (*P*=.10), and having served in the military

(*P*=.03). Despite this low social bonding, they are unlikely to reject democratic laws and norms (*P*=.18), suggesting their bonds to the conventional order are not entirely ruptured.

Unbound and Low-Risk individuals also demonstrate low probabilities for all three low self-control indicators and are rarely afflicted by strain-related risk factors. They are, however, moderately likely to associate with other extremists in their social network (*P*=.63) and justify extremist actions (*P*=.40), suggesting some exposure to criminogenic influences. Additionally, it is rare for those who are *Unbound and Low-Risk* to have a mental illness (*P*=.02) or act alone (*P*=.05). They are, however, more likely to subscribe to a far-right ideology than not (*P*=.57).

One possibility to explain the consistently low indicator probabilities in the *Unbound and Low-Risk* class is that these values may partially reflect the cases with little open-source coverage. Specifically, an overall lack of open-source material on a case may result in a higher prevalence of "(0) No Evidence of Yes" responses across all of the variables in a case. The fact that several variables demonstrate moderate probabilities indicates this class was not entirely lacking information. Nonetheless, it is important when interpreting these findings, particularly of the *Unbound and Low-Risk* class, to keep the caveat in mind that all of these probabilities are indicative of evidence of the variable being present, and thus low probabilities indicate the absence of evidence that the variable was present. The sensitivity analysis in *Section 4.4.1.* aims to mitigate this potential reporting bias in the open-source materials.

Class 6 – Unbound Transitioners

The final class in the LCA model is the smallest of all six classes with a class proportion share of .09. While not demonstrating high probabilities in as many criminogenic risk factors as the *Strained Lone-Actors* or *Strained Learners*, Class 6 does have some degree of criminogenic risk factors, particularly related to experiencing negative life transitions, with a notable absence of protective factors. In this way, these individuals are dubbed “Unbound Transitioners.” Indeed, *Unbound Transitioners* are unlikely to have strong bonds to family (*P*=.21), a spouse or partner (*P*=.15), or prosocial goals or aspirations (*P*=.02). They are also rarely to be gainfully employed (*P*=.19), be involved in their community (*P*=.06), or serve in the military (*P*=.03). However, these individuals are also unlikely to reject democratic values and laws (*P*=.19), indicating a low prevalence of ruptured bonds to the conventional order.

In terms of low self-control, unbound transitioners have low probabilities of demonstrating impulsive behavior (*P*=.31) or having problems controlling their anger (*P*=.30). They do, however, report a relatively high probability of abusing substances, including drugs and/or alcohol (*P*=.65). This may indicate *Unbound Transitioners* need immediate gratification.

Qualifying their naming, *Unbound Transitioners* are very likely to experience a negative life transition (*P*=.95). These transitions are most often prompted by a particular event, such as job loss, divorce, victimization, or medical issue(s). Regardless of the context, it negatively affected the individual’s life in some way. *Unbound Transitioners* are also moderately likely to hold a personal grievance that underpins their ideology (*P*=.64), but are unlikely to perceive a social injustice (*P*=.22), experience prejudice/discrimination (*P*=.01), or be abused (*P*=.27).

In addition to lacking social bonds, seeking immediate gratification, and experiencing unfortunate life events, *Unbound Transitioners* are differentially associated with deviant peers. Specifically, these individuals have a high probability of being exposed to other extremists in their social networks (*P*=.78), and a moderate probability of associating with peers involved in crime or delinquent activities (*P*=.52). While *Unbound Transitioners* do not have a high probability of possessing definitions that justify past extremist actions (*P*=.30) or glorify violence (*P*=.16), they do have a high probability of being previously arrested (*P*=.76). Again, while this may indicate that they were previously punished for deviant behavior, it may also reflect a history of involvement in criminal activities. Finally, the control variables indicate *Unbound Transitioners* had a moderately-low probability of being mentally ill (*P*=.37), rarely acted alone (*P*=.08), and were highly likely to subscribe to a far-right ideology (*P*=.88).

Table 9. Equality of Means Test for Type of Extremist Action with Full Sample (n=731)

Class Comparisons	χ^2	***p***	***df***
Overall Test	2211.31	0.00	10
Class 1 vs. 2	347.83	0.00	2
Class 1 vs. 3	209.6	0.00	2
Class 1 vs. 4	204.89	0.00	2
Class 1 vs. 5	221.74	0.00	2
Class 1 vs. 6	539.4	0.00	2
Class 2 vs. 3	70.4	0.00	2
Class 2 vs. 4	324.5	0.00	2
Class 2 vs. 5	248.21	0.00	2
Class 2 vs. 6	11.66	0.00	2
Class 3 vs. 4	68.1	0.00	2
Class 3 vs. 5	27.87	0.00	2
Class 3 vs. 6	50.46	0.00	2
Class 4 vs. 5	11.27	0.00	2
Class 4 vs. 6	230.09	0.00	2
Class 5 vs. 6	156.63	0.00	2

4.3.3. Distal Outcome Prediction

With the class parameters estimated and described the relationship between the classes and the distal outcome of interest – the type of action extremists engaged in – can now be explored. As described in *Section 3.2.4.2.*, the LTB method is used to investigate this relationship, as this method is recommended for categorical distal outcomes (Asparouhov & Muthén, 2014; Bakk & Kuha, 2020; Bakk & Vermunt, 2016; Collier & Leite, 2017). First, as an overall test to estimate whether there is a relationship between class membership and type of extremist action, Table 9 reports the results of the equality of means test for the type of extremist action between all 6 classes. The overall test indicates a significant relationship between class membership and the type of action an extremist engaged in ($\chi^2 = 2211.31$; $p<.00$), and there are also significant differences between any given class comparison. The type of action an extremist engages in is influenced by their latent class of criminogenic risk.

The LTB method, in turn, adds context to this relationship by estimating the probability an individual in each class will engage in a specific type of extremist action. Table 10 presents the results of the distal outcome prediction. Like the class indicator probabilities displayed in Table 8, the LTB coefficients are also presented in probability scale ranging from 0-1 with higher values indicating a higher probability of observing that outcome.

The LTB method of analysis indicates clear heterogeneity in the type of action extremists engage in across each class. Beginning with violent extremism, the classes with the highest probability of engaging in extremist violence are the *Strained Lone Actors* (*P*=.78) and *Unbound Transitioners* (*P*=.85). A poignant similarity between these two classes is the high likelihood of experiencing a negative life transition, with both classes having a 95% chance of going through some sort of negative transition in their life. Both classes are also likely to hold a personal grievance, have some risk factors indicative of low self-control, and be associated with extremist peers. In terms of differences, *Unbound Transitioners* are less bonded to social institutions than the Strained Lone Actors, who have some social bonds to serve as protective factors. *Strained Lone Actors* are much more likely to act alone and have a mental illness than the *Unbound Transitioners*, and much less likely to subscribe to a far-right ideology. Thus, while these two classes converge on several criminogenic factors, there are clear differences that define the two groups. In this way, the multifinality of extremist violence is substantiated.

Table 10. Distal Outcome Prediction using LTB Method with Full Sample LCA Model

Action Type	Class 1 (Bonded Rebels) .13	Class 2 (Strained Lone Actors) .12	Class 3 (Strained Learners) .20	Class 4 (Pro-Socially Bonded) .22	Class 5 (Unbound and Low-Risk) .23	Class 6 (Unbound Transitioners) .09
Violent Extremism	0.00	0.78	0.38	0.04	0.13	0.85
Nonviolent Criminal Extremism	0.99	0.22	0.33	0.17	0.32	0.07
Nonoffending Extremism	0.01	0.00	0.29	0.79	0.55	0.08

Interestingly, the *Bonded Rebels* are almost exclusively involved in nonviolent criminal extremism (*P*=.99). Their moderately-high degree of social bonding may hinder their acceptance or use of violence as a legitimate means to achieve ideological goals. However, these individuals do have this highest probability of rejecting democratic values, indicating a weak bond to normative rules and laws. This, coupled with their likelihood to justify past extremist actions may indicate definitions favorable towards criminal behavior when it is committed for a cause, and thus influence their decision to engage in extremist crime. Their low level of self-control and moderate-to-low level of strain may similarly contribute to their aversion to violent crime, resulting in engagement in nonviolent crime.

In line with criminological wisdom, individuals in the *Pro-Socially Bonded* class are most likely to engage in nonoffending extremism (*P*=.79). This is consistent with social bond theory (Hirschi, 1969; Sampson & Laub, 1992), as these individuals are highly bonded to social institutions indicating a high presence of protective factors to shield them from crime and deviance. Moreover, the *Pro-Socially Bonded* class are unlikely to experience any low self-control risk factor or most social learning risk factors, with the exception of having extremist peers in their social network. They have moderate levels of strain which may contribute to their involvement in extremist movements, but are unlikely to have a mental illness, act alone, or subscribe to a far-right ideology. Theoretically, the *Pro-Socially Bonded* class may be considered the class with the least criminogenic risk, and this seems to translate to their preference for noncriminal extremist activities as opposed to extremist crime and violence.

Finally, results for the *Strained Learners* class and the *Unbound and Low-Risk* class are less clear in the type of action these extremists engage in. Specifically, the *Strained Learners* have an almost equal probability of engaging in violent extremism (*P*=.38), nonviolent criminal extremist (*P*=.33), or nonoffending extremism (*P*=.29). This class is very likely to experience strain-related risk factors, to be associated with extremist peers, and to justify extremist actions and glorify violence, indicating a high level of criminogenic risk offset only slightly by moderate levels of some protective factors such as being married or having a stable employment history. While previous classes illustrate equifinality in that multiple combinations of factors may lead to the same outcome, the *Strained Learners* class exemplifies multifinality, as individuals who demonstrate this single combination of factors are almost equally likely to engage in violent extremism, nonviolent criminal extremism, or nonoffending extremism.

To a lesser extent, individuals in the *Unbound and Low-Risk* class are similarly mixed on the type of action they have the highest probability of engaging in. Those who are *Unbound and Low-Risk* are most likely to engage in nonoffending extremism (*P*=.55) but are also somewhat likely to engage in nonviolent criminal extremism (*P*=.32). However, these individuals are unlikely to engage in violent extremism (*P*=.13). As a whole, these results indicate that a lack of criminogenic risk, even without salient protective factors, is associated with an aversion to violence more than an aversion to crime in general.

4.3.4. Summary of Key Findings

The results of the LCA model with distal outcome prediction indicate a clear relationship between criminogenic risk and the type of action extremists engage in. For the most part, individuals in latent classes that had higher probabilities of criminogenic risk factors and lower probabilities of criminogenic protective factors were more likely to engage in violent extremism than nonviolent or noncriminal extremism (*Strained Lone Actors*; *Unbound Transitioners*). This is except for the *Strained Learners* class who, while seemingly at a high criminogenic risk, were almost equally likely to engage in all three types of extremist action. Alternatively, classes with a high prevalence of criminogenic protective factors in the form of social bonds were more likely to engage in nonoffending extremism as opposed to extremist crime and violence (*Pro-Socially Bonded*). Those who had some protective factors present but who were likely to reject democratic values and justify extremist actions were overwhelmingly NVCEs (*Bonded Rebels*). Finally, individuals who are neither bonded to social institutions nor exposed to salient criminogenic risk factors (*Unbound and Low-Risk*) are most likely to participate in nonoffending extremism, and when they do offend it is mostly nonviolent crimes.

4.4. Sensitivity Analysis

The results of the preceding analysis indicate that VEs, NVCEs, and NOEs are not a homogenous pool of actors. Rather, there are distinct patterns and combinations of criminogenic risk and protective factors that are associated with each group. However, these results are based on the availability and quality of open-source data available for each case in the sample. It is plausible that there are systematic biases in which cases are reported on more or less in the open-source information that influence the results of the LCA model. Thus, as detailed in *Section 3.2.5.*, three separate LCA models are estimated with samples adjusted by (1) case reliability score, (2) NOE confidence score, and (3) both case reliability score and NOE confidence score. The purpose of these models is to determine if the classes that emerged from the full sample LCA model are sensitive to the (a) quality and quantity of open-source information and (b) the integrity of the NOE sample as a meaningful comparison group.

4.4.1. Reliability Score-Adjusted Sample

As explained in *Section 3.1.3.*, the RPFD uses a reliability scoring tool to grade the reliability of open-source information available for each case. The score ranges from 0-15 and uses a weighted scoring system to account for both the quantity and quality of open-source material. The first sensitivity analysis then, uses the RPFD reliability score to determine if the results of the LCA model change substantively when the cases with lower reliability scores are removed from the sample. By omitting these cases from the sample, this technique ensures that each case included in the analysis meets a standard of available open-source information, and accounts for the potential reporting bias where some cases are systematically reported on less than others.

To determine which cases are lower reliability, the mean reliability score was estimated for the full sample, and any cases below one standard deviation of the mean score were considered low reliability and thus omitted from the sample. The mean reliability score for the full sample was 4.52 with a standard deviation of 2.19. Thus, any cases with a reliability score below 2.33 were deemed low reliability and dropped from the sample. This resulted in approximately 139 cases being removed from the sample. Of these cases, 30 were VEs, 32 were NVCEs, and 77 were NOEs, indicating a greater proportion of NOE cases had low reliability. In total, these omissions resulted in a reliability score-adjusted sample of n=592. The LCA model was then enumerated and estimated with this adjusted sample to ascertain whether the same patterns emerged from the data.

4.4.1.1. Class Enumeration

Table 11 displays the model-fit and diagnostic criteria used to select a class solution for the LCA model using a reliability-adjusted sample. In contrast to the enumeration process using the full sample, the BIC actually favors a 5-class solution for the reliability-adjusted sample. However, the difference in fit between a 5-class solution and a 6-class solution, as indicated by the BIC, is marginal, indicating a 6-class solution is similarly well-fit for the data. The AIC favors a 7-class solution. But, as detailed earlier, the AIC tends to overestimate the number of classes in an LCA model (Bauer & Steinley, 2021), so this criterion should be interpreted with caution.

Table 11. Model Fit and Diagnostic Criteria for Class Solutions 2-7 with Reliability Score-Adjusted Sample

	Model Fit Criteria		Diagnostic Criteria	
Class Solution	**BIC**	**AIC**	**Entropy**	**ALCPP**
2	17102.50	16870.17	.79	**.94**
3	16864.00	16513.32	.80	.91
4	16773.93	16304.89	.81	.90
5	**16745.97**	16158.58	.82	.88
6	16748.73	16042.99	**.86**	.91
7	16781.02	**15956.92**	.85	.89

In terms of diagnostic criteria, the 6-class solution has the best separation between classes. Importantly, compared to the diagnostic criteria for the 5-class solution, the 6-class model shows notable improvements in class separation with an entropy value of .86 and an ALCPP of .91 (versus .82 and .88 for the 5-class model, respectively). These improvements in class separation, coupled with a comparable BIC value, indicate the 6-class solution is the most robust for the reliability-adjusted sample. As a result, a 6-class LCA model is estimated for this sample.

4.4.1.2. Class Estimation

Table 12 presents the results of the 6-class LCA model with the reliability-adjusted sample. The classes that emerged in the full sample LCA also emerge in the reliability-adjusted sample LCA, with comparable class parameters throughout. Specifically, the class proportion shares for each class are consistent between both samples, and the class indicator probabilities that define each class reflect the same class characteristics. Class 1, labelled the *Bonded Rebels*, is characterized by moderate-to-high social bonding and a high indicator probability for justifying past extremist actions (P=.73). Comparing the class indicator probabilities for each variable with those of the *Bonded Rebels* in the full sample LCA, there are no substantial changes in the probabilities for any of the criminogenic factors in the class.

Class 2, the *Strained Lone Actors*, is also very consistent with the *Strained Lone Actors* class in the full sample LCA. In the reliability-adjusted LCA, the *Strained Lone Actors* have high probabilities of experiencing strain-related risk factors – specifically perceiving a social injustice (*P*=.83), having a personal grievance (*P*=.84), and experiencing negative life transitions (*P*=.95) – and are 100% likely to act alone. Compared to the full sample LCA, *Strained Lone Actors* demonstrate slightly lower probabilities for the low self-control risk factors and slightly higher probabilities of justifying extremist actions (*P*=.72 vs. *P*=.62) and glorifying violence (*P*=.68 vs. *P*=.58).

Table 12. 6-Class LCA Model with Reliability Score-Adjusted Sample (n=592)

Variable	Class 1 (Bonded Rebels) .14	Class 2 (Strained Lone-Actors) .10	Class 3 (Strained Learners) .23	Class 4 (Pro-Socially Bonded) .24	Class 5 (Unbound and Low-Risk) .20	Class 6 (Unbound Transitioners) .10
Social Bonds						
Family Bonds	0.13	0.35	0.32	0.31	0.18	0.24
Marital Status	0.63	0.18	0.54	0.59	0.22	0.18
Aspirations	0.32	0.49	0.39	0.53	0.02	0.23
Employment History	0.76	0.54	0.51	0.86	0.23	0.20
Community Involvement	0.13	0.30	0.36	0.64	0.08	0.11
Education	0.69	0.71	0.75	0.84	0.19	0.26
Military Experience	0.10	0.24	0.20	0.07	0.04	0.05
Reject Democratic Values	0.73	0.42	0.58	0.04	0.25	0.12
Low Self-Control						
Impulsive/Thrill-seeking	0.02	0.45	0.40	0.06	0.10	0.49
Problems Controlling Anger	0.00	0.33	0.26	0.01	0.00	0.38
Substance Abuse	0.06	0.22	0.27	0.02	0.09	0.72
Strain						
Perceived Injustice	0.31	0.83	0.88	0.43	0.24	0.29
Personal Grievance	0.20	0.84	0.90	0.30	0.32	0.64
Experience Prejudice/Discrim.	0.00	0.32	0.21	0.35	0.04	0.02
Negative Life Transitions	0.61	0.95	0.91	0.66	0.30	0.97
Prior Abuse	0.01	0.23	0.23	0.06	0.04	0.25
Social Learning						
Extremist Network	0.59	0.00	0.90	0.74	0.69	0.63
Criminal Peers	0.03	0.16	0.35	0.12	0.06	0.58
Extremist Online Spaces	0.05	0.36	0.42	0.09	0.13	0.07

Table 12. (cont'd)

Contact Infamous Extremists	0.07	0.10	0.42	0.32	0.15	0.06
Justify Extremist Actions	0.73	0.72	0.73	0.34	0.43	0.31
Glorify Violence	0.00	0.68	0.84	0.19	0.25	0.18
Prior Arrests	0.20	0.44	0.43	0.19	0.15	0.83
Control Variables						
Mental Illness	0.00	0.66	0.27	0.04	0.04	0.57
Lone actor	0.22	1.00	0.09	0.10	0.03	0.24
Far-right ideology	1.00	0.15	0.30	0.01	0.50	0.72

The *Strained Learners* (Class 3) in the reliability adjusted LCA demonstrate almost identical indicator probabilities for each criminogenic factor as the *Strained Learners* in the full sample LCA. These individuals continue to have a high probability of experiencing strain-related risk factors and are also highly likely to associate with extremist peers (*P*=.90) and hold pro-extremism (*P*=.73) and pro-violence views (*P*=.84). Also unchanged from the full sample LCA is Class 4, the *Pro-Socially Bonded* class, which is characterized by high probabilities for criminogenic protective factors related to social bonds and low probabilities for most criminogenic risk factors except experiencing negative life transitions (*P*=.66) and associating with other extremists in their social network (*P*=.74). The *Unbound and Low-Risk* class (Class 5) is also consistent with the full sample LCA, with low indicator probabilities across the board for all criminogenic risk and protective factors, save that of associating with extremist peers (*P*=.63) and justifying extremist actions (*P*=.40).

Finally, the *Unbound Transitioners* (Class 6) class arguably is the most different in the reliability-adjusted sample LCA from the full sample LCA. These differences, however, do not affect the class's defining characteristics – namely, low probabilities for all social bond factors and a high probability of experiencing a negative life transition (*P*=.97). Instead, the *Unbound Transitioners* in the reliability-adjusted sample LCA are more likely to demonstrate impulsive behaviors (*P*=.49 vs. *P*=.31) and to have a mental illness (*P*=.57 vs. *P*=.37), and less likely to have extremist peers in their social network (*P*=.63 vs. *P*=.78) and to subscribe to a far-right ideology (*P*=.72 vs. *P*=.88).

Overall, the classes estimated in the reliability-adjusted sample are consistent with those estimated in the full sample LCA. While some minute differences exist, the combinations and patterns of factors that define each class are the same in both samples, suggesting the characteristics of the classes are not sensitive to the reliability of open-source information available on a case.

4.4.1.3. Distal Outcome Prediction

Next, the LTB method is used to explore the relationship between classes estimated in the reliability-adjusted sample LCA and the type of action extremists engaged in to determine if the results of the distal outcome prediction are sensitive to the reliability of open-source information. Table 13 presents the equality of means test for the distal outcome, type of extremist action, across each class comparison. The overall χ^2 test indicates a significant relationship between class membership and the type of action extremists engaged in (χ^2=2868909.54, p<.00). Further, every class comparison is significantly different in the type of action the individuals in each class engage in, indicating VEs, NVCEs, and NOEs are distinct in their criminogenic risk.

Table 13. Equality of Means Test for Type of Extremist Action with Reliability Score-Adjusted Sample (n=592)

Class Comparisons	χ^2	***p***	***df***
Overall Test	2868909.54	0.00	10
Class 1 vs. 2	193.17	0.00	2
Class 1 vs. 3	293.65	0.00	2
Class 1 vs. 4	261.81	0.00	2
Class 1 vs. 5	184.16	0.00	2
Class 1 vs. 6	********	0.00	2
Class 2 vs. 3	14.119	0.00	2
Class 2 vs. 4	340.36	0.00	2
Class 2 vs. 5	94.57	0.00	2
Class 2 vs. 6	18	0.00	2
Class 3 vs. 4	189.75	0.00	2
Class 3 vs. 5	34.17	0.00	2
Class 3 vs. 6	55.04	0.00	2
Class 4 vs. 5	51.31	0.00	2
Class 4 vs. 6	473.45	0.00	2
Class 5 vs. 6	166.26	0.00	2

Turning to the LTB estimates, Table 14 presents the probabilities that an individual in each class would engage in violent extremism, nonviolent criminal extremism, or nonoffending extremism. For the most part, the results of the distal outcome prediction are consistent between the full sample and the reliability-adjusted sample. Mirroring the full sample, *Bonded Rebels* are 100% likely to commit nonviolent extremist crimes. Similarly, *Strained Lone Actors* have the highest probability of engaging in violent extremism (P=.78). *Pro-Socially Bonded* individuals are still most likely to engage in nonoffending extremism (P=.81). Finally, *Unbound Transitioners* remain overwhelmingly likely to commit violent extremism (P=.94), even higher than the probability reported in the full sample (P=.85).

The two classes with noticeably different distal outcome probabilities compared to the full sample are the *Strained Learners* and *Unbound and Low-Risk* individuals. In the full sample results, *Strained Learners* were relatively equally likely to engage in all three types of extremist action. In the reliability-adjusted sample, however, *Strained Learners* have the highest probability of committing extremist violence (P=.60), followed by nonviolent criminal extremism (P=.29). They were least likely to engage in nonoffending extremism (P=.11), a probability substantially lower than reported in the full sample (P=.29). The *Unbound and Low-Risk* individuals, alternatively, reported more equal probabilities of engaging in each type of extremist action. Where individuals in this class were most likely to be involved in nonoffending extremism in the full sample (P=.55), those in the reliability-adjusted sample were marginally more likely to commit nonviolent criminal extremism (P=.40) than nonoffending extremism (P=.34), with a slightly lower probability of engage in violent extremism (P=.26). If, as speculated above, the *Unbound and Low-Risk* class represents those cases with less information known about them, then these results indicate the reliability-adjustment may have mitigated the extent to which there is a systematic reporting bias based on the type of action an individual committed given individuals in this class are almost equally likely to have engaged in any of the three types extremist actions.

Overall, the results of the distal outcome prediction in the reliability-adjusted sample are mostly consistent with that of the full sample. The main exceptions to this conclusion are the changes to the *Strained Learners* and *Unbound and Low-Risk* classes in the type of extremist actions they are most likely to engage in. For the most part, however, adjusting the sample to only include cases that meet a standard of quantity and quality of available open-source information does not substantively change the emerging findings on the relationship between classes of criminogenic risk and protective factors and the type of action extremists engage in.

Table 14. Distal Outcome Prediction using LTB Method with Reliability Score-Adjusted Sample LCA Model

Action Type	Class 1 (Bonded Rebels) .13	Class 2 (Strained Lone Actors) .12	Class 3 (Strained Learners) .20	Class 4 (Pro-Socially Bonded) .22	Class 5 (Unbound and Low-Risk) .23	Class 6 (Unbound Transitioners) .09
Violent Extremism	0.00	0.78	0.60	0.03	0.26	0.94
Nonviolent Criminal Extremism	1.00	0.22	0.29	0.16	0.40	0.00
Nonoffending Extremism	0.00	0.00	0.11	0.81	0.34	0.06

4.4.2. Confidence Score-Adjusted Sample

The next sensitivity analysis is conducted to ensure that the NOE sample is a meaningful comparison group by which to compare to VEs and NVCEs. As explained in *Section 3.1.2.*, the NOEs were sampled into the RPFD on a matched sampling design. However, there was variation in the extent to which an NOE could be designated an extremist given they had not engaged in any crime or violence to advance their ideology. Thus, the NOE confidence score was created to bring transparency to this sampling limitation and contextualize the characteristics that qualified an individual to be included as an NOE.

Individuals with higher confidence scores had more evidence of holding extreme ideological beliefs, such as associating with known extremist groups, advocating ideological violence, or participating in rallies or protests. Those with lower confidence scores had less evidence of holding extremist beliefs but had fulfilled one or two of the confidence score indicators, qualifying their inclusion as an NOE. However, because there is less confidence in their designation as a NOE, this sensitivity analysis omits NOE cases with lower confidence scores to ensure the integrity of the NOE sample as a meaningful comparison group. Specifically, this approach improves confidence that the VEs and NVCEs are being compared to individuals who subscribe to extreme belief systems but do not commit crimes or violence to advance them.

The confidence score for the NOE cases was standardized across all cases, ranging from 0-1, with 0 indicating no confidence and 1 indicating complete confidence the individual subscribed to an extreme belief system. The mean confidence score for the NOE cases was .40 with a standard deviation of .19. Thus, any NOE case with a confidence score of less than .21

was considered low confidence and omitted from the sample. This resulted in approximately 47 NOE cases to be dropped, resulting in an adjusted sample of n=684 for analysis.

4.4.2.1. Class Enumeration

Table 15 reports the model fit and diagnostic criteria for the LCA model using the confidence score-adjusted sample. The BIC indicates a 6-class model is the best fit for the data, and the AIC indicates a 7-class model is a better fit. Again, the BIC is the better-performing information criterion for LCA models with categorical indicators, supporting the 6-class solution as the model of choice. The 6-class model also reports the highest entropy value at .86, and an acceptable ALCPP value at .91. As a result, a 6-class LCA model is estimated for the confidence score-adjusted sample.

Table 15. Model Fit and Diagnostic Criteria for Class Solutions 2-7 with Adjusted Confidence Score

	Model Fit Criteria		**Diagnostic Criteria**	
Class Solution	**BIC**	**AIC**	**Entropy**	**ALCPP**
2	19373.96	19133.98	.77	**.93**
3	19070.72	18708.48	.78	.90
4	18976.33	18491.84	.82	.90
5	18884.71	18277.97	.85	.91
6	**18830.83**	18101.83	**.86**	.91
7	18837.87	**17986.62**	**.86**	.90

4.4.2.2. Class Estimation

Table 16 displays the class parameters for a 6-class LCA model using the confidence score-adjusted sample. In line with the reliability-adjusted sensitivity analysis, the confidence score-adjusted LCA model reports remarkably similar results to the full sample LCA. First, the class proportion shares for each class are consistent, with *Strained Learners*, *Pro-Socially Bonded*, *Unbound and Low-Risk* constituting the largest classes, and the *Unbound Transitioners* being the smallest class. In terms of indicator probabilities, the class characteristics are virtually identical between the full sample and confidence score-adjusted LCA models. Indeed, there are no substantive differences to report for any of the criminogenic factors across all six classes. The stability in these class compositions from the full sample LCA to the confidence score-adjusted sample LCA indicate the classes, and their parameters, are not sensitive to the NOE confidence score.

Table 16. 6-Class LCA Model with Confidence Score-Adjusted Sample (n=684)

Variable	Class 1 (Bonded Rebels) .13	Class 2 (Strained Lone-Actors) .13	Class 3 (Strained Learners) .21	Class 4 (Pro-Socially Bonded) .21	Class 5 (Unbound and Low-Risk) .22	Class 6 (Unbound Transitioners) .10
Social Bonds						
Family Bonds	0.11	0.32	0.31	0.33	0.12	0.21
Marital Status	0.64	0.13	0.54	0.52	0.16	0.25
Aspirations	0.32	0.46	0.37	0.46	0.02	0.12
Employment History	0.79	0.47	0.52	0.81	0.19	0.17
Community Involvement	0.12	0.30	0.37	0.58	0.03	0.00
Education	0.73	0.64	0.72	0.83	0.09	0.20
Military Experience	0.09	0.23	0.20	0.05	0.03	0.03
Reject Democratic Values	0.74	0.39	0.57	0.04	0.20	0.17
Low Self-Control						
Impulsive/Thrill-seeking	0.01	0.55	0.37	0.08	0.07	0.32
Problems Controlling Anger	0.00	0.36	0.23	0.01	0.00	0.31
Substance Abuse	0.05	0.38	0.24	0.03	0.03	0.66
Strain						
Perceived Injustice	0.32	0.77	0.88	0.39	0.19	0.21
Personal Grievance	0.21	0.75	0.90	0.30	0.33	0.64
Experience Prejudice/Discrim.	0.00	0.23	0.19	0.32	0.02	0.01
Negative Life Transitions	0.60	0.96	0.88	0.64	0.20	0.95
Prior Abuse	0.01	0.25	0.22	0.06	0.03	0.27
Social Learning						
Extremist Network	0.61	0.12	0.90	0.74	0.64	0.78
Criminal Peers	0.02	0.24	0.34	0.13	0.07	0.53
Extremist Online Spaces	0.04	0.36	0.39	0.10	0.17	0.02

Table 16. (cont'd)

Contact Infamous Extremists	0.07	0.11	0.41	0.27	0.10	0.05
Justify Extremist Actions	0.67	0.61	0.73	0.34	0.43	0.29
Glorify Violence	0.00	0.56	0.81	0.22	0.20	0.17
Prior Arrests	0.16	0.51	0.41	0.19	0.10	0.76
Control Variables						
Mental Illness	0.00	0.71	0.23	0.06	0.02	0.37
Lone actor	0.24	0.95	0.06	0.11	0.04	0.08
Far-right ideology	0.98	0.25	0.29	0.02	0.59	0.88

4.4.2.3. Distal Outcome Prediction

Table 17 reports the results of the equality of means test examining the relationship between class membership and the type of extremist action an individual engaged in. The overall test indicates a significant relationship between class membership and type of extremist action (χ^2 =2057.64, *p*<.00). For the most part, each class comparison indicates a significant difference between the classes. However, the equality of means test between Class 4 (*Pro-Socially Bonded*) and Class 5 (*Unbound and Low-Risk*) does not reach statistical significance (χ^2 =5.46, *p*=.07), albeit it is approaching the significance threshold of p<.05. As a whole, though, the equality of means test indicates class of criminogenic risk significantly influences the type of action extremists engage in, consistent with the full sample LCA model.

Table 17. Equality of Means Test for Type of Extremist Action with Confidence Score-Adjusted Sample (n=684)

Class Comparisons	χ^2	*p*	*df*
Overall Test	2057.64	0.00	10
Class 1 vs. 2	538.33	0.00	2
Class 1 vs. 3	259.08	0.00	2
Class 1 vs. 4	181.26	0.00	2
Class 1 vs. 5	279.08	0.00	2
Class 1 vs. 6	181.26	0.00	2
Class 2 vs. 3	22.19	0.00	2
Class 2 vs. 4	124.5	0.00	2
Class 2 vs. 5	183.45	0.00	2
Class 2 vs. 6	13.09	0.00	2
Class 3 vs. 4	53.95	0.00	2
Class 3 vs. 5	93.33	0.00	2
Class 3 vs. 6	22.30	0.00	2
Class 4 vs. 5	5.46	0.07	2
Class 4 vs. 6	169.200	0.00	2
Class 5 vs. 6	209.65	0.00	2

Table 18 reports the distal outcome prediction results using the LTB approach for the LCA model with the confidence score-adjusted sample. We see similar trends to that of the reliability score-adjusted model. The *Bonded Rebels* are nearly 100% likely to engage in nonviolent criminal extremism. The *Strained Lone Actors* are most likely to commit extremist violence (*P*=.77), with a low probability of engaging in nonviolent criminal extremism (*P*=.24) and virtually no chance of being involved in nonoffending extremism (*P*=.00). The *Strained Learners* follow suit with the reliability score-adjusted sample, in that they differ from the full sample model, where individuals in this class were almost equally likely to engage in any one of the three types of extremist actions. In the confidence score-adjusted model, *Strained Learners* are most likely to engage in violent extremism (*P*=.57) with low probabilities of committing nonviolent criminal extremism (*P*=.28) or nonoffending extremism (*P*=.16).

Consistent with the full sample LCA model, individuals in the *Pro-Socially Bonded* class are very unlikely to engage in violent extremism (*P*=.06). Instead, those who are *Pro-Socially Bonded* have the highest probability of engaging in nonoffending extremism (*P*=.61), followed by nonviolent criminal extremism (*P*=.32). Also consistent with the full sample model, individuals in the Unbound and Low-Risk class are most likely to be involved in nonoffending extremism (*P*=.50), with lower probabilities for committing nonviolent criminal extremism (*P*=.32) and violent extremism (*P*=.17). This is, however, inconsistent with the reliability score-adjusted sample which reported similar probabilities across the three action types. Finally, the *Unbound Transitioners* mirror the findings of both the full sample and reliability-score adjusted models, with these individuals being highly likely to commit extremist violence (*P*=.87) and very unlikely to be a NVCE (*P*=.05) or an NOE (*P*=.08).

Table 18. Distal Outcome Prediction using LTB Method with Confidence Score-Adjusted Sample

Action Type	Class 1 (Bonded Rebels) .13	Class 2 (Strained Lone Actors) .12	Class 3 (Strained Learners) .20	Class 4 (Pro-Socially Bonded) .22	Class 5 (Unbound and Low-Risk) .23	Class 6 (Unbound Transitioners) .09
Violent Extremism	0.00	0.77	0.57	0.06	0.17	0.87
Nonviolent Criminal Extremism	0.99	0.24	0.28	0.32	0.32	0.05
Nonoffending Extremism	0.01	0.00	0.16	0.61	0.50	0.08

4.4.3. Reliability Score and Confidence Score Adjusted Sample

The preceding sensitivity analyses indicate the results of the full sample LCA are not significantly impacted by sample adjustments for case reliability scores or NOE confidence scores. The final sensitivity analysis combines these sample adjustments to analyze a sample that only includes cases with acceptable reliability scores and NOE confidence scores. The purpose is to discern whether the classes estimated in the full sample LCA model substantively change when the sample is adjusted to account for both case reliability scores and NOE confidence scores. In doing so, the reliability and confidence-score adjusted model may produce the most reliable estimates for class parameters and distal outcome probabilities by mitigating the potential reporting bias in the open-source materials while bolstering confidence in the NOE comparison group.

To compose the reliability and confidence score-adjusted sample, cases were omitted from the sample if they reported a reliability score *or* confidence score that was less than one standard deviation of the mean for either metric. As reported in earlier sections, the mean reliability score for the sample was 4.52 with a standard deviation of 2.19, and the mean confidence score for the NOE cases was .40 with a standard deviation of .19. Accordingly, any case that had a case reliability score less than 2.33 was omitted from the sample, and any NOE case that had a confidence score less than .21 was omitted from the sample. This resulted in approximately 174 cases being removed from the sample. Of which, 30 were VEs, 32 were NVCEs, and 112 were NOE cases. The final sample was n=557 cases, composed of 228 VEs, 209 NVCEs, and 120 NOEs.

4.4.3.1. Class Enumeration

Table 18 displays the model fit and diagnostic criteria for the class solutions for the reliability and confidence score-adjusted sample. Like the enumeration for the reliability score-adjusted sample above, the BIC indicates the 5-class solution and 6-class solution are similar in their model-fit, with the 5-class model reporting a marginally lower BIC value. The 6-class solution, however, has higher entropy (.85) and ALCPP value (.90) than the 5-class model, suggesting a better degree of separation between classes. As a result, and consistent with the enumeration decision for the reliability score-adjusted sample, a 6-class LCA model was estimated for the reliability and confidence-score adjusted sample.

Table 19. Model Fit and Diagnostic Criteria for Class Solutions 2-7 with Reliability Score and Confidence Score-Adjusted Sample

	Model Fit Criteria		**Diagnostic Criteria**	
Class Solution	**BIC**	**AIC**	**Entropy**	**ALCPP**
2	16234.17	16005.08	.77	**.93**
3	16019.33	15673.52	.78	.90
4	15953.89	15491.37	.81	.89
5	**15937.41**	15358.19	.82	.88
6	15939.09	15243.15	**.85**	.90
7	15975.04	**15162.39**	**.85**	.89

4.4.3.2. Class Estimation

The 6-class LCA model using the reliability and confidence-score adjusted sample reveals the same class characteristics and parameters as the preceding models. Table 19 presents these results. The class proportion shares remain consistent for each class, with the *Strained*

Learners (.23), *Pro-Socially Bonded* (.23), and the *Unbound and Low-Risk* (.20) classes being the largest classes, and the *Bonded Rebels* (.14), *Strained Lone Actors* (.10), and *Unbound Transitioners* (.10) being smaller in proportion. For the class indicator probabilities, each class remains consistent with the full sample model in the criminogenic factors that characterize it, with some key differences to note.

Compared to the full sample model, the *Strained Lone Actors* in the reliability and confidence-score adjusted sample LCA are slightly less likely to demonstrate impulsive tendencies (*P*=.46 vs. *P*=.55), abuse substances (*P*=.22 vs. *P*=.38) and have extremist peers in their social networks (*P*=.00 vs. *P*=.12). They are, however, slightly more likely to perceive a societal injustice (*P*=.83 vs, *P*=.77), have a personal grievance (*P*=.84 vs. *P*=.76), justify extremist actions (*P*=.72 vs. *P*=.62), and glorify violence (*P*=.67 vs. *P*=.58). These differences from the full sample, however, may actually highlight the factors that characterize the *Strained Lone Actors* even further.

Table 20. 6-Class LCA Model using Reliability and Confidence Score-Adjusted Sample (n=557)

Variable	Class 1 (Bonded Rebels) .14	Class 2 (Strained Lone-Actors) .10	Class 3 (Strained Learners) .23	Class 4 (Pro-Socially Bonded) .23	Class 5 (Unbound and Low Risk) .20	Class 6 (Unbound Transitioners) .10
Social Bonds						
Family Bonds	0.12	0.35	0.33	0.33	0.15	0.25
Marital Status	0.62	0.19	0.54	0.56	0.24	0.18
Aspirations	0.30	0.48	0.40	0.47	0.02	0.24
Employment History	0.77	0.53	0.50	0.82	0.25	0.20
Community Involvement	0.12	0.29	0.37	0.61	0.03	0.12
Education	0.68	0.70	0.76	0.83	0.18	0.26
Military Experience	0.09	0.23	0.20	0.07	0.06	0.05
Reject Democratic Values	0.77	0.40	0.60	0.05	0.28	0.11
Low Self-Control						
Impulsive/Thrill-seeking	0.01	0.46	0.42	0.09	0.10	0.50
Problems Controlling Anger	0.00	0.31	0.27	0.01	0.02	0.28
Substance Abuse	0.06	0.22	0.28	0.03	0.09	0.74
Strain						
Perceived Injustice	0.32	0.83	0.90	0.46	0.24	0.28
Personal Grievance	0.20	0.84	0.91	0.33	0.36	0.64
Experience Prejudice/Discrim.	0.00	0.32	0.21	0.32	0.03	0.02
Negative Life Transitions	0.64	0.97	0.92	0.68	0.31	0.96
Prior Abuse	0.01	0.24	0.24	0.08	0.05	0.25
Social Learning						
Extremist Network	0.62	0.00	0.91	0.76	0.69	0.64
Criminal Peers	0.03	0.17	0.37	0.14	0.06	0.59
Extremist Online Spaces	0.04	0.37	0.43	0.11	0.14	0.07
Contact Infamous Extremists	0.07	0.10	0.42	0.32	0.15	0.07

Table 20. (cont'd)

Justify Extremist Actions	0.74	0.72	0.73	0.37	0.49	0.30
Glorify Violence	0.00	0.67	0.84	0.24	0.29	0.17
Prior Arrests	0.20	0.45	0.44	0.19	0.16	0.82
Control Variables						
Mental Illness	0.00	0.67	0.28	0.05	0.04	0.57
Lone actor	0.21	1.00	0.10	0.08	0.04	0.24
Far-right ideology	1.00	0.16	0.30	0.02	0.53	0.72

While still low, several of the indicator probabilities for the *Unbound and Low-Risk* class increased in the reliability and confidence score-adjusted LCA. Specifically, the probability of these individuals rejecting democratic values increased from .18 in the full sample model to .28 in the reliability and confidence score-adjusted sample model. Moreover, *Unbound and Low-Risk* individuals in the current model were slightly more likely to experience a negative life transition (*P*=.31 vs. *P*=.19) and glorify violence (*P*=.29 vs. *P*=.18) than those in the full sample LCA. Finally, the *Unbound Transitioners* in the reliability and confidence score-adjusted LCA are more likely than those in the full sample model to be involved in their community (*P*=.12 vs. *P*=.00), have demonstrated impulsive behaviors (*P*=.50 vs. *P*=.31), have a history of substance abuse (*P*=.74 vs. *P*=.65), have a mental illness (*P*=.57 vs. *P*=.37), and to act alone (*P*=.08 vs. *P*=.24). However, these individuals are less likely to have extremist peers in their social network than they were in the full sample LCA (*P*=.64 vs. *P*=.78).

These findings suggest that, while the underlying patterns and trends that define these classes are not sensitive to the case reliability scores or NOE confidence scores, there are some differences in the probabilities for select criminogenic factors in certain classes. Nonetheless, the stability of the class structures across all the sensitivity analyses improves confidence in the class characteristics and profiles that are emerging from the LCA.

4.4.3.3. Distal Outcome Prediction

As shown in Table 20, the equality of means test indicates an overall significant relationship between class membership and the type of extremist action individuals engaged in for the reliability and confidence score-adjusted sample LCA model ((χ^2 =486983.01, p<.00). This is consistent with the full sample model and the other sensitivity analyses, in that there is a clear connection between class of criminogenic risk and extremist action of choice.

Table 21. Equality of Means Test for Type of Extremist Action with Reliability and Confidence Score-Adjusted Sample (n=557)

Class Comparisons	χ^2	*p*	*df*
Overall Test	486983.01	0.00	10
Class 1 vs. 2	191.22	0.00	2
Class 1 vs. 3	242.19	0.00	2
Class 1 vs. 4	184	0.00	2
Class 1 vs. 5	238.41	0.00	2
Class 1 vs. 6	***********	0.00	2
Class 2 vs. 3	8.01	0.02	2
Class 2 vs. 4	181.18	0.00	2
Class 2 vs. 5	106.19	0.00	2
Class 2 vs. 6	15.66	0.00	2
Class 3 vs. 4	124.3	0.00	2
Class 3 vs. 5	42.79	0.00	2
Class 3 vs. 6	44.19	0.00	2
Class 4 vs. 5	33.51	0.00	2
Class 4 vs. 6	365.97	0.00	2
Class 5 vs. 6	241.63	0.00	2

Table 21 displays the results for the LTB distal outcome prediction. Most of the classes demonstrate similar probabilities for each type of extremist action as reported in the full sample model. *Bonded Rebels* remain 100% likely to engage in nonviolent criminal extremism. *Strained Lone Actors* are still most likely to commit extremist violence (P=.78) and slightly likely to be an NVCE (P=.22), with virtually no chance of engaging in nonoffending extremism (P=.00). Alternatively, those in the *Pro-Socially Bonded* class are highly likely to be NOEs (P=.77) and unlikely to engage in either violent extremism (P=.04) or nonviolent criminal extremism (P=.17). *Unbound Transitioners*, interestingly, became even more likely to engage almost exclusively in violent extremism in the reliability and confidence score-adjusted sample, reporting a probability of P=.98 compared to P=.85 in the full sample model.

The key differences between the full sample model and the reliability and confidence score-adjusted sample model are the same as those reported in the sensitivity analysis with only the reliability score-adjusted sample (*Section 4.4.1.*). Specifically, *Strained Leaners* in the full sample model were similarly likely to engage in any one of the three types of extremist actions. In the reliability and confidence score-adjusted sample model, *Strained Learners* are most likely to be involved in violent extremism (P=.64), with low probabilities of engaging in either nonviolent criminal extremism (P=.29) or nonoffending extremism (P=.07). Those in the *Unbound and Low-Risk* class, however, demonstrate comparable probabilities for each action type in the reliability and confidence score-adjusted model, whereas in the full sample model these individuals were disproportionately likely to be NOEs. Evidently, these two classes are the most sensitive to the case reliability scores and NOE confidence scores when estimating their likelihood of engaging in specific types of extremist actions.

Table 22. Distal Outcome Prediction using LTB Method with Confidence Score-Adjusted Sample

Action Type	Class 1 (Bonded Rebels) .14	Class 2 (Strained Lone Actors) .10	Class 3 (Strained Learners) .23	Class 4 (Pro-Socially Bonded) .23	Class 5 (Unbound and Low-Risk) .20	Class 6 (Unbound Transitioners) .10
Violent Extremism	0.00	0.78	0.64	0.06	0.28	0.98
Nonviolent Criminal Extremism	1.00	0.22	0.29	0.17	0.39	0.00
Nonoffending Extremism	0.00	0.00	0.07	0.77	0.33	0.03

4.5. Summary

This chapter employed a rigorous analytic strategy to address two key research questions about how criminogenic risk and protective factors may be differentially related to the type of action extremists engaged in. The first research question sought to understand how different criminogenic factors, drawn from various criminological perspectives, covaried to form distinct classes of criminogenic risk. Six classes of criminogenic risk emerged from an LCA model, each of which being characterized by unique patterns of criminogenic risk and protective factors. The second research question focused on whether the class of criminogenic risk was related to the type of extremist action an individual was engaged in – namely, violent extremism, nonviolent criminal extremism, or nonoffending extremism. The LTB method for predicting distal outcomes from latent class models was used to estimate this relationship, and the results show a significant relationship between class of criminogenic risk and type of extremist action.

Additionally, a series of sensitivity analyses were conducted to bolster confidence in these results. Specifically, the sample was adjusted based on the reliability of the open-source material available on a case, and the confidence that the cases included in the matched NOE sample subscribed to an extreme belief system and were thus a meaningful comparison group. Overall, the results from the sensitivity analyses suggested that the characteristics of each class were stable and consistent across all sample adjustments, indicating the patterns that emerged from the LCA were not sensitive to potential biases in the data. The results of the LTB method were also consistent through each sensitivity analysis, although the *Strained Learners* and *Unbound and Low-Risk* class did demonstrate some sensitivity to the sample adjustments.

Taken together, this chapter presented a data driven analysis that revealed important differences in the criminogenic risk and protective factors experienced by VEs, NVCEs, and

NOEs. The next chapter discusses the key findings that emerged from this analysis in greater detail, explores the practical and theoretical implications of these findings, and considers how future research on extremist crime and violence may build on this study.

CHAPTER 5: DISCUSSION AND CONCLUSIONS

The final chapter of this dissertation proceeds in four sections. The first section will critically review the key findings that emerged from the analysis. The second section will examine the implications of these findings in three areas: (1) theoretical contributions, (2) methodological advancements, and (3) policy and practice. The third section examines the limitations of the study and considers the improvements future research can make in this field of research. Finally, the chapter concludes with a summative review of this dissertation.

5.1. Review of Key Findings

This section examines each finding from the analysis within the broader context of theory and extant research. Importantly, while most findings were stable across the sensitivity analyses, several findings changed when case reliability scores and NOE confidence scores were adjusted for. As a result, it is important to specify that the findings examined here are based on the results of the LCA model and distal outcome prediction following the case reliability score and confidence score-adjusted sensitivity analysis (*Section 4.4.3.*). This model mitigates the influence of potential biases in open-source data, which are discussed in detail in *Section 5.3*, and consequently produces the most robust and interpretable results.

Overall, the findings illustrate the equifinality and multifinality of violent extremism. Several classes, characterized by different patterns of criminogenic factors, were similarly likely to engage in violent extremism. Alternatively, no class was 100% likely to commit extremist violence, leaving the possibility that an individual with the same combination of factors would engage in nonviolent criminal or nonoffending extremism. Use of LCA allowed for these variations to be empirically modelled, providing valuable insight into the relationship between criminogenic factors and violent extremism.

5.1.1. Strain-Related Risk Factors and Violent Extremism

The common denominator for the classes that were most likely to engage in violent extremism was a high probability of strain-related risk factors. While experiencing abuse or prejudice/discrimination was rare across all six classes, *Strained Lone Actors*, *Strained Learners*, and *Unbound Transitioners* were highly likely to experience a negative life transition. *Strained Lone Actors* and *Strained Learners* were additionally likely to perceive an injustice in society and hold a personal grievance that underpins their ideology. All three classes were highly likely to commit extremist violence as opposed to nonviolent or noncriminal extremist actions.

Importantly, perceived injustices and personal grievances are theorized to initiate radicalization processes (Borum, 2003; Hafez & Mullins, 2014; Hamm & Spaaij, 2017; McCauley & Moskalenko, 2008; Moghaddam, 2005; Sageman, 2008). In the same way, scholars assert that negative life events and transitions drive individuals towards radical belief systems to try to address or cope with new adverse life conditions (Bouhana, 2019). Albeit this analysis was unable to discern temporal ordering, so the extent to which these factors initiated an individual's radicalization is unclear. However, these findings suggest that the types of individuals most likely to commit extremist violence are those who hold a personal grievance, perceive a societal injustice, and/or experience a negative life transition.

Importantly, the findings on strain-related factors contrast prior work that found an insignificant relationship between strain to self-reported support for violent extremism (Nivette et al., 2017) and far-right extremism (Skoczylis & Andrews, 2022). This discrepancy may be attributed to differences in the dependent variable, as the distinction between support for extremism and actual engagement in extremist actions is relevant (Khalil et al., 2022; McCauley & Moskalenko, 2014; 2017). These findings also substantiate the connection between personal grievances, perceived injustices, and engagement in violent extremism (Borum, 2003; Hafez & Mullins, 2014; Hamm & Spaaij, 2017; McCauley & Moskalenko, 2008; Moghaddam, 2005; Sageman, 2008), a theoretical relationship that has received limited empirical examination.

These findings may be further understood through Agnew's (1992) GST by considering prosocial coping skills. Strain is not the sole driver for any of these classes, and other criminogenic factors may influence one's ability to utilize prosocial coping skills to address their grievances – an attribute that may be more strongly associated with support for extremism than personal strains themselves (Nivette et al., 2017). The *Strained Lone Actors* are likely to be mentally ill, lack strong social bonds, and hold favorable views on the use of crime and violence to advance extremist causes. *Strained Learners* are even more likely to hold favorable views on extremist violence and are also highly likely to associate with extremist peers in their social networks. *Unbound Transitioners* are unlikely to hold any prosocial bonds and are similarly associated with other extremists. All of these factors may compound the feelings of strain derived from negative stimuli by limiting one's ability to identify and utilize legal and prosocial coping mechanisms to address the sources of their strain (Agnew, 1992; 2010). The alternative, in such cases, is crime and violence driven by ideological goals.

Another perspective is to consider the outcomes of classes that were unlikely to experience strain-related risk factors. *Bonded Rebels*, *Pro-Socially Bonded*, and *Unbound and Low-Risk* individuals were all unlikely to engage in violent extremism. While each class except *Unbound and Low-Risk* were at least moderately likely to experience a negative life transition, the *Bonded Rebels* and *Pro-Socially Bonded* classes were not likely to demonstrate other strain risk factors. *Unbound and Low-Risk* individuals were unlikely to experience any strain-related risk factor, including having a negative life transition. A commonality between the *Bonded*

Rebels and *Pro-Socially Bonded* is the presence of several protective factors that are discussed in the next section, which can provide outlets for healthy coping mechanisms (Agnew, 2010).

A primary takeaway from these findings, then, is that strain-related risk factors alone may not be sufficient to drive involvement in violent extremism. The absence of prosocial bonds, the presence of learning mechanisms, or experiencing a mental illness could impact the coping mechanisms an aggrieved individual may use to address the strains they feel. Additionally, this finding highlights the advantages of using a multifactor approach for studying violent extremism and leveraging criminological theory to help explain the patterns of factors that emerge from the data, as the linkages between these variables would be less clear without theoretical guidance.

5.1.2. Social Bonds and the Aversion to Violence

Criminogenic protective factors, which are theorized through social bond theory to bolster individuals' ability to resist involvement in crime and violence (Hirschi, 1969; Sampson & Laub, 1990), have received mixed results in differentiating violent extremists from their nonviolent counterparts (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2022). The findings from the LCA, however, indicate that classes with high social bonding, or a high presence of criminogenic protective factors, have an aversion to violence and instead utilize nonviolent or noncriminal means for advancing their cause.

Bonded Rebels overwhelmingly engaged in nonviolent criminal extremism. The reason for this may lie in their criminogenic risk and protective factors. Of all the classes, *Bonded Rebels* are most likely to be married, and were highly likely to be regularly employed and have attended college. These positive life events may indicate resilience to extreme or violent ideals, which has been linked to less support for extremism (Skoczylis & Andrews, 2022). They may also constitute 'turning points' which facilitate desistance from criminal behavior (Sampson &

Laub, 1990). Juxtaposed to this prosocial bonding is the *Bonded Rebels* tendency to reject democratic laws and norms and justify previous extremist attacks. In this way, *Bonded Rebels* are not inclined to abide by conventional laws and norms when advancing their ideological goals. However, their bonds to prosocial institutions may place boundaries on the actions they are willing to commit; namely, violence. Instead, they use nonviolent crimes such as material support, fraud, or property crimes to forward their movement.

Supporting the social bond model further, individuals in the *Pro-Socially Bonded* class are mostly involved in nonoffending extremism and are unlikely to engage in extremist crime or violence. They are highly likely to be bonded to prosocial institutions but do not demonstrate defiance towards normative law and order that the *Bonded Rebels* do. In this way, *Pro-Socially Bonded* individuals are resilient to anti-social behaviors, even when used to support their cause. *Pro-Socially Bonded* individuals are also likely to experience negative life transitions, indicating the social bonds they hold are strong enough to outweigh the influence of criminogenic risk factors that may give way to crime and violence. While they are involved in nonoffending extremist activities such as rallying or protesting, they act within the parameters of the law to not jeopardize their bonds to prosocial institutions.

Alternatively, those who lack social bonds may be more inclined to engage in extremist violence. The *Unbound Transitioners,* as touched on above, are wholly disconnected from prosocial institutions and are highly likely to experience a negative transition in their life and associate with extremist peers. The lack of criminogenic protective factors indicates these individuals are less shielded from the influence of extremist beliefs that risk factors may expose them to (Lösel et al., 2020). Additionally, *Unbound Transitioners* have less to lose by engaging in crime and violence because they are not strongly invested in prosocial institutions (Laub &

Sampson, 1993). This may explain why the *Unbound Transitioners* are more likely to commit extremist violence than nonviolent or noncriminal extremism.

Findings to this point support the relationship between social bonds and involvement in violent versus nonviolent and noncriminal extremism. The *Unbound and Low Risk* class provides further context on this relationship. Individuals in this class were unlikely to be bonded to prosocial institutions but were also unlikely to experience other criminogenic risk factors. In this way, they are neither shielded from deviance nor at-risk of it. However, the *Unbound and Low Risk* class was similarly likely to engage in violent, nonviolent criminal, and nonoffending extremism. Comparing this class to the *Unbound Transitioners* class, these findings suggest an absence of social bonds may not be enough on its own to facilitate involvement in violent extremism, and other criminogenic factors are necessary to mobilize an extremist to violence – a testament to the importance of a multifactor approach.

5.1.3. Influence of Social Learning Factors

Unlike criminogenic factors drawn from strain and social bond perspectives, results are less clear on the role of social learning risk factors in differentiating violent, nonviolent criminal, and nonoffending extremists. Five of the six classes estimated in the LCA model reported a moderate-to-high probability of associating with extremist peers in their social network, the only exception being the *Strained Lone Actors* class. As a result, the connection between differential association and engagement in specific types of extremist actions is unclear because each class differed in the type of extremist action they were most likely to be involved in. *Bonded Rebels* were engaged in nonviolent criminal extremism almost 100% of the time. *Strained Learners* and *Unbound Transitioners* most often committed extremist violence. *Pro-Socially Bonded* individuals were most likely to be engaged in nonoffending extremism. Finally, the *Unbound and Low-Risk* class was similarly associated with all three types of extremist action.

All of these classes were likely to associate with extremist peers but were also most likely to commit different types of extremist actions, indicating that having extremist peers is not exclusively associated with any one type of extremist action. This finding contradicts prior work suggesting that violent extremists are more likely to have extremist peers than nonviolent extremists (LaFree et al., 2018; Pritchett & Moeller, 2022; Wolfowicz & Perry et al., 2021). However, it is important to note that this variable did not capture the type of actions extremist peers were involved in. Given all individuals in the sample subscribed to an extreme belief system, it makes sense they would have peers who shared their beliefs. That does not mean their peers were driving them towards criminal behavior. That said, only the *Strained Learners* and *Unbound Transitioners* were moderately likely to associate with criminal peers, with the rest of the classes being unlikely to have friends engaged in criminal activity. These two classes were most likely to be involved in extremist violence, suggesting differential associations with criminal peers may impact the actions an extremist engages in. This relationship is further contested though, given *Strained Lone Actors*, who were unlikely to associate with extremist or criminal peers, were most likely to engage in violent extremism.

Findings were similarly mixed regarding criminogenic factors indicative of one's definitions of behavior. Classes with moderate-to-high probabilities of justifying extremist actions, specifically *Bonded Rebels*, *Strained Lone Actors*, and *Strained Learners*, were most likely to engage in criminal extremism. This is in line with social learning theory, as individuals who hold definitions favorable to criminal behavior are more inclined to commit it themselves (Akers, 2011; Matsueda, 1988). Of those classes though, *Strained Lone Actors* and *Strained*

Learners were likely to glorify violence committed to advance ideological goals, whereas *Bonded Rebels* were unlikely to do so. This distinction is reflected in their actions, as *Bonded Rebels* were most likely to be involved in nonviolent crimes whereas *Strained Lone Actors* and *Strained Learners* had a higher probability of committing violent crimes, suggesting the definitions that underpin their behavior inform the actions they chose to engage in both in terms of legality and severity. This connection is further substantiated by the *Pro-Socially Bonded* class, who were unlikely to justify extremist actions or glorify ideological violence, and in turn rarely engaged in violent or nonviolent criminal extremism.

Not all the findings support this connection, though. The *Unbound Transitioners* class had the highest likelihood of committing violent extremism, but these individuals were unlikely to justify extremist actions or glorify ideological violence. Definitions of behavior, in this class, do not translate to the actions they are most likely to engage in. This finding contradicts the predictions of social learning theory (Akers, 2011). However, it is important to note that both factors were based on expressions of pro-crime and pro-violence definitions. It is possible that these individuals held such definitions but did not openly express them, which poses additional challenges to the practice of estimating criminogenic risk.

Extremists rarely contacted infamous or incarcerated extremists before acting, with the *Strained Learners* being the only class with a moderate probability of doing so. As a result, there was no clear evidence to suggest imitation was a strong differentiator of extremists based on the type of action they committed. Similarly, the role of differential reinforcement is unclear. The *Unbound Transitioners* were the only class with a high probability of being previously arrested, but they were also most likely to commit extremist violence. This finding may reflect the imperfectness of previous arrests as an indicator for differential reinforcements, as having prior arrests may also represent a criminal history which empirical studies have found is correlated with involvement in violent extremism as opposed to nonviolent extremism (Becker, 2021; LaFree et al., 2018).

In all, criminogenic risk factors drawn from social learning theory may lead to violent extremism when co-occurring with other criminogenic factors, such as potent strains (*Strained Learners*) or absence of prosocial bonds (*Unbound Transitioners*). However, social learning factors are not strong differentiators of extremists based on the type of action they are involved in. Extremists who engaged in all types of extremist actions, including nonviolent criminal (*Bonded Rebels*) or nonoffending extremism (*Pro-Socially Bonded*), had some exposure to social learning risk factors. Moreover, extremists who were not exposed to these factors were similarly likely to engage in violent extremism (*Strained Lone Actors*) as those that were exposed. Again, the equifinality and multifinality of extremist violence are highlighted in the current set of findings.

5.1.4. Rarity of Low Self-Control Factors

Low self-control factors were the least pronounced of the four paradigms which criminogenic factors were drawn from. This is unsurprising, as the empirical literature has contested the extent to which terrorists or extremists should demonstrate low self-control given the planning, preparation, and patience often required to carry out terroristic plots (Denson et al., 2012; Gottfredson & Hirschi, 2000; Ravenscroft, 2020). However research suggests low self-control is a relevant factor given the spontaneous and opportunistic nature that characterizes some types of ideologically motivated attacks (Iganski, 2008; Sweeney & Perliger, 2018). Available evidence supports the connection between low self-control and extremism about outcomes such as radical attitudes and behaviors (Wolfowicz et al., 2021), violent extremist intentions (Rottweiler & Gill, 2020), and self-reported political action (Pauwels & Svennson, 2017). But the findings from this dissertation offer limited support for these connections.

Strained Lone Actors and *Strained Learners* were moderately likely to demonstrate impulsive or thrill-seeking behaviors but were unlikely to have problems controlling their anger and abusing substances. *Unbound Transitioners,* on the other hand, were highly likely to have a history of substance abuse and moderately likely to demonstrate impulsive behaviors. Importantly, these three classes were the most likely to engage in violent extremism. Considering the three classes that were least likely to commit extremist violence (*Bonded Rebels*, *Pro-Socially Bonded,* and *Unbound and Low-Risk*) had a near-zero probability of observing any of the three low self-control factors, these findings indicate a relationship between low self-control factors and involvement in extremist violence. However, the overall low probability of observing low self-control factors across all six classes indicates limited support for the strength of this connection.

5.1.5. Lone Actors and Mental Illness

While not one of the main criminogenic factors of interest, the findings regarding lone actors are interesting. One point reiterated in the literature on lone actors is that there is not a uniform profile of a lone actor (de Roy van Zuijdewijn & Bakker, 2016; Gill et al., 2014; Lindekilde et al., 2019; McCauley & Moskalenko, 2014; Spaaij, 2010, 2011). With that said lone actors may have similar experiences or share behavioral traits and characteristics that distinguish them from other extremists (Hamm & Spaaij, 2017; McCauley & Moskalenko, 2014). The findings from the current analyses support this contention. Lone actors are collectively similar in their criminogenic risk and protective factors compared to other extremists. The *Strained Lone Actor* class is almost 100% likely to be a lone actor, and every other class has a notably low probability of acting alone. In this way, lone actors are largely homogenous in the patterns of criminogenic risk and protective factors they experience, and the combination of factors that emerged in the *Strained Lone Actors* class may characterize most of the lone actors in the sample.

Importantly, the *Strained Lone Actors* are the only class with a high probability of observing a mental illness. When adjusting the sample for case reliability scores, *Unbound Transitioners* were moderately likely to be mentally ill, but this probability increase occurred in tandem with an increased likelihood of acting alone. Corner and Gill (2015) found lone actors were 13 times more likely to have a mental health issue than group-affiliated terrorists, and other studies have similarly reiterated the relevance of mental illness in lone actor terrorism (de Roy van Zuijdewijn & Bakker, 2016; Gruenewald et al., 2013; Hamm & Spaaij, 2017; Kenyon et al., 2023). Findings from this dissertation lend further support to this connection, which is cause for concern given *Strained Lone Actors* were most likely to be engaged in violent extremism rather than nonviolent or noncriminal action.

5.2. Implications

This section examines the implications of this dissertation in three key dimensions: theory, methodology, and policy and practice. The section begins by considering how this study and its findings contribute to our theoretical understanding of the criminology of violent extremism. Next, the methodological advancements of this dissertation are assessed in terms of how the current methodological approach improved on approaches leveraged in prior empirical studies. Finally, the section concludes with an examination of the practical implications of this study by exploring how these findings may inform counterterrorism efforts seeking to prevent radicalized individuals from mobilizing to crime and violence.

5.2.1. Theoretical Contributions

Section 5.1. revealed several important findings relevant to the theoretical frameworks that criminogenic risk and protective factors were drawn from for this dissertation. But it is important to situate the role of theory in this dissertation before speaking to how these findings contribute to our understanding of the criminology of violent extremism. This study was exploratory, in that no theoretical predictions were explicitly tested or validated. Instead, this dissertation used theory in an informative capacity to (a) help guide the selection of criminogenic risk and protective factors most relevant to the study of violent extremism and (b) to explain the relationships that emerged between criminogenic factors, as well as between patterns of criminogenic factors and types of extremist actions.

The preceding sections detailed the findings in terms of the theoretical perspectives that the criminogenic factors were drawn from and independent support for each perspective. The theoretical contributions of this dissertation, however, extend beyond independent support of criminogenic factors. Indeed, the purpose of this study was to demonstrate how factors from multiple theoretical perspectives can be considered simultaneously to provide a more complete understanding of why some extremists engage in violence and others do not. As the findings above highlight, the multi-factor approach revealed key relationships between criminogenic factors that collectively impact the likelihood an individual would engage in violent extremism.

However, it is important to clarify that the goal of this dissertation was not to advance an integrated theory on the criminology of violent extremism. Theoretical integration involves merging concepts and/or propositions from two or more theoretical models into a single framework with the goal of developing a more comprehensive explanation of crime and deviance (Krohn & Eassey, 2014; Liska et al., 1989; Tittle, 1989). The practice of integration is a point of contention in the criminological literature, but numerous scholars support it as an avenue of theoretical development (Bernard & Snipes, 1998; Elliot, 1985; Pearson & Weiner, 1985; Tittle, 1995; Thornberry, 1987). Tittle (1995) remarks, “theoretical integration is mandated by the logic of science,” stating that, “observing regularities and seeking their explanation will lead one to see that some explanations can be subsumed under more comprehensive general explanatory schemes, or theories” (p. 89). Other scholars reiterate the additional benefits of theory integration, such as reducing the quantity and improving the quality of existing criminological theories (Bernard & Snipes, 1998), or encouraging consideration for theoretical perspectives outside of the schools of thought most concentrated on (Pearson & Weiner, 1985).

However, theoretical integration is not always viewed favorably. One argument is that building integrated theoretical models may lead to more complex and complicated frameworks that could preclude feasible empirical testing (Krohn & Eassey, 2014). Another critique by Hirschi (1979; 1989) argues against integrating theories based on incompatible theoretical assumptions (see also Kornhauser, 1978). He claims that if two theories that make different assumptions about human behavior are integrated, then the assumptions of one of those theories will inevitably be violated. For example, social bond theory assumes humans are innately drawn to deviant behavior, whereas social learning theory assumes humans learn to deviate. If these two perspectives were to be integrated into a single framework, their underlying assumption conflict with one another (Hirschi, 1989; Krohn & Eassey, 2014). Because of this, Hirschi’s viewpoint is that theories of crime and deviance must remain ‘separate and unequal’ to preserve the assumptions that underpin each theory’s propositions and encourage competition between theories to determine which theory is best (Hirschi, 1979; 1989)

A key point in Hirschi's (1989) argument against theoretical integration is that integrationists attribute ownership of variables to specific theories, which results in little-to-no overlap between variables across different theoretical perspectives. This practice, he claims, makes integration easy to accomplish because the data do not support one theory over the other, but rather support both theories simultaneously (Hirschi, 1989). He argues that theories do not own variables, and the assumptions, proposed relationships, and causal structures that compose the theory are equally important to the variables it includes (Hirschi, 1989). Bernard and Snipes (1998) counter that the integration debate has centered too much on theory and not enough on the "observable variables and the observable relationships among them" (p. 122). While they agree with Hirschi (1989) that theories do not own variables, Bernard and Snipes (1998) argue that the notion of theoretical ownership should be abandoned, and integration should be ground in a pursuit of determining which variables are related to crime and why. In their view, interpreting criminological theories based on their variables and relationships among them gives way to integration.

The practice of integration is not one the current study was equipped to undertake. The data and variables used, though novel and robust, are limited in many ways which precludes causal conclusions. These limitations are discussed in detail in *Section 5.3*. Nonetheless, this dissertation provides an initial exploration into how criminogenic factors from multiple theoretical perspectives co-occur and covary, which is directly in line with how Bernard and Snipes (1998) argue theoretical variables should be interpreted in order to facilitate integrative pursuits. Further, the findings of this study do support the possibility of an integrated theory for understanding extremist crime and violence. The criminogenic factors included clearly held interrelationships with another that impacted the type of extremist action they were involved in.

The presence of strain-related risk factors was most strongly associated with violent extremism when there were weak prosocial bonds, some degree of low self-control, and/or social learning factors also present. Those with prosocial bonds were most likely to not engage in crime or violence only when other criminogenic risk factors were not present. Those without prosocial bonds were only likely to be involved in violent extremism when other criminogenic risk factors were present. These patterns of factors are telling in terms of which combinations of factors may be most consequential for explaining involvement, or noninvolvement, in extremist crime and violence.

These findings further support the advocations from terrorism scholars calling for more attention to be directed towards integrated theories (Freilich et al., 2024; Khalil & Dawson, 2023). Some integrated theories already exist but lack adequate empirical testing. For example, situational action theory (SAT) contends the interaction between an individual's propensity for crime and exposure to criminogenic settings condition the likelihood a person will engage in crime, and draws from multiple criminological paradigms including low self-control, social learning, social bond, and strain perspectives (Wikström, 2017; Wikström & Bouhana, 2016). Because SAT is mechanism-based, several studies have offered partial tests of the framework in application to extremism, but data limitations, including inadequate measurement and use of cross-sectional data, have precluded full tests of the model (Pauwels & Svensson, 2016; Schils & Pauwels, 2014; 2016).

Importantly, theoretical integration does not need to be limited to criminology when attempting to better explain violent extremism. While criminological theory may be useful for explaining why someone who holds extremist beliefs mobilizes to crime and violence, theories from other fields of study can provide instructive insight into the dimensions of violent extremism and radicalization that criminological theory may not explain. For example, theories from social psychology may help explain why individuals become involved in extremism in the first place (Borum, 2003; Kruglanski et al., 2014; Moghaddam, 2005, Sageman, 2008; Wiktorowicz, 2004). Other bifurcated models can help contextualize the distinction between radical beliefs and radical actions (Khalil et al., 2022; McCauley & Moskalenko, 2014; 2017). The field of extremism research may benefit from considering how these frameworks, which advance our understanding of radicalization processes, can complement existing criminological theories that explain why radicalized individuals may mobilize to extremist crime and violence.

5.2.2. Methodological Advancements

This dissertation employed a robust methodology that improves on several methodological limitations in prior research. First, this study utilized data on extremists who had actually engaged in some form of action. Prior studies examining the relationship between criminogenic factors and violent extremism mostly used proxy measures for violent extremist intentions or propensities (Perry et al., 2018; Rottweiler & Gill, 2020; Rottweiler et al., 2022). Findings from these studies are undoubtedly important, but as Rottweiler et al. (2022) put it, "it is difficult to establish if and how behavioral intentions are translated into actual behavior" (p. 840). This dissertation overcomes the challenge posed by this disconnect by examining extremists who actually engaged in specific forms of ideologically motivated behavior. Some works did examine self-reported political action (De Waele & Pauwels, 2014; Pauwels & Schils, 2016; Schils & Pauwels, 2014; Schils & Pauwels, 2016), but these data are limited in several ways (Junger-Tas, 1999), including accuracy of recollection (Freilich et al., 2024).

Second, within the limited research that has considered samples of individuals who committed extremist actions, previous studies have yet to leverage a sample of nonoffending extremists to compare to extremists who engaged in crime and violence. Most studies utilize the PIRUS dataset, which relies on a nonviolent category that includes both nonviolent criminal and nonoffending extremists (Becker, 2021; LaFree et al., 2018; Pritchett & Moeller, 2021). This conflation between nonviolent criminal and nonoffending extremism limits prior studies' ability to draw conclusions related to criminogenic factors, given some of their comparison group did engage in criminal behavior even if it was nonviolent.

The findings from this dissertation further imply this conflation is problematic. Results from the LCA model indicate nonviolent criminal extremists and nonoffending extremists are distinct from one another in terms of the criminogenic risk and protective factors they experience. Thus, by separating these two groups based on the legality of their actions, conclusions can be more clearly drawn when comparing each group to violent extremists. Specifically, this approach allows for exploration into (1) the criminogenic factors that distinguish extremists who engage in ideologically motivated crime from those who do not, as well as (2) the criminogenic factors that distinguish extremists who use violence from those that do not. The clarity in these comparisons can only be attained when the comparison groups are clearly and meaningfully operationalized.

Third, the field has been stagnant in employing analytic techniques that adequately capture the equifinality and multifinality of extremist violence. Studies have frequently used the 'garbage-can' approach (De Waele & Pauwels, 2012; Becker, 2021; LaFree et al., 2018; Nivette et al., 2017; Pauwels & Schils, 2016; Pritchett & Moeller, 2021; Thijs et al., 2022; Turner et al., 2022), where a slate of variables of interest are simultaneously considered in a multivariate regression model. This approach is productive for examining the independent net effects of particular variables, but does not speak to the accumulative, interactive nature of risk and protective factors (Wolfowicz et al., 2021). Scholars have called for more attention to be directed towards data-driven methodologies that model how factors co-occur and cluster together to examine the equifinal and multifinal nature of violent extremism (Clemmow et al., 2022; Gill, 2015).

Answering this call, this dissertation presents the first known study to (a) apply LCA, a probabilistic mixture modeling technique, to estimate classes of criminogenic risk and protective factors in a sample of extremists, and (b) utilize the LTB approach to assess the relationship between these classes of criminogenic factors and the type of action extremists in the sample were involved in (Lanza et al., 2013). Use of the LTB approach improves on prior work by incorporating a distal outcome prediction method that accounts for classification error in modal assignment. This is important, as the limited research that has employed LCA with distal outcome prediction to evaluate risk and protective factors for violent extremism has utilized the basic classify-analyze approach for distal outcome prediction which can bias the results by assuming perfect class assignment (see *Section 3.2.4.*; Clemmow et al., 2022). Accordingly, this dissertation advances the literature on risk and protective factors for violent extremism by leveraging a novel methodological approach that had yet to be employed in this field of study.

Moreover, the data-driven, model-based approach in LCA produces findings that can speak to both the equifinality and multifinality of violent extremism. Multiple classes, with distinct combinations of criminogenic factors, had a high probability of engaging in violent extremism – this is equifinality. On the other hand, classes with a high probability of engaging in extremist violence also had, to varying degrees, a chance of being involved in nonviolent criminal or nonoffending extremism – this is multifinality. Future research can use this methodological approach to explore the equifinality and multifinality of violent extremism further by considering different risk and protective factors or different behavioral outcomes.

5.2.3. Policy and Practice

The findings of this study are pertinent to numerous implications for policy and practice. To reiterate, the focus of this dissertation is on the secondary level of prevention in the public health-informed approach. At this level, interventions are designed to identify individuals who hold radical beliefs and intervene before they mobilize to extremist crime or violence (Jackson et al., 2019). Understanding the factors that may drive individuals towards crime or violence is essential for secondary level prevention efforts. In this way, criminological theory provides an instructive foundation for (a) identifying relevant factors and (b) explaining why certain factors may lead to criminal behavior. Thus, the implications discussed here should be interpreted in the context of secondary prevention efforts. The goal of these efforts is not to prevent individuals from adopting radical beliefs or to facilitate deradicalization. Rather, the goal is to divert individuals who may hold extreme beliefs away from violence and towards nonviolent and noncriminal means for expressing their ideological convictions.

First, reliable and valid risk assessment tools are valuable resources for practitioners in estimating one's propensity for mobilizing to violence. These tools can be structured a number of different ways (van der Heide et al., 2019), but ultimately the capacity in which risk and protective factors are integrated is critical. Specifically, scholars have criticized the utilization of a cumulative risk assessment model, whereby more risk factors equate to a higher risk, in application to extremism involvement (Borum, 2015; van der Heide et al., 2019). In some cases, few risk factors, particularly one's that work in conjunction with one another, may lead to radicalization to violence (Pressman et al., 2018). Thus, the relationships between risk factors should be considered, as findings from this dissertation show that some combinations are more likely to associate with involvement in violent extremism than others.

Additionally, involvement in violent extremism is not exclusive to a single pattern of criminogenic factors. Counterintuitive cases demonstrate the imperfectness of classifications and the impracticality of developing an algorithmic or statistically driven tool that perfectly predicts extremist violence while excluding nonviolent or noncriminal cases. In this way, practitioners should diligently bear in mind the equifinality and multifinality of violent extremism, because no risk assessment tool will be a perfect predictor of involvement in extremist violence versus other types of extremist actions. The findings of the LCA and distal outcome prediction illustrate the plausibility that an individual who does not fit the anticipated profile of a violent extremist will engage in violence, and that individuals who do fit the profile of a violent extremist may commit other type of extremist actions. As a result, clinical judgements by experts with knowledge of violent extremism can allow for risk estimations to be made within the context of situational and individual case conditions as opposed to rigid objective prescriptions.

With that said, it is necessary to include objective criteria for assessing one's risk so as to enable tests of reliability and validity. Results from this study indicate there are clear quantitative patterns in the manifestation of criminogenic risk and protective factors and statistical relationships between these patterns and involvement in extremist violence. If policies and procedures are to be standardized and uniformly implemented, it is necessary that practices are at least partially grounded in objective criteria for estimating one's risk of extremism so that decisions can be subject to repeated examination. Accordingly, a structured professional judgement (SPJ) approach, where structured criteria and expert opinion are employed simultaneously to establish objective measures while remaining flexible and adaptable to professional intuition, may be most effective (Hart & Vargan, 2023; van der Heide et al., 2019). SPJ tools, such as the Violent Extremism Risk Assessment (VERA-2R; Pressman et al., 2018), do exist and are being used in professional contexts, but have several issues that limit their use including accessibility, definitional problems, and behaviors of focus (Hart & Vargan, 2023). Thus, more research is needed to empirically validate these tools and their effectiveness in assisting practitioners in the process of identifying potentially radicalized persons and preventing radicalization to violence.

Moreover, a strong information-sharing apparatus is essential to identify and help individuals at risk of mobilizing to violence. Findings from the current study reveal a high probability of observing numerous behaviors potentially indicative of an inclination towards extremist violence, such as glorification of violence, rejecting democratic values/norms, demonstrating impulsive behaviors, problems regulating anger, expressing personal grievances or perceived injustices, and associating with extremist or criminal peers, to name a few. These behaviors do not occur in a vacuum, and are likely to be observed by other people, including peers and family members. Educational initiatives that inform potential bystanders on possible warning signs and avenues of reporting could prove beneficial for making sure these behaviors do not go undetected by the proper authorities (Jackson et al., 2019).

Additionally, programs such as the Nationwide Suspicious Activity Reporting Initiative (NSI) and Behavioral Threat Assessment Integration (BTAI), which are housed in the U.S. National Threat Evaluation and Reporting Office (NTER), are important for institutionalizing governmental responses to situations where concerning behaviors are demonstrated. Specifically, the NSI facilitates information-sharing between local, state, and federal law enforcement agencies (DHS, 2022c). Alternatively, the BTAI aims to equip professionals with knowledge of techniques and practices to identify individuals potentially at risk of committing acts of terrorism or targeted violence based on observable behaviors and mitigate the potential threat (DHS, 2022b). In conjunction with Center for Prevention Programs and Partnerships' (CP3) local prevention framework (DHS, 2022a), these programs may be useful for providing professionals access to relevant information on potentially radicalized persons while ensuring case management is guided by best practice and coordinated by trained partners.

Further, practical implications can be derived from the independent factors that saliently distinguish classes most likely to commit extremist violence versus those that are most likely to engage in nonviolent and noncriminal actions. First, the findings from this dissertation indicate a direct focus on mitigating the impact of strain-related risk factors may be effective. Primary prevention efforts that seek to prevent radical beliefs from taking hold could benefit from programming that addresses personal grievances or perceived injustices before they give way to radicalization (Jackson et al., 2019). Secondary prevention efforts, however, should focus on interventions that help radicalized individuals resolve negative emotions that come from difficult life events, personal grievances, or perceived societal injustices.

Specifically, it should not be overlooked that the impact of strains may be conditioned by the availability of legal, prosocial coping mechanisms (Agnew, 1992). In each class where strain-related risk factors were prevalent, there were other criminogenic factors, or absence of factors, that could impact one's ability to address their strains through nonviolent and noncriminal means. Policymakers should look towards interventions that insert positive coping mechanisms into the lives of individuals who may hold extreme beliefs and are at-risk for mobilizing to violence. One promising avenue is cognitive behavioral initiatives, which seek develop individual's cognitive fortitude in managing anger, expressing empathy, and solving problems, amongst other goals, within communities (Aly et al., 2014; Fisher et al., 2008; Sheikh et al., 2011). Such programs may prevent radicalization to violence by helping at risk individuals control their emotions and resolve their grievances peacefully rather than mobilizing to extremist violence.

In the same vein, this dissertation found that strong prosocial bonds may be important in preventing involvement in violent extremism. Community-oriented approaches should bear in mind the salience of these factors as promising avenues for shielding at-risk individuals from involvement in extremist violence. Protective factors such as being married, being involved in the community, and being employed were defining characteristics of classes who were most likely to engage in nonviolent and noncriminal extremism. Individuals who are married, involved in the community, in school, and/or maintain consistent employment are more occupied and therefore have less time to explore extremist narratives and commit extremist actions. Employment has garnered pragmatic attention, and scholars have advocated for the utility of employment programs, particularly in the study of deradicalization and reintegrating former extremists into society. As Rabasa et al. (2010) put it, "…it is important that a disengaged extremist find employment and feel productive, independent, and capable of providing for his or her family. Stable employment helps boost the self-esteem of former extremists and wean them off the practical support that the radical organization had offered" (p. 21). Accordingly, counterterrorism professionals should invest in programs that help at risk individuals find and maintain gainful employment.

Lastly, the finding regarding mental illness and lone actors warrants practical consideration. This connection should be properly heeded, especially considering social isolation has been linked to an increased rate of mental illness (de Roy van Zuijdewijn & Bakker, 2016).

However, the accessibility of mental health resources is an ongoing issue in the criminal justice system (Vogel et al., 2014). There is no shortage of issues with both identifying people in need of mental health interventions as well as connecting them to the proper services to treat their condition. General efforts to improve access to mental health care could pay dividends for helping isolated and aggrieved individuals who are dealing with a mental illness receive the appropriate treatment they need. Counterterrorism programs could also benefit from establishing strong partnerships with mental health service providers to connect those at-risk of mobilizing to extremist violence who may require treatment for mental illness.

5.3. Limitations and Future Research

The findings and implications of this dissertation are important, but there are several limitations in methodology that warrant discussion to contextualize these contributions. First, the study uses data from the RPFD, which is an open-source dataset. Open-source data is a powerful tool for studying rare events such as terrorism and violent extremism, as there is limited official data available on these events (Greene-Colozzi et al., 2021; Gruenewald & Klein, 2015). Empirical tests have also shown that open-source data provides greater quantity and quality of information on rare events than official agency data, with the added advantage that researchers are not limited by the variables an agency elects to report (Parkin & Gruenewald, 2017). Because of this, researchers developing open-source datasets can include variables of interest that are relevant to the phenomena under study but not captured in official data sources (Parkin & Gruenewald, 2017).

Despite its advantages, open-source data is limited in several ways. First, open-source data is reliant on the availability of open-source information on a case. Numerous efforts were dedicated to ensuring the information collected and codified into the RPFD was comprehensive and reliable, but it is possible that certain information was misreported by outlets, misinterpreted by coders, or missing from the available sources altogether. The prevalence of missing data is often cited as a weakness of open-source datasets (Freilich et al., 2014; LaFree et al., 2018; Safer-Lichtenstein et al., 2017). This is particularly problematic when media coverage is uneven, with some cases receiving more attention than others (Greene-Colozzi et al., 2021). Chermak and Gruenewald (2006) found that most domestic terrorist incidents in the U.S. receive little-to-no media attention, with a select few cases being reported on extensively. The most heavily covered incidents were those that resulted in casualties, involved members of domestic terrorist groups, targeted airlines, or used hijacking as an attack strategy. While these findings are dated, Chermak and Gruenewald (2006) shed light on how cases with certain characteristics are more likely to receive media coverage than others, which introduces a reporting bias in open-source data.

This consideration is particularly relevant to this dissertation, as the type of incidents under study differ in their legality and severity, which can ultimately impact how much they are reported on. For example, if cases with casualties receive more media coverage on average (Chermak & Gruenewald, 2006), then violent extremist cases will systematically be covered more in the open-source material than cases involving nonviolent crimes or no crime at all. This possibility is substantiated when examining the cases omitted from the reliability score-adjusted sample. While 30 VEs and 32 NVCEs were deemed low-reliability and thus omitted from the sample, approximately 77 NOEs were excluded. The high quantity of NOE cases with low reliability scores suggests that this category of extremists received less open-source coverage than VE or NVCE cases.

The issue of reporting bias becomes more concerning when considering the current study's coding scheme was based on the presence or absence of evidence indicating that a certain variable was observed in the open-source material. The purpose of this strategy was to minimize the amount of missingness in the dataset. However, because the open-source material could be biased towards certain types of incidents, coding for "*Evidence of Yes*" or "*No Evidence of Yes*" could result in a higher frequency of "*No Evidence of Yes*" responses for variables in nonviolent and noncriminal cases than violent cases. This possibility necessitates that the results of this dissertation are interpreted with caution, particularly given LCA is based on a probability function that estimates the probability of observing a "1" response, or an "*Evidence of Yes*" response. As a result, the differences reported between violent, nonviolent criminal, and nonoffending extremists may reflect differences in the presence or absence of evidence available on certain variables for each type of extremist rather than 'true' differences that manifest in reality.

It is important to note that this dissertation did take extensive steps to account for this potential bias in the results by using the RPFD case reliability score as a criterion for inclusion in the sample and re-running the analysis to determine if the results were sensitive to this adjustment. Cases were deemed unreliable if their reliability score was below one standard deviation of the average case reliability score for the sample. While this threshold does not remove the potential that some cases have remarkably high reliability scores, it does ensure that cases included in the sample must have a minimum level of information available in order to be analyzed. This way, cases with little-to-no information are not included in analysis, as their inclusion would likely result in most variables reporting "*No Evidence of Yes*" responses and thus biasing the probability estimates for indicator probabilities downward in the LCA model. This does appear to be the case, as when the sample was adjusted for case reliability scores, the indicator probabilities increased for numerous variables, particularly those that were defining characteristics of the estimated classes. Accordingly, while it remains plausible that some cases included in the reliability-score adjusted samples received more media coverage than others, the influence of the reporting bias in the open-source data is mitigated through this strategy.

Nevertheless, future research can improve the data limitations in this study in two ways. First, more work is needed on increasing the reliability and robustness of open-source data and the results produced from analyses using open-source data. A recent article by Klein et al. (2024) using open-source data on school shootings from The American School Shooting Study (TASSS), demonstrates a novel method for estimating the probability of observing missingness in a variable and adjusting the data to account for this missingness. Another study by Ackerman and Pinson (2016) proposed a schema to evaluate and capture the validity and credibility of event-level data in open-sources, including the credibility of the source, certainty an event occurred, and confidence in event detail variables. These innovative approaches are increasingly important for bolstering the reliability and credibility of open-source data, and future research should continue to investigate how the robustness of open-source data can be improved.

Second, future research should explore other data options for assessing the prevalence of certain criminogenic mechanisms in samples of extremists. Data that bolsters credibility, reliability, and validity while also mitigating missing data is essential for advancing empirical examinations in this field of study. For example, Gomez et al. (2022) interviewed a sample of Islamist extremists in Spain to explore the risk and protective factors they experience. Such approaches, though resource-intensive, can provide rich information that advances our understanding of radicalization and mobilization to extremist violence.

The issue of measurement should also not be overlooked. The current dissertation assessed criminogenic factors. While these factors indicate the manifestation of certain theoretical concepts, they are not validated measure for these concepts. Specifically, measurement of criminogenic factors was limited to the presence or absence of a factor, but it was not indicative of other elements such as strength, duration, or temporal ordering. For example, the analysis captured the presence or absence of extremist peers. However, the analysis did not capture how frequently the individual was in contact with these peers, how long they associated with these peers, or if their association with these peers came before or after their subscription to extremist beliefs. The same shortcomings limit the measurement of the other criminogenic factors analyzed in this dissertation, including factors related to prosocial bonds, strains, low self-control, and other social learning factors.

Particularly as it concerns the low self-control factors, it is possible that the findings regarding low self-control were influenced by the use of behavioral versus attitudinal measures.[12] Gottfredson and Hirschi (1990; Hirschi & Gottfredson, 1993) propose self-control as an individual trait, and claim it is most appropriately measured through manifestations of noncriminal behavior that indicate the elements of self-control; namely impulsivity, thrill-seeking, need for immediate gratification, etc. However, this gives way to perhaps the most notable critique of low self-control theory in that it is tautological, meaning it is measured by the very behaviors it aims to explain (i.e. crime and analogous acts) (see Akers, 1991). As a result, some scholars have opted for cognitive or attitudinal measures, such as the Grasmick et al. (1993) scale, to assess self-control. The comparability between cognitive and behavioral measures has been studied, and findings indicate similar predictive capacity in both approaches (Tittle et al., 2003). Further, other scholars describe the behavioral approach as "within the spirit of Gottfredson and Hirschi's theory" (Piquero et al., 2005: 68). In contrast, more recent work

[12] For a full discussion of the low self-control measurement issue, see Marcus (2004).

contends there are reliability issues in behavioral measures and suggests behavioral and attitudinal self-report measures tap into differential response processes (see Dang et al., 2020). Additionally, in their meta-analysis, Walters (2016) found the Grasmick et al. (1993) scale was equally correlated with behavioral measures of low self-control and crime/delinquency itself. These findings suggest attitudinal and behavioral measures of self-control could be measuring separate constructs and may substantiate the claim that Gottfredson and Hirschi's conception of self-control is tautological (Walters, 2016). Therefore, while prior theoretical and empirical work supports the use of behavioral indicators to measure low self-control, the findings of this study are nonetheless limited by the underlying issue of measuring self-control through behavior. Moreover, it is plausible that attitudinal measures may produce different results than those observed in this study.

Again, it is important to note that the purpose of this dissertation was to assess criminogenic risk and protective factors, which are observable markers of underlying theoretical mechanisms (Clemmow et al., 2022), and use criminological theory to explain the observed relationships in the LCA model. The purpose was not to conduct an empirical test of these theories and their concepts in their relationship to involvement in violent extremism, as detailed in *Section 5.2.1*. The findings should be interpreted with this proper context in mind, and future research that seeks to conduct empirical tests of these theories should employ validated measures for the theoretical concepts under study.

Additionally, as prior scholars have asserted, theories do not own variables (Bernard & Snipes, 1998; Hirschi, 1989). The same is true for criminogenic risk and protective factors. While this dissertation organized criminogenic factors within each criminological perspective, there is overlap in how the factors may be theoretically situated. For instance, substance abuse was considered as an indicator for low self-control because it involves participating in behaviors that produce immediate gratification despite the long-term consequences (Clevenger et al., 2016). However, substance abuse may also be considered as a coping mechanism to address feelings of strain (Agnew, 1992). Another example is rejecting democratic values, which was used to indicate a ruptured bond to the conventional belief system. This risk factor may have alternatively been situated as an indicator for definitions of behavior in the social learning perspective. Again, criminogenic factors are observable markers of underlying causal mechanisms, and while theory can be used to explain their manifestation, these explanations are not always exclusive and may overlap in some ways. Future research should bear this overlap in mind when examining criminological variables from multiple perspectives.

Finally, the criminogenic factors utilized in this study are not exhaustive, and future research should consider other risk and protective factors to extremism that may be relevant. The selection of criminogenic factors for this study was determined by (a) theoretical relevance, (b) empirical support, and (c) availability in the RPFD. It is very plausible that there were variables that are theoretically and empirically relevant that the RPFD did not capture, or variables that were not situated within criminological frameworks that were not included. As discussed above, future research should draw on risk and protective factors from disciplines outside of criminology such as psychology, social work, political science, and others to capture a wider scope of factors that may be relevant in distinguishing violent, nonviolent criminal, and nonoffending extremists.

5.4. Conclusion

This dissertation conducted an empirical exploration into how violent extremists differ from their nonviolent and noncriminal extremist counterparts in the criminogenic risk and protective factors they demonstrate. By leveraging a multifactor approach to investigate criminogenic factors from multiple criminological perspectives, while also improving on methodological shortcomings in prior research, this study contributes to the growing evidentiary base on the criminology of violent extremism. Specifically, findings from this study suggest extremist are most likely to engage in violent extremism when they experience strain-related risk factors that co-occur with low self-control factors, social learning factors, or an absence of protective factors in the form of social bonds Those most likely to commit nonviolent crimes are largely characterized by prosocial bonds with a tendency to reject the values and norms of democratic society and endorse prior acts of extremist crime and violence. Finally, extremists with strong prosocial bonds and without salient criminogenic risk factors are very unlikely to engage in extremist crime or violence, and instead are mostly involved in nonoffending extremism.

Taken together, this study supports the claim that violent extremists are different from nonviolent and nonoffending extremists in the criminogenic risk and protective factors they experience. However, this study also reiterates the equifinality and multifinality of extremist violence. Not all extremists who commit violence will demonstrate a similar pattern of criminogenic factors, in the same way that extremists who demonstrate similar patterns of criminogenic factors will not all engage in the same type of action. Findings from this study represent data-derived probabilistic patterns, not hard-and-fast prescriptions for the combinations of factors that characterize each type of extremist. Thus, it is imperative to interpret these findings with equifinality and multifinality in mind. Future research investigating this line of work must do the same to bring organization and understanding to the heterogenous nature of violent extremism.

On that note, the implications of this study are consequential for both research and practice. Future work can use these findings as a starting point for developing an integrated framework on the criminology of violent extremism, though improvements to data and measurement are necessary to meet these ends. Researchers can also leverage the methodological scheme employed in this study to conduct explorations into how other risk and protective factors co-occur with one another to collectively influence one's decision to engage in violence versus alternative pathways. Finally, programs and policymakers working on secondary-level prevention efforts can use these findings to guide practice and inform interventions that are evidence-based, theoretically informed, and effective at preventing extremists from mobilizing to acts of crime and violence.

REFERENCES

Achen, C. H. (2005). Let's put garbage-can regressions and garbage-can probits where they belong. *Conflict Management and Peace Science, 22*(4), 327-339.

Ackerman, G. A. (2003). Beyond arson? A threat assessment of the Earth Liberation Front. *Terrorism and Political Violence, 15*(4), 143-170.

Ackerman, G. A., & Pinson, L. E. (2016). Speaking truth to sources: Introducing a method for the quantitative evaluation of open sources in event data. *Studies in Conflict & Terrorism, 39*(7-8), 617-640.

Adamczyk, A., Gruenewald, J., Chermak, S. M., & Freilich, J. D. (2014). The relationship between hate groups and far-right ideological violence. *Journal of Contemporary Criminal Justice, 30*(3), 310-332.

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology, 30*(1), 47-88.

Agnew, R. (2010). A general strain theory of terrorism. *Theoretical Criminology*, *14*(2), 131-153.

Akers, R. L. (1991). Self-control as a general theory of crime. *Journal of Quantitative Criminology*, *7*(2), 201-211.

Akers, R. L. (2001). Social learning theory. In R. Paternoster & R. Bachman (Eds.), Explaining criminals and crime: Essays in contemporary criminological theory (pp. 192–210). Los Angeles, CA: Roxbury.

Akers, R. L. (2011). *Social learning and social structure: A general theory of crime and deviance*. Transaction Publishers.

Akers, R. L., & Silverman, A. L. (2014). Toward a social learning model of violence and terrorism. In *Violence* (pp. 27-44). Routledge.

Akins, J. K., & Winfree Jr, L. T. (2016). Social learning theory and becoming a terrorist: New challenges for a general theory. *The Handbook of the Criminology of Terrorism*, 133-149.

Aly, A., Taylor, E., & Karnovsky, S. (2014). Moral disengagement and building resilience to violent extremism: An education intervention. *Studies in Conflict & Terrorism, 37*(4), 369-385.

Al Baghal, T. (2014). Estimating Support for Extremism and Its Correlates: The Case of Pakistan. *ASK. Research & Methods, (23*), 35-56.

Altunbas, Y., & Thornton, J. (2011). Are homegrown Islamic terrorists different? Some UK evidence. *Southern Economic Journal*, *78*(2), 262-272.

Arneklev, B. J., Cochran, J. K., & Gainey, R. R. (1998). Testing Gottfredson and Hirschi's "low self-control" stability hypothesis: An exploratory study. *American Journal of Criminal Justice*, *23*, 107-127.

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.

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using M plus. *Structural Equation Modeling: A Multidisciplinary Journal, 21*(3), 329-341.

Asparouhov, T., & Muthén, B. (2021). Auxiliary variables in mixture modeling: Using the bch method in Mplus to estimate a distal outcome model and an arbitrary secondary model. *Mplus Web Notes, 21*(11), 1-80

Atran, S. (2010). *Pathways to and from violent extremism: The case for science-based field research.* Statement Before the Senate Armed Services Sub-committee on Emerging Threats & Capabilities. Retrieved from: https://artisinternational.org/articles/Atran_Statement_Before_the_Senate.pdf

Bak, M., Tarp, K. N., & Liang, C. S. (2019). Defining the Concept of 'Violent Extremism.'. *Geneva Paper 24/19, The Geneva Centre for Security Policy*.

Bakk, Z., & Kuha, J. (2021). Relating latent class membership to external variables: An overview. *British Journal of Mathematical and Statistical Psychology, 74*(2), 340-362.

Bakk, Z., Tekle, F. B., & Vermunt, J. K. (2013). Estimating the association between latent class membership and external variables using bias-adjusted three-step approaches. *Sociological Methodology, 43*(1), 272-311.

Bakk, Z., & Vermunt, J. K. (2016). Robustness of stepwise latent class modeling with continuous distal outcomes. *Structural equation modeling: A Multidisciplinary Journal, 23*(1), 20-31.

Barker, E. D., & Riley, H. (2022). The role of trauma and mental health in violent extremism. *XCEPT*.

Barry-Walsh, J., James, D. V., & Mullen, P. E. (2020). Fixated Threat Assessment Centers: preventing harm and facilitating care in public figure threat cases and those thought to be at risk of lone-actor grievance-fueled violence. *CNS spectrums, 25*(5), 630-637.

Bauer, D.J., Steinley, D. (2021, May 24-28). *Latent class/cluster analysis and mixture modeling* [PowerPoint Slides]. Curran-Bauer Analytics LLC. Durham, NC.

Becker, M. H. (2021). When extremists become violent: examining the association between social control, social learning, and engagement in violent extremism. *Studies in Conflict & Terrorism, 44*(12), 1104-1124.

Bejan, V., & Parkin, W. S. (2015). Examining the effect of repressive and conciliatory government actions on terrorism activity in Israel. *Economics Letters, 133*, 55-58.

Benassi, M., Garofalo, S., Ambrosini, F., Sant'Angelo, R. P., Raggini, R., De Paoli, G., ... & Piraccini, G. (2020). Using two-step cluster analysis and latent class cluster analysis to classify the cognitive heterogeneity of cross-diagnostic psychiatric inpatients. *Frontiers in Psychology, 11*, 1085.

Bernard, T. J., & Snipes, J. B. (1996). Theoretical integration in criminology. Crime and Justice, 20, 301-348.

Bernatzky, C., Costello, M., & Hawdon, J. (2021). Who produces online hate?: An examination of the effects of self-control, social structure, & social learning. *American Journal of Criminal Justice*, 1-20.

Bock, E. M., & Hosser, D. (2014). Empathy as a predictor of recidivism among young adult offenders. *Psychology, Crime & Law, 20*(2), 101-115.

Borum, R. (2003). Understanding the terrorist mind-set. FBI L. *Enforcement Bull., 72*, 7.

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

Borum, R. (2015). Assessing risk for terrorism involvement. *Journal of Threat Assessment and Management, 2*(2), 63.

Bouhana, N. (2019). The moral ecology of extremism: A systemic perspective. *UK Commission for Countering Violent Extremism*.

Bray, B. C., Lanza, S. T., & Tan, X. (2015). Eliminating bias in classify-analyze approaches for latent class analysis. *Structural equation modeling: A Multidisciplinary Journal, 22*(1), 1-11.

Breslow, N. E. (1996). Statistics in epidemiology: the case-control study. *Journal of the American Statistical Association*, *91*(433), 14-28.

Burgess, R. L., & Akers, R. L. (1966). A differential association-reinforcement theory of criminal behavior. *Soc. Probs.*, *14*, 128.

Burruss, G. W., Howell, C. J., Maimon, D., & Wang, F. (2021). Website defacer classification: A finite mixture model approach. *Social Science Computer Review*, 0894439321994232.

Candilis, P. J., Cleary, S. D., Dhumad, S., Dyer, A. R., & Khalifa, N. (2021). Classifying terrorism: a latent class analysis of primary source socio-political and psychological data. *Behavioral Sciences of Terrorism and Political Aggression*, 1-18.

Capellan, J. A. (2015). Lone wolf terrorist or deranged shooter? A study of ideological active shooter events in the United States, 1970–2014. *Studies in Conflict & Terrorism*, *38*(6), 395-413.

Carson, J. V. (2014). Counterterrorism and radical eco-groups: A context for exploring the series hazard model. *Journal of Quantitative Criminology*, *30*, 485-504.

Carson, J. V., Dugan, L., & Yang, S. M. (2020). A comprehensive application of rational choice theory: how costs imposed by, and benefits derived from, the US federal government affect incidents perpetrated by the radical eco-movement. *Journal of Quantitative Criminology*, *36*, 701-724.

Carson, J. V., & Turner, N. D. (2024). The role of ideology in terrorist attack intentions and outcomes. *Terrorism and Political Violence, 36*(1), 90-112.

Chan, H. C., & Chui, W. H. (2017). The influence of low self-control on violent and nonviolent delinquencies: A study of male adolescents from two Chinese societies. *The Journal of Forensic Psychiatry & Psychology, 28*(5), 599-619.

Chapple, C. L. (2005). Self-control, peer relations, and delinquency. *Justice Quarterly*, *22*(1), 89-106.

Chermak, S., Freilich, J., & Suttmoeller, M. (2013). The organizational dynamics of far-right hate groups in the United States: Comparing violent to nonviolent organizations. *Studies in Conflict & Terrorism, 36*(3), 193-218.

Chermak, S. M., & Gruenewald, J. (2006). The media's coverage of domestic terrorism. *Justice Quarterly, 23*(4), 428-461.

Chermak, S., & Gruenewald, J. A. (2015). Laying a foundation for the criminological examination of right-wing, left-wing, and Al Qaeda-inspired extremism in the United States. *Terrorism and Political Violence, 27*(1), 133-159.

Clarke, R. V. G., & Newman, G. R. (2006). *Outsmarting the terrorists*. Praeger Security Intl.

Cleland, C. M., Rothschild, L., & Haslam, N. (2000). Detecting latent taxa: Monte Carlo comparison of taxometric, mixture model, and clustering procedures. *Psychological Reports, 87*(1), 37-47.

Clemmow, C., Bouhana, N., Marchment, Z., & Gill, P. (2022). Vulnerability to radicalisation in a general population: a psychometric network approach. *Psychology, Crime & Law*, 1-29.

Clemmow, C., Rottweiler, B., Wolfowicz, M., Bouhana, N., Marchment, Z., & Gill, P. (2023). The whole is greater than the sum of its parts: Risk and protective profiles for vulnerability to radicalization. *Justice Quarterly*, 1-27.

Clemmow, C., Gill, P., Bouhana, N., Silver, J., & Horgan, J. (2022). Disaggregating lone-actor grievance-fuelled violence: Comparing lone-actor terrorists and mass murderers. *Terrorism and Political Violence, 34*(3), 558-584.

Clevenger, S. L., Navarro, J. N., & Jasinski, J. L. (2016). A matter of low self-control? Exploring differences between child pornography possessors and child pornography producers/distributers using self-control theory. *Sexual Abuse, 28*(6), 555-571.

Cloward, R. A., & Ohlin, L. E. (2013). *Delinquency and opportunity: A study of delinquent gangs*. Routledge.

Coccia, M. (2018). A theory of general causes of terrorism: high population growth, income inequality and relative deprivation. *Archives of Psychology*, *2*(4).

Cohen, A. K. (1955). *Delinquent boys; The culture of the gang*. Free Press.

Cohen, M. A. (1988). Pain, suffering, and jury awards: A study of the cost of crime to victims. *Law & Soc'y Rev., 22*, 537.

Collier, Z. K., & Leite, W. L. (2017). A comparison of three-step approaches for auxiliary variables in latent class and latent profile analysis. *Structural Equation Modeling: A Multidisciplinary Journal, 24*(6), 819-830.

Conger, R. D. (1976). Social control and social learning models of delinquent behavior a synthesis. *Criminology*, *14*(1), 17-40.

Conklin, M. (2021). Capitol Offense: Is Donald Trump guilty of inciting a riot at the Capitol?. *U. St. Thomas JL & Pub. Pol'y*, *15*, 483.

Corner, E., Bouhana, N., & Gill, P. (2021). Updating and Organizing Our Knowledge of Risk and Protective Factors for Lone-Actor Terrorism 1. In *Terrorism Risk Assessment Instruments* (pp. 116-136). IOS Press.

Corner, E., & Gill, P. (2015). A false dichotomy? Mental illness and lone-actor terrorism. *Law and Human Behavior, 39*(1), 23.

Cushman, F., Gray, K., Gaffey, A., & Mendes, W. B. (2012). Simulating murder: the aversion to harmful action. *Emotion, 12*(1), 2.

Dang, J., King, K. M., & Inzlicht, M. (2020). Why are self-report and behavioral measures weakly correlated?. *Trends in Cognitive Sciences, 24*(4), 267-269.

Denson, T. F., DeWall, C. N., & Finkel, E. J. (2012). Self-control and aggression. *Current Directions in Psychological Science, 21*(1), 20-25.

Department of Homeland Security (DHS). (2022a). Center for Prevention Programs and Partnership. *Author*. Retrieved from: https://www.dhs.gov/sites/default/files/2022-02/The%20Center%20for%20Prevention%20Programs%20and%20Partnerships.pdf

Department of Homeland Security (DHS). (2022b). Behavioral Threat Assessment Integration. *Author*. Retrieved from: https://www.dhs.gov/btai

Department of Homeland Security (DHS). (2022c). Nationwide Suspicious Activity Reporting Initiative. *Author*. Retrieved from: https://www.dhs.gov/nationwide-suspicious-activity-reporting-initiative

De Ridder, D. T., Lensvelt-Mulders, G., Finkenauer, C., Stok, F. M., & Baumeister, R. F. (2012). Taking stock of self-control: A meta-analysis of how trait self-control relates to a wide range of behaviors. *Personality and Social Psychology Review*, *16*(1), 76-99.

De Roy van Zuijdewijn, J., & Bakker, E. (2016). Analysing personal characteristics of lone-actor terrorists: Research findings and recommendations. *Perspectives on Terrorism, 10*(2), 42-49.

DiStefano, C., & Kamphaus, R. W. (2006). Investigating subtypes of child development: A comparison of cluster analysis and latent class cluster analysis in typology creation. *Educational and Psychological Measurement, 66*(5), 778-794.

Dornschneider, S. (2016). *Whether to kill: The cognitive maps of violent and nonviolent individuals*. University of Pennsylvania Press.

Dugan, L., & Chenoweth, E. (2012). Moving beyond deterrence: The effectiveness of raising the expected utility of abstaining from terrorism in Israel. *American Sociological Review, 77*(4), 597-624.

Duran, C. (2021). Far-left versus Far-right Fatal Violence: An Empirical Assessment of the Prevalence of Ideologically Motivated Homicides in the United States. *Criminology, Criminal Justice, Law & Society, 22*(2), 33-49.

De Waele, M. S., & Pauwels, L. (2014). Youth involvement in politically motivated violence: why do social integration, perceived legitimacy, and perceived discrimination matter?. *International Journal of Conflict and Violence (IJCV), 8*(1), 134-153.

Elliott, D. S. (1985). The assumption that theories can be combined with increased explanatory power: Theoretical integrations. *Theoretical methods in criminology*, 123-149.

Fahey, S., & LaFree, G. (2015). Does country-level social disorganization increase terrorist attacks?. *Terrorism and Political Violence, 27*(1), 81-111.

Farrington, D. P., Ttofi, M. M., & Piquero, A. R. (2016). Risk, promotive, and protective factors in youth offending: Results from the Cambridge study in delinquent development. *Journal of Criminal Justice, 45*, 63-70.

Fisher, D., Abel, M. N., & McCann, W. S. (2023). Differentiating violent and non-violent extremists: Lessons from 70 years of social control theory. *Journal for Deradicalization,* (34), 28-49.

Fisher, D. G., & Dugan, L. (2019). Sociological and criminological explanations of terrorism. *The Oxford Handbook of Terrorism, 163*.

Fisher, D., & Kearns, E. M. (2023). The Theorizing of Terrorism Within Criminology. *Journal of Research in Crime and Delinquency*, 00224278231156754.

Fox, B., & Escue, M. (2022). Evaluating and comparing profiles of burglaries developed using three statistical classification techniques: Cluster analysis, multidimensional scaling, and latent class analysis. *Psychology, Crime & Law, 28*(1), 34-58.

Freilich, J. D., Adamczyk, A., Chermak, S. M., Boyd, K. A., & Parkin, W. S. (2015). Investigating the applicability of macro-level criminology theory to terrorism: A county-level analysis. *Journal of Quantitative Criminology, 3*1, 383-411.

Freilich, J. D., & Chermak, S. M. (2009). Preventing deadly encounters between law enforcement and American far-rightists. *Crime Prevention Studies, 25*(1), 141-172.

Freilich, J. D., Chermak, S. M., Belli, R., Gruenewald, J., & Parkin, W. S. (2014). Introducing the United States extremist crime database (ECDB). *Terrorism and Political Violence, 26*(2), 372-384.

Freilich, J. D., Chermak, S. M., Connell, N. M., Klein, B. R., & Greene-Colozzi, E. A. (2022). Using open-source data to better understand and respond to American school shootings: Introducing and exploring the American School Shooting Study (TASSS). *Journal of School Violence, 21*(2), 93-118.

Freilich, J. D., Chermak, S. M., & Gruenewald, J. (2015). The future of terrorism research: A review essay. *International Journal of Comparative and Applied Criminal Justice, 39*(4), 353-369.

Ghatak, S., & Gold, A. (2017). Development, discrimination, and domestic terrorism: Looking beyond a linear relationship. *Conflict management and peace science*, *34*(6), 618-639.

Gill, P. (2015). Toward a scientific approach to identifying and understanding indicators of radicalization and terrorist intent: Eight key problems. *Journal of Threat Assessment and Management, 2*.

Gill, P., Horgan, J., & Deckert, P. (2014). Bombing alone: Tracing the motivations and antecedent behaviors of lone-actor terrorists. *Journal of forensic sciences*, *59*(2), 425-435.

Gill, P., Clemmow, C., Hetzel, F., Rottweiler, B., Salman, N., Van Der Vegt, I., ... & Corner, E. (2021). Systematic review of mental health problems and violent extremism. *The Journal of Forensic Psychiatry & Psychology, 32*(1), 51-78.

Gill, P., Corner, E., McKee, A., Hitchen, P., & Betley, P. (2022). What do closed source data tell us about lone actor terrorist behavior? A research note. *Terrorism and Political Violence, 34*(1), 113-130.

Gill, P., Silver, J., Horgan, J., Corner, E., & Bouhana, N. (2021). Similar crimes, similar behaviors? Comparing lone-actor terrorists and public mass murderers. *Journal of Forensic Sciences*, *66*(5), 1797-1804.

Gill, P., & Young, J. K. (2011). Comparing role-specific terrorist profiles. Available at SSRN 1782008.

Gladfelter, A. S., Lantz, B., & Ruback, R. B. (2017). The complexity of hate crime and bias activity: Variation across contexts and types of bias. *Justice Quarterly, 34*(1), 55-83.

Gómez, A., Atran, S., Chinchilla, J., Vázquez, A., López-Rodríguez, L., Paredes, B., ... & Davis, R. (2022). Willingness to sacrifice among convicted Islamist terrorists versus violent gang members and other criminals. *Scientific Reports, 12*(1), 2596.

Goodwill, A., & Meloy, J. R. (2019). Visualizing the relationship among indicators for lone actor terrorist attacks: Multidimensional scaling and the TRAP-18. *Behavioral Sciences & the Law, 37*(5), 522-539.

Gottfredson, M. & Hirschi, T. (1990) *A General Theory of Crime*. Stanford University Press. Stanford, CA.

Gottfredson, M. R. (2011). Sanctions, situations, and agency in control theories of crime. *European Journal of Criminology, 8*(2), 128-143.

Grasmick, H. G., Tittle, C. R., Bursik Jr, R. J., & Arneklev, B. J. (1993). Testing the core empirical implications of Gottfredson and Hirschi's general theory of crime. *Journal of Research in Crime and Delinquency, 30*(1), 5-29.

Greene-Colozzi, E. (2022). Mitigating the harm of public mass shooting incidents through situational crime prevention [Doctoral Dissertation]. *City University of New York*.

Gruenewald, J. (2011). A comparative examination of homicides perpetrated by far-right extremists. *Homicide studies*, *15*(2), 177-203.

Gruenewald, J., Allison-Gruenewald, K., & Klein, B. R. (2015). Assessing the attractiveness and vulnerability of eco-terrorism targets: A situational crime prevention approach. *Studies in Conflict & Terrorism, 38*(6), 433-455.

Gruenewald, J., Chermak, S., & Freilich, J. D. (2013). Distinguishing “loner” attacks from other domestic extremist violence: A comparison of far-right homicide incident and offender characteristics. *Criminology & Public Policy, 12*(1), 65-91.

Gruenewald, J., & Pridemore, W. A. (2012). A comparison of ideologically-motivated homicides from the new extremist crime database and homicides from the supplementary homicide reports using multiple imputation by chained equations to handle missing values. *Journal of Quantitative Criminology*, *28*(1), 141-162.

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.

Hart, S. D., & Vargen, L. (2023). Violence risk/threat assessment and management of extremist violence: The structured professional judgement approach. *Violent extremism: A Handbook of Risk Assessment and Management.*

Haugstvedt, H., & Koehler, D. (2021). Armed and Explosive? An Explorative Statistical Analysis of Extremist Radicalization Cases with Military Background. *Terrorism and Political Violence,* 1-15.

Hamm, M. S., & Spaaij, R. (2017). *The age of lone wolf terrorism*. Columbia University Press.

Harms, J. (2017). The war on terror and accomplices: An exploratory study of individuals who provide material support to terrorists. *Security Journal*, *30*, 417-436.

Hawdon, J., & Costello, M. (2020). Learning to hate: Explaining participation in online extremism. In *Radicalization and Counter-Radicalization* (Vol. 25, pp. 167-182). Emerald Publishing Limited.

Hay, C., & Forrest, W. (2006). The development of self-control: Examining self-control theory's stability thesis. *Criminology*, *44*(4), 739-774.

Higgins, G. E., & Makin, D. A. (2004). Self-control, deviant peers, and software piracy. *Psychological reports*, *95*(3), 921-931.

Hirschi, T. (1969). Causes of delinquency. *Routledge*. Abington, Oxon.

Hirschi, T. (1979). Separate and unequal is better. *Journal of Research in Crime and Delinquency, 16*(1), 34-38.

Hirschi, T. (1989). Exploring alternatives to integrated theory. *Theoretical Integration in the Study of Deviance and Crime: Problems and prospects*, 37-49.

Hirschi, T., & Gottfredson, M. R. (2000). In defense of self-control. *Theoretical Criminology, 4*(1), 55-69.

Hoffman, B. (2017). *Inside terrorism*. Columbia university press.

Holt, T. J., Bossler, A. M., & May, D. C. (2012). Low self-control, deviant peer associations, and juvenile cyberdeviance. *American Journal of Criminal Justice*, *37*, 378-395.

Holt, T. J., Freilich, J. D., & Chermak, S. M. (2017). Internet-based radicalization as enculturation to violent deviant subcultures. *Deviant Behavior*, *38*(8), 855-869.

Horgan, J., Gill, P., Bouhana, N., Silver, J., & Corner, E. (2016). Across the universe? A comparative analysis of violent radicalization across three offender types with implications for criminal justice training and education. *UCL Discovery*.

Horgan, J., Shortland, N., & Abbasciano, S. (2018). Towards a typology of terrorism involvement: A behavioral differentiation of violent extremist offenders. *Journal of Threat Assessment and Management, 5*(2), 84.

Testimony of James Jarboe, FBI, before US House of Representatives Subcommittee on Forests and Forest Health, February 12, 2002, p. 1.

Iganski, P. (2008). Criminal law and the routine activity of 'hate crime'. *Liverpool Law Review, 29*(1), 1-17.

Jackson, B.A., Rhoades, A.L., Reimer, J.R., Lander, N., Costello, K., & Beaghley, S. (2019). *Practical terrorism prevention: Reexamining U.S. national approaches to addressing the threat of ideologically motivated violence* (RR-2647-DHS). Homeland Security Operational Analysis Center (HSOAC): Rand Corporation. Retrieved from: https://www.rand.org/pubs/research_reports/RR2647.html

Jasko, K., LaFree, G., & Kruglanski, A. (2017). Quest for significance and violent extremism: The case of domestic radicalization. *Political Psychology*, *38*(5), 815-831.

Jeanis, M. N., Fox, B. H., & Muniz, C. N. (2019). Revitalizing profiles of runaways: A latent class analysis of delinquent runaway youth. *Child and Adolescent Social Work Journal, 36*(2), 171-187.

Jeffery, C. R. (1995). Criminal behavior and learning theory. In *Contemporary Masters in Criminology* (pp. 175-186). Boston, MA: Springer US.

Jensen, M. A., Atwell Seate, A., & James, P. A. (2020). Radicalization to violence: A pathway approach to studying extremism. *Terrorism and Political Violence*, *32*(5), 1067-1090.

Jensen, M., LaFree, G., James, P. A., Atwell-Seate, A., Pisoiu, D., Stevenson, J., & Picarelli, J. (2016). Final report: Empirical assessment of domestic radicalization (EADR). College Park, MD: *National Consortium for the Study of Terrorism and Responses to Terrorism, 8*.

Jongman, A. J. (2017). *Political terrorism: A new guide to actors, authors, concepts, data bases, theories, and literature*. Routledge.

Junger-Tas, J., & Marshall, I. H. (1999). The self-report methodology in crime research. *Crime and Justice, 25*, 291-367.

Keatley, D. A., Knight, S., & Marono, A. (2021). A Crime Script Analysis of Violent and Nonviolent Extremists. *Studies in Conflict & Terrorism*, 1-18.

Kenyon, J., Baker-Beall, C., & Binder, J. (2023). Lone-actor terrorism–a systematic literature review. *Studies in Conflict & Terrorism, 46*(10), 2038-2065.

Kerodal, A. G., Freilich, J. D., & Chermak, S. M. (2016). Commitment to extremist ideology: Using factor analysis to move beyond binary measures of extremism. *Studies in Conflict & Terrorism*, *39*(7-8), 687-711.

Khalil, J., & Dawson, L. L. (2023). Understanding involvement in terrorism and violent extremism: theoretical integration through the ABC Model. *Terrorism and Political Violence*, 1-16.

Khalil, J., Horgan, J., & Zeuthen, M. (2022). The attitudes-behaviors corrective (ABC) model of violent extremism. *Terrorism and Political Violence, 34*(3), 425-450.

Khoshnood, A., Ohlsson, H., Sundquist, J., & Sundquist, K. (2021a). Swedish rape offenders—a latent class analysis. *Forensic Sciences Research, 6*(2), 124-132.

Khoshnood, A., Ohlsson, H., Sundquist, J., & Sundquist, K. (2021b). Firearm-related homicide in Sweden: a latent class analysis of suspected offenders. *Crime & Delinquency*, 00111287211046519.

Klein, B. R., Gruenewald, J., & Smith, B. L. (2017). Opportunity, group structure, temporal patterns, and successful outcomes of far-right terrorism incidents in the United States. *Crime & Delinquency, 63*(10), 1224-1249.

Klein, B. R., Trowbridge, J., Schnell, C., & Lewis, K. (2024). Characteristics and obtainment methods of firearms used in adolescent school shootings. *JAMA pediatrics, 178*(1), 73-79.

Knight, S., Keatley, D., & Woodward, K. (2022). Comparing the different behavioral outcomes of extremism: A comparison of violent and non-violent extremists, acting alone or as part of a group. *Studies in Conflict & Terrorism, 45*(8), 682-703.

Kornhauser, R. R. (1978). Social sources of delinquency: An appraisal of analytic models. *University of Chicago Press*. Chicago.

Krohn, M. D., & Eassey, J. M. (2014). Integrated theories of crime. *The Encyclopedia of Theoretical Criminology*, 1-6.

Krohn, M. D., & Massey, J. L. (1980). Social control and delinquent behavior: An examination of the elements of the social bond. *The Sociological Quarterly*, *21*(4), 529-544.

Kruglanski, A. W., Fernandez, J. R., Factor, A. R., & Szumowska, E. (2019). Cognitive mechanisms in violent extremism. *Cognition*, *188*, 116-123.

Kruglanski, A. W., Gelfand, M. J., Bélanger, J. J., Sheveland, A., Hetiarachchi, M., & Gunaratna, R. (2014). The psychology of radicalization and deradicalization: How significance quest impacts violent extremism. *Political Psychology, 35*, 69-93.

Kuha, J. (2004). AIC and BIC: Comparisons of assumptions and performance. *Sociological Methods & Research, 33*(2), 188-229.

Kunst, J. R., & Obaidi, M. (2020). Understanding violent extremism in the 21st century: the (re) emerging role of relative deprivation. *Current Opinion in Psychology*, *35*, 55-59.

Lacy, M. G. (1997). Efficiently studying rare events: Case-control methods for sociologists. *Sociological Perspectives, 40*(1), 129-154.

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., & Dugan, L. (2007). Introducing the global terrorism database. *Terrorism and Political Violence, 19*(2), 181-204.

LaFree, G., Jensen, M. A., James, P. A., & Safer-Lichtenstein, A. (2018). Correlates of violent political extremism in the United States. *Criminology, 56*(2), 233-268.

Lankford, A. (2013). "A Comparative Analysis of Suicide Terrorists and Rampage, Workplace, and School Shooters in the United States from 1990-2010. *Homicide Studies, 17*(3), 255–274.

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling: A Multidisciplinary Journal, 20*(1), 1-26.

Laub, J. H., & Sampson, R. J. (1993). Turning points in the life course: Why change matters to the study of crime. *Criminology, 31*(3), 301-325.

Leader, S. H., & Probst, P. (2003). The earth liberation front and environmental terrorism. *Terrorism and Political Violence, 15*(4), 37-58.

Liem, M., van Buuren, J., de Roy van Zuijdewijn, J., Schönberger, H., & Bakker, E. (2018). European lone actor terrorists versus "common" homicide offenders: An empirical analysis. *Homicide Studies, 22*(1), 45-69.

Lindekilde, L., Malthaner, S., & O'Connor, F. (2019). Peripheral and embedded: Relational patterns of lone-actor terrorist radicalization. *Dynamics of Asymmetric Conflict, 12*(1), 20–41.

Liska, A. E., Krohn, M. D., & Messner, S. F. (1989). Strategies and requisites for theoretical integration in the study of crime and deviance. *Theoretical integration in the study of deviance and crime: Problems and prospects*, 1-19.

Lösel, F., Bender, D., Jugl, I., & King, S. (2020). Resilience against political and religious extremism, radicalization, and related violence: A systematic review of studies on protective factors. *Understanding recruitment to organized crime and terrorism*, 55-84.

Longshore, D., Chang, E., & Messina, N. (2005). Self-control and social bonds: A combined control perspective on juvenile offending. *Journal of Quantitative Criminology*, *21*, 419.

Lucas, R. (2022). Where the Jan. 6 insurrection investigation stands, one year later. *NPR*. Retrieved from: https://www.npr.org/2022/01/06/1070736018/jan-6-anniversary-investigation-cases-defendants-justice

Lum, C., Kennedy, L. W., & Sherley, A. (2006). Are counter-terrorism strategies effective? The results of the Campbell systematic review on counter-terrorism evaluation research. *Journal of Experimental Criminology, 2*, 489-516.

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.

Mandala, M., & Freilich, J. D. (2018). Disrupting terrorist assassinations through situational crime prevention. *Crime & Delinquency, 64*(12), 1515-1537.

Mascaro, L., Fox, B., Lolita, B.C. (2021). 'Clear the Capitol,' Pence pleaded, timeline of riot shows. *AP News*. Retrieved from: https://apnews.com/article/capitol-siege-army-racial-injustice-riots-only-on-ap-480e95d9d075a0a946e837c3156cdcb9

Matsueda, R. L. (1988). The current state of differential association theory. *Crime & Delinquency, 34*(3), 277-306.

McCauley, C., & Moskalenko, S. (2008). Mechanisms of political radicalization: Pathways toward terrorism. *Terrorism and Political Violence, 20*(3), 415-433.

McCauley, C., & Moskalenko, S. (2014). Toward a profile of lone wolf terrorists: What moves an individual from radical opinion to radical action. *Terrorism and Political Violence, 26*(1), 69-85.

McCauley, C., & Moskalenko, S. (2017). Understanding political radicalization: The two-pyramids model. *American Psychologist, 72*(3), 205.

McCauley, C., Moskalenko, S., & Van Son, B. (2013). Characteristics of lone-wolf violent offenders: A comparison of assassins and school attackers. *Perspectives on Terrorism, 7*(1), 4–24.

Merton, R. K. (1938). Social structure and anomie. *American Sociological Review, 3*(5), 672-682.

Mills, C. E. (2020a). Hatred simmering in the melting pot: An analysis of hate crime in New York City, 1995–2010. *Justice Quarterly, 37*(3), 486-513.

Mills, C. E. (2020b). A common target: anti-Jewish hate crime in New York City communities, 1995-2010. *Journal of Research in Crime and Delinquency, 57*(6), 643-692.

Moghaddam, F. M. (2005). The staircase to terrorism: A psychological exploration. *American Psychologist, 60*(2), 161.

Monahan, J. (2016). The individual risk assessment of terrorism: Recent developments. *The Handbook of the Criminology of Terrorism*, 520-534.

Moskalenko, S., Freilich, J. D., Chermak, S., Gruenewald, J., & McCauley, C. (2023). Growth opportunities in American and British terrorism research. *Dynamics of Asymmetric Conflict*, 1-26.

National Security Council. (2021). National strategy for countering domestic terrorism. *The White House*. Retrieved from: https://www.whitehouse.gov/wp-content/uploads/2021/06/National-Strategy-for-Countering-Domestic-Terrorism.pdf

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

Nivette, A., Eisner, M., & Ribeaud, D. (2017). Developmental predictors of violent extremist attitudes: A test of general strain theory. *Journal of Research in Crime and Delinquency*, *54*(6), 755-790.

Nodeland, B., & Morris, R. (2020). A test of social learning theory and self-control on cyber offending. *Deviant Behavior*, *41*(1), 41-56.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(4), 535-569.

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science, 4*(4), 440.

Nylund-Gibson, K., Grimm, R. P., & Masyn, K. E. (2019). Prediction from latent classes: A demonstration of different approaches to include distal outcomes in mixture models. *Structural Equation Modeling: A Multidisciplinary Journal, 26*(6), 967-985.

Onursal, R., & Kirkpatrick, D. (2021). Is extremism the 'new' terrorism? The convergence of 'extremism' and 'terrorism' in British parliamentary discourse. *Terrorism and Political Violence, 33*(5), 1094-1116.

Owen, T., & Fox, S. (2011). Experiences of shame and empathy in violent and non-violent young offenders. *Journal of Forensic Psychiatry & Psychology, 22*(4), 551-563.

Parkin, W. S., & Gruenewald, J. (2017). Open-source data and the study of homicide. *Journal of Interpersonal Violence, 32*(18), 2693-2723.

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.

Pauwels, L. J., & Svensson, R. (2017). How robust is the moderating effect of extremist beliefs on the relationship between self-control and violent extremism?. *Crime & Delinquency, 63*(8), 1000-1016.

Pearson, F. S., & Weiner, N. A. (1985). Toward an integration of criminological theories. *J. Crim. L. & Criminology, 76*, 116.

Pedahzur, A., Perliger, A., & Weinberg, L. (2003). Altruism and fatalism: The characteristics of Palestinian suicide terrorists. *Deviant Behavior, 24*(4), 405-423.

Perliger, A., Koehler-Derrick, G., & Pedahzur, A. (2016). The gap between participation and violence: Why we need to disaggregate terrorist 'profiles'. *International Studies Quarterly, 60*(2), 220-229.

Perry, G., Wikström, P. O. H., & Roman, G. D. (2018). Differentiating right-wing extremism from potential for violent extremism: the role of criminogenic exposure. *International Journal of Developmental Science, 12*(1-2), 103-113.

Phillips, B. J. (2017). Deadlier in the US? On lone wolves, terrorist groups, and attack lethality. *Terrorism and Political Violence, 29*(3), 533-549.

Piazza, J. A. (2011). Poverty, minority economic discrimination, and domestic terrorism. *Journal of Peace Research*, *48*(3), 339-353.

Piquero, A. R., MacDonald, J., Dobrin, A., Daigle, L. E., & Cullen, F. T. (2005). Self-control, violent offending, and homicide victimization: Assessing the general theory of crime. *Journal of Quantitative Criminology, 21*(1), 55-71.

Pratt, T. C., & Cullen, F. T. (2000). The empirical status of Gottfredson and Hirschi's general theory of crime: A meta-analysis. *Criminology*, *38*(3), 931-964.

Precht, T. (2007). *Home grown terrorism and Islamist radicalisation in Europe*. Research report funded by the Danish Ministry of Justice.

Pressman, D. E., Duits, N., Rinne, T. and Flockton, J. (2018). VERA-2R Violent Extremism Risk Assessment Version 2 Revised: A structured professional judgement approach. Utrecht: *Nederlands Instituut voor Forensische Psychiat-rie en Psychologie*.

Pritchett, S., & Moeller, K. (2022). Can social bonds and social learning theories help explain radical violent extremism?. *Nordic Journal of Criminology, 23*(1), 83-101.

Pyrooz, D. C., LaFree, G., Decker, S. H., & James, P. A. (2018). Cut from the same cloth? A comparative study of domestic extremists and gang members in the United States. *Justice Quarterly*, *35*(1), 1-32.

Rabasa, A., Pettyjohn, S. L., Ghez, J. J., & Boucek, C. (2010). Deradicalizing islamist extremists. *RAND Corp Arlington VA National Security Research Div*. Retrieved from: https://apps.dtic.mil/sti/pdfs/ADA534160.pdf

Ravenscroft, I. (2020). Terrorism, religion and self-control: An unexpected connection between conservative religious commitment and terrorist efficacy. *Terrorism and Political Violence, 32*(8), 1819-1834.

Rottweiler, B., & Gill, P. (2020). Conspiracy beliefs and violent extremist intentions: The contingent effects of self-efficacy, self-control and law-related morality. *Terrorism and Political Violence*, 1-20.

Rottweiler, B., Gill, P., & Bouhana, N. (2020). Individual and environmental explanations for violent extremist intentions: a German nationally representative survey study. *Justice Quarterly*, 1-22.

Saeed, L., & Syed, S. H. (2018). Insights into selected features of Pakistan's most wanted terrorists. *Terrorism and Political Violence, 30*(1), 47-73.

Safer-Lichtenstein, A., LaFree, G., & Loughran, T. (2017). Studying terrorism empirically: What we know about what we don't know. *Journal of Contemporary Criminal Justice, 33*(3), 273-291.

Sageman, M. (2008). A strategy for fighting international Islamist terrorists. *The Annals of the American Academy of Political and Social Science, 618*(1), 223-231.

Sawyer, J. P., & Hienz, J. (2016). What makes them do it? Individual-level indicators of extremist outcomes. *The Handbook of the Criminology of Terrorism*, 47-61.

Select Committee to Investigate the January 6th Attack on the United States Capitol. (2022). Final report. *U.S. Government Publishing Office*. Retrieved from: https://www.govinfo.gov/content/pkg/GPO-J6-REPORT/pdf/GPO-J6-REPORT.pdf

Schils, N., & Pauwels, L. J. (2016). Political violence and the mediating role of violent extremist propensities. *Journal of Strategic Security*, *9*(2), 70-91.

Schumann, S., Clemmow, C., Rottweiler, B., & Gill, P. (2024). Distinct Patterns of Incidental Exposure to and Active Selection of Radicalizing Information Indicate Varying Levels of Support for Violent Extremism. *PLoS One*, *19*(2), e0293810.

Scrivens, R., Wojciechowski, T. W., Freilich, J. D., Chermak, S. M., & Frank, R. (2022). Differentiating Online Posting Behaviors of Violent and Nonviolent Right-Wing Extremists. *Criminal Justice Policy Review*, 08874034221095398.

Scruton, R. (2007). *The Palgrave Macmillan dictionary of political thought*. Springer.

Sea, J., Beauregard, E., & Lee, S. (2020). Crime scene behaviors and characteristics of offenders with mental illness: a latent class analysis. *Journal of Forensic Sciences, 65*(3), 897-905.

Silber, M. D., Bhatt, A., & Analysts, S. I. (2007). *Radicalization in the West: The homegrown threat* (pp. 1-90). New York: Police Department.

Simi, P., Sporer, K., & Bubolz, B. F. (2016). Narratives of childhood adversity and adolescent misconduct as precursors to violent extremism: A life-course criminological approach. *Journal of Research in Crime and Delinquency, 53*(4), 536-563.

Sheikh, S., Sarwar, S., & Reed, C. (2011). Teaching methods that help to build resilience to extremism: Rapid Evidence Assessment. *UK Department For Education*. Retrieved from: https://dera.ioe.ac.uk/3597/1/3597_DFE-RR120.pdf

Shetty, N., Shemko, M., Vaz, M., & D'souza, G. (2006). An epidemiological evaluation of risk factors for tuberculosis in South India: a matched case control study. *The International Journal of Tuberculosis and Lung Disease*, *10*(1), 80-86.

Skoczylis, J., & Andrews, S. (2022). Strain theory, resilience, and far-right extremism: the impact of gender, life experiences and the internet. *Critical Studies on Terrorism*, *15*(1), 143-168.

Smith, B. L., & Damphousse, K. R. (1996). Punishing political offenders: The effect of political motive on federal sentencing decisions. *Criminology*, *34*(3), 289-322.

Spaaij, R. (2010). The enigma of lone wolf terrorism: An assessment. *Studies in Conflict & Terrorism*, *33*(9), 854–870.

Spaaij, R. (2011). Understanding lone wolf terrorism: Global patterns, motivations and prevention. *Springer Science & Business Media*.

Stephens, W., Sieckelinck, S., & Boutellier, H. (2021). Preventing violent extremism: A review of the literature. *Studies in Conflict & Terrorism, 44*(4), 346-361.

Stephenson, M., Giller, H., & Brown, S. (2010). *Effective practice in youth justice*. Routledge.

Sullivan, B. A., Freilich, J. D., & Chermak, S. M. (2019). An examination of the American far right's anti-tax financial crimes. *Criminal Justice Review*, *44*(4), 492-514.

Sutherland, E. H., Cressey, D. R., & Luckenbill, D. F. (1992). *Principles of criminology*. Altamira Press.

Sweeney, M. M., & Perliger, A. (2018). Explaining the spontaneous nature of far-right violence in the United States. *Perspectives on Terrorism, 12*(6), 52-71.

Sykes, G. M., & Matza, D. (2017). Techniques of neutralization: A theory of delinquency. In *Delinquency and Drift Revisited, Volume 21* (pp. 33-41). Routledge.

The United States Attorney's Office: District of Columbia. (2022). One year since the Jan. 6 attack on the capitol. *United States Department of Justice*. Retrieved from: https://www.justice.gov/usao-dc/one-year-jan-6-attack-capitol

Thijs, F., Rodermond, E., Kleemans, E. R., & van de Weijer, S. G. (2022). Violent and Nonviolent Terrorist Suspects: a Comparative Analysis Based on Data from the Netherlands. *European Journal on Criminal Policy and Research*, 1-21.

Thijssen, G., Masthoff, E., Sijtsema, J., & Bogaerts, S. (2023). Understanding violent extremism: Socio-demographic, criminal and psychopathological background characteristics of detainees residing in Dutch terrorism wings. *Criminology & Criminal Justice*, *23*(2), 290-308.

Thornberry, T. P. (1987). Toward an interactional theory of delinquency. *Criminology*, *25*(4), 863-892.

Tittle, C. R. (1995). *Control balance: Toward a general theory of deviance*. Routledge.

Tittle, C. R., Ward, D. A., & Grasmick, H. G. (2003). Self-control and crime/deviance: Cognitive vs. behavioral measures. *Journal of Quantitative Criminology, 19*(4), 333-365.

Turner, M. G., & Piquero, A. R. (2002). The stability of self-control. *Journal of Criminal Justice*, *30*(6), 457-471.

Turner, N. D., Chermak, S. M., & Freilich, J. D. (2023). An empirical examination on the severity of lone-actor terrorist attacks. *Crime & Delinquency, 69*(5), 915-942.

Turner, N., Holt, T. J., Brewer, R., Cale, J., & Goldsmith, A. (2022). Exploring the Relationship between Opportunity and Self-Control in Youth Exposure to and Sharing of Online Hate Content. *Terrorism and Political Violence*, 1-16.

Tyler, T. R. (2006). Restorative justice and procedural justice: Dealing with rule breaking. *Journal of Social Issues*, *62*(2), 307-326.

Van der Heide, L., Van der Zwan, M., & Van Leyenhorst, M. (2019). The practitioner's guide to the galaxy: A comparison of risk assessment tools for violent extremism. *International Centre for Counter-Terrorism*, doi: 10.19165/2019.1.07

Vazsonyi, A. T., Mikuška, J., & Kelley, E. L. (2017). It's time: A meta-analysis on the self-control-deviance link. *Journal of criminal justice*, *48*, 48-63.

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis, 18*(4), 450-469.

Vermunt, J. K., & Magidson, J. (2004). Latent class analysis. *The SAGE Encyclopedia of Social Sciences Research Methods, 2*, 549-553.

Victoroff, J. (2005). The mind of the terrorist: A review and critique of psychological approaches. *Journal of Conflict Resolution, 49*(1), 3-42.

Victoroff, J., Adelman, J. R., & Matthews, M. (2012). Psychological factors associated with support for suicide bombing in the Muslim diaspora. *Political Psychology*, *33*(6), 791-809.

Vogel, M., Stephens, K. D., & Siebels, D. (2014). Mental illness and the criminal justice system. *Sociology Compass, 8*(6), 627-638.

Walters, G. D. (2016). Are behavioral measures of self-control and the Grasmick self-control scale measuring the same construct? A meta-analysis. *American Journal of Criminal Justice, 41*(2), 151-167.

Weller, B. E., Bowen, N. K., & Faubert, S. J. (2020). Latent class analysis: a guide to best practice. *Journal of Black Psychology, 46*(4), 287-311.

Wikström, P. O. H. (2017). Crime as alternative: Towards a cross-level situational action theory of crime causation. In *Beyond Empiricism* (pp. 1-37). Routledge.

Wikström, P. O. H., & Bouhana, N. (2017). Analyzing radicalization and terrorism: A situational action theory. *The Handbook of the Criminology of Terrorism*, 175-186.

Wiktorowicz, Q. (Ed.). (2004). *Islamic activism: A social movement theory approach*. Indiana University Press.

Wolfe, S. E., & Higgins, G. E. (2009). Explaining deviant peer associations: An examination of low self-control, ethical predispositions, definitions, and digital piracy. *W. Criminology Rev.*, *10*, 43.

Wolfgang, M. E., Ferracuti, F., & Mannheim, H. (1967). *The subculture of violence: Towards an integrated theory in criminology* (Vol. 16). London: Tavistock Publications.

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., Perry, S., Hasisi, B., & Weisburd, D. (2021). Faces of radicalism: Differentiating between violent and non-violent radicals by their social media profiles. *Computers in Human Behavior, 116*, 106646.

Yang, S. M., & Jen, I. C. (2018). An evaluation of displacement and diffusion effects on eco-terrorist activities after police interventions. *Journal of Quantitative Criminology, 34*, 1103-1123.