

## ABSTRACT

Title of Thesis: EXAMINING THE ASSOCIATION  
BETWEEN SOCIAL MEDIA AND VIOLENT  
EXTREMISM: A SOCIAL LEARNING  
APPROACH

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In recent years, the use of social media has become more prevalent across the United States. Social media, through the use of personalization algorithms, allows for exposure to extremist content and is able to create intimate groups, where like-minded individuals can communicate with each other. This study considers that, though some traditional theorists posit that learning only occurs in face to face contexts, the elements of learning described in social learning theory may also be present online. Using a set of logistic regressions to test the association between exposure to social media and personalization algorithms and violent extremism, I find (1) exposure to social media and to personalization algorithms is positively correlated with violent extremism and (2) the relationships between exposure to social media and personalization algorithms and violent extremism are explained by age, foreign

fighter status and the year of extremist behavior. I discuss the implications of these findings for theory, future research and policy.

EXAMINING THE ASSOCIATION BETWEEN SOCIAL MEDIA AND  
VIOLENT EXTREMISM: A SOCIAL LEARNING APPROACH

by

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## Dedication

This thesis is dedicated to my family and friends, without whose support, love and encouragement this thesis would not have come to fruition.

## Acknowledgements

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## List of Abbreviations

Social Learning Theory-----SLT

Multiple imputation through chain equations-----MICE

## Chapter 1: Introduction

Sutherland (1947) identifies differential association as the process through which individuals learn to engage in crime. The main proposition of the theory posits that delinquency occurs when an individual has an increased exposure to definitions in favor of violating the law compared to those unfavorable of violating the law. These definitions develop from interactions between an individual and their close family and peers. Akers (1990) expands this idea of differential association in social learning theory (SLT) and posits that there are certain mechanisms of the learning process that influence the development of these associations. More specifically, these mechanisms include the presence of definitions, differential reinforcement and imitation that allow for differential association and subsequent learning to occur. Both Akers' (1990) SLT and Sutherland's (1947) theory of differential association have been well tested and supported throughout criminological research (Pratt et al., 2010; Cullen, Agnew, & Wilcox, 2014) .

However, this long research tradition has only begun to evolve with the development of social media. Within the last 10 to 15 years, social media platforms have drastically transformed the way that individuals interact with each other and with media content. It is entirely probable that the way an individual is exposed to both prosocial and antisocial definitions has changed since the advent of social media.

In the United States, social media usage has become increasingly popular and widespread among adults (Greenwood, Perrin, & Duggan, 2016). Duggan (2015) finds that 62% of all adults in the United States use Facebook and, within this group,

70% use the network daily. From 2011 to 2015, there was a significant increase in the proportion of U.S. adults using major social media platforms (Duggan, 2015). With the expansive reach of social media, it is extremely important to understand how it is used and the role it plays in the process of learning different narratives. Social media not only creates a virtual space to engage with friends and family—it provides a forum for organizations to disseminate information efficiently and cost-effectively. However, social media usage is not limited to legal or legitimate organizations like businesses, rather extremist organizations have turned to social media as a forum for intergroup communication and, more importantly, to attract new members (Europarat, 2007; Hoffman, 2017).

In addition to group self-promotion, social media has enabled the dissemination of politically extremist narratives in support of violence (Weimann, 2016) to both those with and without prior exposure to this content. While not all exposure comes from groups, some organizations have used social media to target vulnerable individuals online. Because messages can be masked in the form of videos of reasonable interest, such as a newly released pop song, individuals may be unaware of the propaganda they are being exposed to (Europarat, 2007). This initial introduction to extremist ideology may then lead to subsequent engagement with the ideology and can possibly result in continued communication between individuals and others who share extremist views.

Platforms like Instagram, Twitter or Facebook, among others provide a context where interested individuals can ask questions about an organization, ranging from the groups' goals and tactics, to how to travel to join the group (LaFree, 2017).

For some, the internet can provide ideas about expertise, ideology and co-offenders, as well as strategies for who to attack and how (Gill et al., 2017; Weimann, 2016). LaFree (2017) notes that even though engagement with extremist narratives is not dependent on the internet, the internet creates an additional space that can foster violent extremism. Gill et al. (2017) explain that violent radicalization is cyber-enabled; the internet operates in different ways for different people. Due to the extensive reach of social media and its ability to spread ideological content, it is important to understand what role, if any, social media plays in encouraging violent extremism as compared to non-violent extremism.

According to business strategists Ruder Finn Innovation Studios Asia, Facebook monitors user behavior to personalize advertisements based on an individual's interests, political views, travel habits, and preferred news sources (Ko, 2016). By creating algorithms<sup>1</sup> to alter the content presented to users, Facebook attracts the business of companies looking to advertise their products ("How Does Facebook Make Its Money?," n.d.). Although social media platforms like Facebook have developed algorithms with a goal of making profits, the use of these algorithms may push individuals with similar interests together, creating "echo chambers."

O'Hara and Stevens (2015) define echo chambers as homogenous settings that increase exposure to like-minded information over contradictory views. Echo chambers can influence the information that individuals see and thus, may alter the frequency of exposure to certain definitions. Specifically, Pauwels and Schils (2016)

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<sup>1</sup> An algorithm is a computer code that allows platforms to alter content to show individuals posts they will be interested in rather than showing them all the content in chronological order (Agrawal, 2016).

discuss echo chambers on social media as settings where the mechanisms of social learning (differential association, differential reinforcement, definitions and imitation) are present and may influence the development of extremist ideologies.

Though the technological advancements that have allowed for the growth and development of social media occurred after Sutherland originally explained differential association, Sutherland doubted that any type of media would have the same impact on learning as face to face interaction. According to Sutherland (1947), differential association occurs only from face-to-face environments and in-person interaction. As highlighted by Cressey (1965), the presence of intimate groups is extremely important in learning. Cressey also argues that sources like movies, television and newspapers are not important and though they can expose the individual to some delinquent ideas, these ideas will not manifest into behavior unless they are reinforced by an intimate group (Cressey, 1965; Empey, 1978). Challenging these explanations, Akers (2009) explains that media (such as TV, movies, and video games) can have significant influences on learning through imitation and vicarious reinforcement. He highlights that along with primary groups, media sources can also have effects in exposure to criminal patterns and behavior models.

Given the ability of social media platforms, like Facebook, to create intimate groups (Klinger & Svensson, 2015), it is plausible that social media may be important when considering the learning process. Currently, learning theorists have not adequately considered the possibility that interactions on social media could be relevant in influencing deviant behavior and, more specifically, engagement in violent extremism.

To date, with few exceptions, there has been little research that compares extremists who engage in violence to those who use non-violent actions in support of their ideology (Borum, 2011a; Della Porta & LaFree, 2011). Borum (2011) highlights engagement in extremist behavior as a complex process that occurs at diverse stages characterized by different mechanisms. These mechanisms interact in various contexts for different people, emphasizing the importance of understanding differences when researching engagement in extremist behavior (Borum, 2011). Borum also calls for the use of social science theories to aid in further understanding these differences. Though some extant research has applied criminological theories to violent extremism, further research may prove beneficial in understanding this process. Specifically, when considering SLT, we know that intimate groups are the source of differential associations (Cressey, 1965). However, it is important to consider that groups can develop both online and offline. Klinger and Svensson (2014:10) argue that social media platforms may be able to create these groups as they facilitate “geographically spread niche networks” where like-minded individuals can socialize. While extant research examines the role of peers in violent extremism, it does not adequately address how both online and offline networks interact and lead to violent extremism.

Though efforts have been made to identify the factors frequently related to violent extremism, most of this literature remains unconvincing (Neumann & Kleinmann, 2013; Gill, 2015). Additionally, none of the current projects on radicalization include at-risk individuals who did not radicalize to the point of committing violence (Jensen et al., 2016). By not comparing individuals who engage

in violence to those who do not engage in violence, radicalization literature fails to understand the pathway from ideology to violence among those who are ideologically committed (Borum, 2011b). The proposed study seeks to add to criminological literature on both violent extremism and the influence of social media by using SLT as a framework for understanding how these outlets may play a role in violent extremism. Extant literature by Suler (2004), Holt (2007) and Holt et al. (2015), discusses the changes in beliefs that can occur on social media and the transition of these beliefs to the off-line world. However, current literature on the impact of social media on subsequent violence is lacking and what exists has many limitations. While prior research suggests that social networks and peer relationships can influence engagement in violent extremism (Sageman, 2004; Lafree, Jensen, James, & Safer-Lichtenstein, 2018), it fails to adequately address how online peer relationships may influence extremist behavior as well.

In the current study, I use the Profiles of Individual Radicalization in the United States (PIRUS) dataset collected by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) to understand the relationship between exposure to social media during radicalization and engagement in violent extremism. As defined by the PIRUS team, radicalization is “the psychological, emotional and behavioral processes by which an individual or group adopts an ideology that promotes the use of violence for the attainment of political, economic, religious, or social goals” (Jensen et al., 2016: 8). In this thesis, I explore the following research questions: (1) Are political extremists with social media exposure during their radicalization more likely to engage in violent extremism, compared to



other ideologically motivated political extremists? and (2) Are political extremists with exposure to a social media platform using personalization algorithms more likely to engage in violent extremism, compared to other ideologically motivated political extremists?

The sample consists of 347 individuals who engaged in ideologically motivated illegal behavior in the United States between the years of 2005 and 2016. The restriction of 2005 as the earliest year is due to decisions by the PIRUS team to only code social media information on those individuals whose ideologically motivated behavior took place during or after 2005. Other sources such as Duggan and Brenner (2013) also identify 2005 as the earliest date of data collection on social media usage. In this research, I explore whether SLT offers a useful framework for understanding the influence of social media in creating an environment that fosters engagement in violent extremism, and whether there is an additional effect of social media on violent extremism for those individuals who report having radicalized social networks.

In the forthcoming paper, I begin with an overview of relevant literature to understand SLT and its current applications to violent extremism. Then, I discuss the concept of social media as a mechanism for social learning that may lead to engagement in violent extremism. In the next section, I review relevant literature on SLT, social media and violent extremism. Next, I include an explanation of the PIRUS data, my analytic plan, the independent and dependent variables, as well as the methodology and strategies for addressing missing data. I will then discuss the

results and conclude with a discussion of relevant findings, including limitations and future directions.

## Chapter 2: Social Learning Theory: Literature Review

Sutherland's (1947) theory of differential association claims that criminal behavior is learned, just as any type of behavior is learned. "Criminals learn both the techniques of committing crime and the definitions favorable to crime" (Sutherland and Cressey, 1960: 78). Sutherland defines *differential association*, the main proposition of the theory, as occurring when "a person becomes delinquent because of an excess of definitions favorable to law violation over definitions unfavorable to violation of law" (Sutherland & Cressey, 1960: 78). Differential associations can fluctuate in duration, priority, intensity and frequency; meaning that the likelihood of learning a definition increases when an individual is exposed to that definition more often, for longer periods of time, at an earlier time, and from an intimate individual. Sutherland (1947) explains that the process through which individuals learn these definitions is not any different from the process through which they learn prosocial behavior. The learning process encompasses multiple different aspects including techniques, interpretations of the law, rationalizations, and motives and attitudes about crime.

Learning occurs through direct communication with others, solely intimate personal groups (Cressey, 1965; Cullen et al., 2014). Sutherland (1947) highlights these intimate groups as being integral to the learning process and cites contact with these groups as the critical element of differential association. When explaining the propositions of Sutherland's differential association, Cressey (1965:51) argues that

“what we should study if we are going to establish a theory for explaining criminal conduct, is in a word, *words*.” Individuals do not inherently lack self-control, rather they learn criminal behavior through justifications from intimate personal groups that include symbols and, more importantly, language (Empey, 1978). Cressey (1965:51) also explains that “criminal behavior is, like other behaviors, attitudes, beliefs, and values which a person exhibits, the *property of groups*, not of individuals.” This focus on the importance of closeness between personal contacts suggests that interaction with non-intimate communication (for example, television or radio) will not have the same effect as communication with intimate groups (Cressey, 1965). However, as Klinger and Svensson (2015) explain social media can foster the development of networks independent of geographic barriers, it may then be plausible that these online networks may also influence the duration, priority, intensity and frequency of definitions.

Akers’ (1990) social learning theory (SLT) extends Sutherland’s (1947) differential association model and aims to explain the mechanisms through which learning occurs. While Sutherland (1947) explains that individuals learn criminal behavior through communication with others, his theory lacks an explanation of the causal mechanisms of how these definitions translate to criminal behavior. Akers’ argument is rooted in Sutherland’s belief that individuals learn to participate in crime through their exposure and adoption of definitions that support crime but goes on to be a much broader theory that includes aspects of behavior procurement, persistence and desistence (Akers, 1985). The likelihood that an individual will engage in deviant behavior increases compared to their probability of engaging in normative behavior

when they differentially associate with others who promote definitions that support criminal behavior and engage in criminal behavior themselves (Akers, 1998). The individual's high level of exposure to notable deviant models, their ideas about the desirability of criminal behavior in certain situations and their perceptions of greater rewards than punishments for their behavior can mediate the process of differential association (Akers, 1998). Akers (2009) counters Sutherland's description of media as "relatively unimportant" (Sutherland, 1947: 6) and explains how it can have significant influences on individuals through the mechanisms of learning.

Specifically, Akers (1989; 1990) explains that this learning process occurs through four mechanisms identified as *differential association*, *definitions*, *differential reinforcement* and *imitations* that have a causal effect on an individual's delinquent behavior. Differential association is operationalized similarly to Sutherland's definition and Akers contends that the contexts where someone develops differential associations are the same contexts that expose them to the rest of the mechanisms of social learning. The most important groups are family and close friends, but other groups that develop from schools, churches and neighborhood contexts can influence the individual as well.

In SLT, Akers et al. (1989) explain *definitions* as attitudes and rationalizations that an individual gives to a specific behavior. These definitions are what categorize engagement in a behavior as right or wrong. The likelihood of an individual engaging in a behavior increases when their attitudes support that behavior and decreases when their attitudes do not support that behavior (Akers et al., 1989). Definitions are beliefs that enable criminal behavior in the right circumstance, rather than compelling an

individual to engage in crime. Additionally, Akers et al. (1989) explain *differential reinforcement* as an individual's perception of the rewards and punishments of engaging in a behavior. When deciding to engage in a behavior an individual will weigh past and present experiences along with perceptions of future rewards and punishments (Akers et al., 1989). The final element of SLT, *imitation*, is the idea that individuals are more likely to engage in a behavior after seeing another person engaging in that behavior. The person engaging in the behavior (primary vs. secondary social group) and the specific behavior can moderate this imitation process. All four of these mechanisms interact in time and across different opportunity structures to create contexts in which crime can occur. Akers (1990) explains that there are reciprocal and feedback effects within these mechanisms that make up a complex process of social learning.

Akers (2009) explains that primary groups made up of family are important in the early stages of an individual's life, but beginning at adolescence other sources, such as the media, can be important. According to Akers, the media (i.e. TV, movies and video games) can effect individuals through modeling, reinforcement, and moral desensitization toward criminal behavior. The media may provide either neutralizing or positive definitions for a specific behavior. Specifically, for an expanding proportion of people, the priority, duration, frequency and intensity of exposure to content presented in the media has become so strong that it can even outweigh opposing views from primary groups with whom contact has become less frequent, shorter and less intense. The media can provide exposure to both other groups and

sources of criminal and noncriminal behavior models as sources for imitation (Akers, 2009).

Looking at extant research, Pratt et al. (2010) find support for SLT in the criminological literature; however, there is a limited application of SLT to understanding violent extremism. Extensive literature on SLT highlights well supported evidence that peers are extremely important to the learning process (Cullen, Agnew & Wilcox, 2014). Knowing that peer relationships are an important source of social learning, it is only logical to ask whether peers influence violent extremism as well.

#### *Using SLT to Explain Political Violence*

Traditionally, criminologists have applied SLT to understand the dichotomy between an individual engaging in crime and not engaging in crime. However, when differentiating between those who engage in political extremism, LaFree et al. (2018) find support for the explanatory power of criminological theories to differentiate between violent and non-violent behavior. Specifically, LaFree et al. (2018) apply social control, SLT, and other criminological perspectives to understand engagement in violent political extremism compared to non-violent political extremism. Looking specifically at the merit of applying SLT to engagement in political violence, LaFree et al. (2018) find that radical peers have a significant positive effect on an individual's engagement in violent extremism compared to non-violent extremism.

Similarly, Becker (2017) aims to understand whether SLT, social bonds theory, and interactional theory have any explanatory power when it comes to predicting violent extremism compared to non-violent extremism in PIRUS. The

findings suggest that social bonds decrease the likelihood of violent extremism while SLT related variables are associated with an increased likelihood of violent extremism compared to non-violent extremism. Becker (2017) suggests that there is some merit in not only applying criminological theories to terrorism research, but also using these schools of thought to explain the dichotomy between violent and non-violent extremism.

These findings (Becker, 2017; LaFree et al., 2018) suggest that social learning from peers may influence violent political extremism differentially than non-violent political extremism. However, the characteristics of these peers and an understanding of where these relationships come from are both unknown. Due to the growth of social media platforms, peer networks can manifest both online and offline calling for research to understand whether SLT is applicable to online experiences and may lead to violence from online experiences the same way it does for offline experiences.

Additionally, though not a direct application of SLT, Sageman (2004) identifies friends and family as playing an important role in the organization of terrorist networks. His explanation supports LaFree et al. (2018) and Becker's (2017) findings that SLT can explain the influence peers have on violent extremism. Sageman explains that it is not formal organizations but close networks of friends and family that connect individuals to the group. Sageman (2004) also argues that friends can have a direct impact on an individual's behavior through imitation as friends can serve as examples through which individuals learn about and join groups. Based on this research, friends and peer networks appear to influence an individual's own involvement with an extremist ideology. Though Sageman's work focuses on peer

networks that are face-to-face, it may be possible to extend these relationships to online networks. It is plausible then that peer networks on social media can serve as an influence to lead individuals on a path toward violent extremism as well, similarly to those found in face-to-face peer networks.

### *The relationship between online exposure and offline behavior*

To study the relationship between social media and violent extremism, it is important to first understand whether online experiences can transition to behavioral changes offline. Suler (2004) suggests that due to “online disinhibition,” individuals will be able to distinguish between their online and offline lives and may not translate online experiences to offline behavior. According to Suler, the online disinhibition effect occurs when “people say and do things in cyberspace that they wouldn’t ordinarily say and do in the face-to-face world. They loosen up, feel less restrained and express themselves more openly” (p. 321). Suler discusses multiple factors in cyberspace that allow individuals to express suppressed feelings through the deterioration of psychological barriers. The main factor of dissociative anonymity occurs when individuals can distinguish between their online and off-line lives and therefore do not feel as vulnerable expressing their feelings online. The internet also allows for invisibility, through which individuals can maintain anonymity, and asynchronicity where people do not interact in real time and thus do not have to cope with another’s reactions immediately. Additionally, Suler defines solipsistic introjection as occurring when an individual reads another person’s messages as a voice in their own head and this message intertwines with their own psyche. This process leads to dissociative imagination where individuals split their online fiction



from the realities of the offline world. According to Suler, by minimizing the impact of status, wealth, race, or gender the online world puts everyone on an even playing field and creates an ideal environment for online disinhibition to occur.

While Suler (2004) argues that disinhibition will manifest as a disconnect between an individual's online and offline behavior, Pyrooz et al (2015) explain two different ways that behaviors and identities are developed online. The first manifestation is "web-facilitated," where individuals create a secret version of themselves that is separate from friends, family, co-workers and law enforcement. For these individuals, groups of like-minded others in online communities facilitate their deviant behavior, allowing individuals to preserve their anonymity. The second group are considered "web-enhanced," where the online persona reflects the individual's offline behavior and identity. Weimann (2006) explains that it is through this manifestation of online identities that ideological debates take place online that lead to violence offline. For these individuals there is a blurred line between their online and offline identity and behavior, which leads to fluidity between their online and offline worlds (Pyrooz, Decker, & Moule, 2015).

With the "web-enhanced" manifestation, Holt (2007; 2015) suggests that online activity can translate into offline behavior. Studying hackers specifically, Holt (2007) argues that hacker subculture can transcend the digital world and influence relationships in the offline world. According to Holt, cyberspace has allowed for the creation of many deviant and criminal subcultures fostering the development of social movements around the globe. A message posted on Facebook or any other web forum can easily reach a wide audience of those already supportive and potential new

supporters. In this way, social media is integral to creating a collective identity, which can transition online activism to offline behavior. By allowing individuals to maintain communication with others, social media provides the context for individuals to become socialized to the main elements of a movement (Holt, Freilich, Chermak, & McCauley, 2015; Gerstenfeld, Grant, & Chiang, 2003).

The exposure to definitions on social media creates a space where some individuals may take on the definitions they see. Not all individuals who hold extremist ideas will transition into violent behavior, but social media may aid this transition by driving interested individuals toward videos and propaganda that promote violence over non-violence (Pauwels & Schils, 2016a). The transition of online beliefs to offline behavior is imperative to understand in the context of social media exposure to extremist content and violent extremism. Given that beliefs developed in cyberspace can extend to the off-line world (Holt, 2007; 2015; Pyrooz et al., 2015), exposure to extremist content online may have behavioral consequences for violent extremism in the off-line world.

#### *The influence of social media on behavior*

Extant literature has aimed to study the influence of social media on the development of extremist attitudes and behaviors in different ways. Pauwels and Schils (2016) use SLT as a framework when studying exposure to extremist content on social media and subsequent political violence. Using self-reports from Belgian adolescents and young adults, the study analyzes the relationship between exposure to extremist content through social media and self-reported political violence. The researchers operationalize violence in two ways: (1) violence against people, and (2)

violence against property (i.e. damaging property), for political or religious reasons. The independent variables include multiple measures of exposure to extremist content on social media. Pauwels and Schils (2016) hypothesize that extremist content on social media is related to political violence when controlling for background variables (i.e. age, religion, nativity), strain variables, moral values, peer influences, and personality characteristics (i.e. low self-control, moral values).

The results support Pauwels and Schils (2016) hypothesis, as they find that exposure to extremist content online has positive significant impacts on both self-reported politically motivated violence against property and people. The results show significant effects for those individuals who actively turn to extremist narratives online rather than those who accidentally interact with extremist content.

Additionally, the findings suggest that offline relationships with delinquent and racist friends have a significant association with self-reported political violence. Though it appears that online exposure to extremist content is associated with both property violence and violence against persons, limitations inherent to self-reports of young adults and youth, such as memory recall and other self-reporting biases might influence the validity of these measures. Due to these limitations, an extension of this application of SLT could measure the difference between engagement in politically motivated property violence and violence against persons using measures of known behavior. Pauwels and Schils (2016) treat both acts against people and against property as violent behaviors, though these behaviors may be distinctive and can develop through different pathways. They also find support for other theoretical

perspectives that may also explain political violence thus moderating the support for SLT.

Additionally, research by Kramer et al. (2014) finds that changes in exposure to material on social media can manifest in attitudinal changes in individuals. Using an experimental design, the researchers test whether exposure to other people's emotions on Facebook leads to an individual posting content that expresses the same emotions. After manipulating exposure to both positive and negative emotions, evidence shows that increased exposure to a specific emotion is related to an increased presence of that emotion in subsequent Facebook statuses over a 1-week period. These findings provide evidence that exposure to other people's behavior on social media can affect an individual's subsequent behavior. At some level, this might support the SLT principle of imitation, that by seeing others post negative or positive messages individuals are more likely to then adopt those respective emotions themselves. Though these findings do not necessarily support the idea that exposure to content online will manifest into offline behavior, they emphasize that exposure online can alter future online behavior.

Extant research shows that exposure to content on social media can relate to the elements of SLT (Kramer et al., 2015) and that SLT is applicable to understanding violent extremism (Becker, 2017; LaFree et al., 2018; Pauwels & Schils, 2016). Additionally, knowing that peer groups are important for engagement with extremist ideology (Sageman, 2004), that intimate groups are the critical element of SLT (Sutherland, 1947), and that social media may create these peer networks (Klinger &

Svensson, 2015), I propose the following hypothesis about the relationship between radicalization on social media and engagement in violent extremism:

H<sub>1</sub>: Compared to other ideologically motivated political extremists, those with social media exposure during their radicalization will be more likely to engage in violent extremism.

#### *Social Media Algorithms and SLT*

As previously explained, intimate groups are the integral part of differential association and by influencing the creation of these groups and exposure to certain content, social media platforms can manipulate the mechanisms of social learning by changing the frequency, duration and intensity of messages. Platforms like Facebook track a user's likes, shares, comments and even measure how much time they spend on posts to understand their content preferences. Facebook (and others) tailors users' news feeds to show content that is specific to their interests ensuring their continued usage of the platform (Ko, 2016). By keeping users interested, social media platforms can continue to target them with specific advertisements that serve as both profits and fit within their identified business model. As explained by Dijck and Poell (2013), social media organizations aim to connect either users to each other or users to advertisers by using personalization algorithms. The goal of these algorithms is to make social media more individualized and interesting to users, but extant research explains that they may lead to the creation of echo chambers that could potentially have negative consequences for users (Klinger and Svensson, 2014).

O'Hara and Stevens (2015: 402) define echo chambers as homogenous settings that allow for an increased exposure to like-minded information over

opposing ideas. Echo chambers are created on social media by what is known as a *filter bubble* (Pauwels, Brion, Schils, & Easton, 2014). A filter bubble changes the individual's environment and "dictates which opportunities and immediate situations are made available" in a process through which "certain content [is] made more available or even recommended to them based on the algorithm's perceptions of their preferences" (Wolfowicz, n.d. : 1). The personalization algorithms' function as a filter bubble allowing for the content a user sees and/or does not see to change based on their past behavior. After a period of time, individuals are confined to these filter bubbles that are personalized and can create further exposure to their own biases (Hawdon, 2012). This filter bubble then leads to the presence of echo chambers by increasing exposure to certain beliefs and allowing for differential reinforcement of these beliefs.

The algorithm's process of filtering content creates positive feedback loops where previous engagement with certain media results in continued exposure to similar content. Additionally, these feedback loops lead to a reduction in exposure to contradictory definitions. By only presenting one-sided definitions, feedback loops increase differential reinforcement and allow differential associations to develop that reinforce violence over non-violence (Wood, 2017). In cases where an echo chamber develops around certain views, this can lead to an increase in the frequency of exposure to messages in support of these ideas. This process can then foster learning and lead to an individual developing polarized views that are supportive of extremist ideology and violent behavior (Pauwels & Schils, 2016a; Wolfowicz, n.d.). These polarized views are reinforced through the feedback loops that allow for an individual

to develop more extreme opinions that then lead to them engaging in violence over non-violence in support of their ideology.

Sunstein (2007; 2009) explains echo chambers as the context through which the internet may be able to support political sovereignty. By leading individuals to like-minded posts and information, echo chambers create a space in which polarization can occur (O'Hara & Stevens, 2015). Within echo chambers, extreme narratives are able to drown out the more moderate views resulting in an environment characterized by polarized attitudes supporting violent extremism over non-violent extremism (Davies, Neudecker, Ouellet, Bouchard, & Ducol, 2016; Geeraerts, 2012).

O'Hara and Stevens (2015) discuss three ways in which the internet could lead to this polarization. First, due to the personalization of messages, those in online settings begin to see an increased amount of information supporting one side of an argument. Second, this leads individuals to adopt these definitions themselves. Finally, the development of extreme positions leads these individuals to unify with their peers who share these ideas and this unity circles back to further the development of their extreme positions (O'Hara & Stevens, 2015).

According to Neumann (2013), there is no one piece of online propaganda that will radicalize an individual; rather, online radicalization is a gradual process related to the duration of exposure to content. Echo chambers can create an environment where definitions supportive of extreme positions will become normalized by increasing the frequency of exposure to these definitions (Pauwels & Schils, 2016a). For example, due to the homogeneity of definitions presented, there is no reason why echo chambers will not provide exposure to content that encourages

individuals to view violence as commendable and prestigious. Not only do echo chambers influence attitudes, but they can also provide exposure to other individuals who have engaged in violent political extremism. The exposure to these behaviors can lead to an individual imitating these behaviors themselves (Pauwels & Schils, 2016a). Echo chambers may then foster polarization leading to growth of extreme views in support of violence over non-violence.

### *The impact of personalization algorithms*

Any argument that personalization algorithms are deterministic and can dictate everything an individual is shown on social media is naïve, as it would ignore the role that individual behavior plays in the development of an echo chamber. Bessi et al. (2016) analyze cognitive factors that lead individuals to become involved in echo chambers by analyzing the behavior of users with the same content on Facebook and YouTube. The study explores user interaction with videos posted on science and conspiracy pages, citing these as contradictory messages, where science seeks to dispel tested knowledge and conspiracy messages aim to spread unconfirmed rumors. The study sample consists of 400 users who have commented at least 100 times on social media. This sample allows an understanding of the polarization process as it occurs through an individual's commenting behavior.

In the findings, it appears that some individuals only comment on one type of online content from the beginning while others begin by interacting with information supporting multiple narratives. Within this latter group, individuals end up polarized in one of the two narratives. During this process, behavioral changes can manifest as comments on posts supporting the views most frequently presented to them. Bessi et



al. (2016) find support that exposure to contrasting evidence forces individuals to interact with one or the other type of information and brings them into an echo chamber where they become more frequently exposed to supporting definitions of these narratives. It is evident that echo chambers play a role in exposure to content on social media for those well exposed to a certain ideology, as well as those with limited exposure to this ideology.

Looking specifically at the ability of algorithms to alter definitions presented to users on social media, Bakshy et al. (2015) find that in the presence of a personalization algorithm there was an 8% decrease in exposure to opposing views for liberal users and a 5% decrease for conservative users. These results offer support for the notion that algorithms can manipulate the definitions presented and result in a decrease in the exposure to content opposing an individual's current views leading to an increased presence of one-sided definitions. Additionally, Nikolov and colleagues (2015) find a similar reduction in definitions, citing that, due to algorithms on Facebook, 25% of politically conservative users saw a decrease in exposure to contrary views, while liberal users saw a 50% reduction of contrary views. Both Bakshy et al. (2015) and Nikolov and colleagues (2015) find decreases in contrary views for both politically conservative and liberal individuals, suggesting that algorithms may influence the exposure to certain definitions. The exposure to one-sided definitions may then influence differential association. Given the support that algorithms on social media can alter exposure to certain definitions over others and can lead to polarization (O'Hara and Stevens, 2015), I propose the following hypothesis:

H<sub>2</sub>: Compared to other ideologically motivated political extremists, those with exposure to a social media platform using personalization algorithms will be more likely to engage in violent extremism.

To summarize, I will use PIRUS data to examine the relationship between radicalization on social media and violent extremism. By using SLT as a framework for this relationship, I aim to answer two main research questions: (1) Are political extremists with social media exposure during their radicalization more likely to engage in violent extremism, compared to other ideologically motivated political extremists? and (2) Are political extremists with exposure to a social media platform using personalization algorithms more likely to engage in violent extremism, compared to other ideologically motivated political extremists?

## Chapter 3: Data and Methods

In this chapter I describe the data and methodology that I use in this thesis. I begin with an explanation of the PIRUS dataset, including a description of data collection and strengths and weaknesses of the data. I then discuss the analytic sample, followed by the dependent and independent variables that I used in this analysis. Following this discussion, I explain the methodology beginning with a discussion of missing data followed by a description of the logistic regression analysis.

### Data

PIRUS is a cross-sectional dataset built using information from publicly available sources on individuals who radicalized in the United States between 1945

and 2016. The dataset includes individuals who espouse Far Right, Far Left, Islamist, or Single Issue<sup>2</sup> ideologies and have engaged in either violent or non-violent actions motivated by their ideology.

The PIRUS research team conducted data collection and coding in multiple stages. Using a multitude of publicly available open sources<sup>3</sup>, START researchers began by searching for any individuals known to have radicalized in the United States and recorded preliminary information on these individuals. This original list contained 3,900 individuals subsequently coded based on a set of inclusion criteria (explained below) to determine suitability for inclusion in the dataset in the second stage of data collection. All information was coded from open sources including publicly available court documents, newspapers (e.g. Wall Street Journal, The New York Times), public FBI reports, the Southern Poverty Law Center, peer-reviewed academic journal articles, police reports, and journalistic accounts (books and documentaries), among others (Jensen et al., 2016).

All individuals included in the PIRUS dataset had to meet a specific set of inclusion criteria. Individuals must have radicalized in the United States, have espoused or currently espouse (at time of extremist behavior) ideological motives, and there must be evidence that their behavior is linked to the ideological motives he/she espoused or espouses. In addition to these criteria, the individual must also

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<sup>2</sup> The PIRUS codebook defines those with a single issue ideology as “motivated by a single issue, rather than a broad ideology.” For example, this includes groups like the Puerto Rican independence movement, anti-abortion extremists, and members of the Jewish Defense League, among others.

<sup>3</sup> The specific sources utilized by the research team include newspapers, websites (e.g. government, terrorist group, research centers/institutions), books, documentaries, court records, police reports, peer-reviewed articles, LexisNexis, any information posted by the individual being researched (e.g. social media accounts, personal blogs), psychological evaluations/reports and witness transcribed interviews.

meet one of the following five criteria: (1) was arrested, (2) was indicted for a crime, (3) was killed as a result of his or her ideological activities, (4) is/was a member of a designated terrorist organization<sup>4</sup>, or (5) was associated with an extremist organization whose leader(s) or founder(s) has/have been indicted of an ideologically motivated violent offense. The inclusion criteria focus on radicalization that occurs inside the United States, meaning that the individual's radicalization process began and most, if not all, of it occurred while they lived in the United States.

After determining which individuals met the inclusion criteria (from the list of 3,900), researchers randomly sampled this list and coded the selected individuals for the 147 variables included in the dataset<sup>5</sup>. The variables included in the dataset cover relevant background, contextual and ideological information on the individuals and are antecedent to their date of engagement in either violent or non-violent extremist behavior. After coding the initial random sample, researchers went back over three waves and included those individuals from their original list who fit the inclusion criteria. To ensure reliability among coders, approximately 10% of the individuals in the data were double-coded. This allowed researchers to use the Krippendorff's alpha procedure to test for inter-rater reliability in these double-coded cases. Researchers calculated three different scores for each wave of data collection; (1) 0.68, (2) 0.73, and (3) 0.76. Using 0.7 as the standard for acceptable reliability, Jensen et al. (2016)

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<sup>4</sup> By the PIRUS research team, membership is defined very broadly and includes cases where the individual is declared by the government to be part of the organization, is tied to the group in the media or if they claim membership with a group without the acknowledgement of the organization (Jensen et al., 2016)

<sup>5</sup> It is unclear how many individuals met the inclusion criteria at this time and how many were included in the random sample. There is no recording of these values that was available to me.

are confident in the reliability of the data and highlight that coding practices improved with each wave of data collection.

During these initial phases of data collection, PIRUS researchers did not collect information on social media usage, however, later retrospectively coded additional variables (including social media usage) for those cases in the sample where individuals engaged in extremist behavior in 2005 or later. The PIRUS team coded the social media variables using the same methodology as the rest of the variables and specifically searched for information about the platforms used by the individual, the role social media played in their radicalization, the activities they engaged in on social media and the frequency of their social media usage. At present, the complete PIRUS dataset includes 1,867 individuals engaged in extremist behavior between 1947 and 2016 coded on 162 variables.

#### *Strengths and limitations of PIRUS*

Given that researchers collected data from a variety of open sources, the depth of information available is highly dependent on the reporting behavior of these news sources. Though the PIRUS team identifies specific criteria that an individual must meet before researchers consider them suitable for inclusion in the data set, these criteria overlook the critical first step. For inclusion in the dataset, an individual must first come to the attention of either law enforcement or the media. This excludes individuals who engage in extremism but remain unidentified.

According to the Final Report of PIRUS released by START (2016), the PIRUS team undertook a conservative coding strategy to address the gaps in information available from open sources. Researchers treated information not

explicitly stated in any sources as missing, rather than treating it as “not occurring”. This strategy is commonly used across other datasets that also rely on open sources for data collection (Safer-Lichtenstein, LaFree, & Loughran, 2017) However, given this process there are concerns with missing data in PIRUS.

Despite these limitations, PIRUS is still useful for studying the proposed relationship because it currently provides the most extensive available data on the attributes, backgrounds and behaviors of extremist individuals in the United States (Jensen et al, 2016). Moreover, compared to past research on extremism, PIRUS includes individuals who have engaged in both violent and non-violent extremism. According to Borum (2011), extant research lacks this variation in the dependent variable as most of these data sources only include individuals who have engaged in violent extremism and exclude those who engage in non-violent actions motivated by their ideology. Additionally, much of the past research has focused only on one specific ideology and PIRUS includes those who have engaged in extremist behavior across multiple ideologies (Jensen et al, 2016). The inclusion of 162 individual level variables has made PIRUS a comprehensive data source available to study the relationships between these individual attributes and engagement in both violent and non-violent extremism.

### *Analytic Sample*

In this study, I restrict the sample using two separate criteria. The first is that I only include those individuals whose ideologically motivated behavior took place during or after 2005. I use this sample restriction because social media usage first began in 2005 (Duggan, 2015) and the individuals engaging in extremist behavior

before this time would not have had the opportunity to be exposed to social media.

Second, I only include those cases which have complete information on the dependent variable (violent-nonviolent) and the two independent variables (exposure to social media and whether the platforms they use employ personalization algorithms). By restricting the sample to those with complete information on these two variables, I can test my hypotheses without using missing data strategies to estimate the primary variables of interest. The analytic sample used for this research consists of 347 observations.

### Variables

In Table 1, I list all the variables included in the analysis and report also the proportion of observations for each variable that are missing. To test the hypothesized relationships, I use a dependent variable, *Violent*, and a set of independent variables along with control variables. The following section explains the way these variables are operationalized and why they are important for inclusion in this analysis.

Table 1. Descriptive Statistics

<b>Variable Name</b>	<b>N</b>	<b>Mean</b>	<b>Std. Dev</b>	<b>Min</b>	<b>Max</b>	<b>% Missing</b>
Violent	347	.697	.460	0	1	0.00
Social Media	347	.542	.499	0	1	0.00
Algorithm	347	.504	.501	0	1	0.00
Intimate Social Group	284	.447	.498	0	1	18.16
Group Membership	347	.637	.482	0	1	0.00
Education	193	.575	.496	0	1	44.38
Male	347	.922	.268	0	1	0.00
Previous Criminal Activity	242	.748	1.06	0	3	30.26
Far Right	347	.331	.471	0	1	0.00
Islamist	347	.516	.500	0	1	0.00
Age	345	33.475	13.738	17	80	0.58

Foreign Fighter	347	.352	.478	0	1	0.00
Year	347	2011.49	3.519	2005	2016	0.00

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### *Dependent Variable*

The dependent variable, *Violent*, is a dichotomous variable that measures if an individual engaged in violent extremism. This measure captures the first ideologically motivated behavior reported in publicly available sources. Because all individuals included in the data have committed some type of illegal behavior, this variable distinguishes between violent and non-violent behavior. Those individuals coded as violent (=1) must have actively participated in an operation/attack that either resulted in or intended to result in casualties or injuries. Additionally, individuals charged with conspiracy to kill or injure but were interdicted in the plotting phase are also coded as violent. Specific behaviors accounted for in this measure include murder, assault, armed robbery, kidnapping, bombing and arson. Comparatively, behaviors considered non-violent (=0) include illegal protests, vandalism, possession of illegal weapons, and tax fraud, among others. When coding *Violent*, researchers made specific decisions to treat a case as violent in a situation where the individual intended to cause death or injury to another person and had a plan for violence, though unsuccessful. Researchers worked to identify intent and in cases where intent for violence was not present they treated that behavior as non-violent. For example, though arson is considered violent, if it was apparent from sources that the individual tried to avoid human injury (e.g., burning a business in the middle of the night) then researchers would treat this as a non-violent behavior because it lacked intent of injury or death. Since engagement in ideologically motivated behavior is necessary



for inclusion in the data, there is no missing data on this variable. *Violent* is temporally the last variable in the data and all other variables are antecedent to this ideologically motivated violent or non-violent behavior<sup>6</sup>. Within the sample, 69.7% of individuals engaged in violent extremism.

### *Independent Variables*

The independent variable, *Social Media*, is a dummy variable measuring whether the individual was exposed to online social media during their radicalization and/or mobilization. Online social media can encompass any type of electronic platform that allows users to communicate by creating online communities to share information, ideas, personal messages, and other content like videos and images. In this study, online social media includes Facebook, Twitter, YouTube, Vimeo, Instagram, Tumblr, Google Plus, Skype, MySpace, 4chan, Reddit, Ask.fm, WhatsApp, Kik, Paltalk, VK, personal blogging websites (e.g. Wordpress, Blogger, LiveJournal, etc.), other non-encrypted software, and other encrypted or unspecified encrypted software.

For the current study, this variable is recoded from its original coding as (0) no evidence that social media played a role, (1) played a role but was not the primary means of radicalization or mobilization and (3) was the primary means of radicalization for the individual. Here, I dichotomize *Social Media* as a “yes” (=1) for individuals for whom social media (1) played a role but was not the primary means of

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<sup>6</sup> Any information reported in the sources pertaining to events after the date of engagement in the identified ideologically motivated behavior is excluded and not represented in any of the variables in the dataset or this analysis.

radicalization or mobilization or (2) was the primary means of radicalization for the individual, and “no” (=0) for individuals for whom social media did not play a role in their radicalization/mobilization. I find that 54.2% of the individuals in my sample report exposure to social media.

Additionally, I use an independent variable, *Algorithm*, to measure the difference between exposure to platforms that use personalization algorithms (e.g. Facebook) and those that do not (e.g. WhatsApp). Since there is variation in the use of personalization algorithms among different social media platforms, this variable highlights the difference between these platforms and their influence on violent extremism.

To create the Algorithm variable, I conducted a search of relevant sources (including official platform websites and news articles) to determine which of these platforms uses personalization algorithms and which does not<sup>7</sup>. When making this determination, I accounted for the time when each platform began using personalization to ensure that the algorithms were used prior to the ideologically motivated behavior engaged in by the individual using that platform. Of the 19 different platforms included in the sample, 11 of them used algorithms<sup>8</sup>. I coded all individuals who used at least one social media platform that uses an algorithm as a “yes” (=1) and all individuals who used platforms that did not employ algorithms or did not use any type of social media (original measure *Social Media*=0) as the “no”

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<sup>7</sup> Sources used for determining the presence of algorithms included Agrwal (2016), Manjoo (2016), (Marie & Carlton (2015), Patel (2016), Salihefendic (2015), and Stone (2007).

<sup>8</sup> The platforms that I identified as using personalization are Facebook, Twitter, YouTube, Vimeo, Instagram, Tumblr, Google Plus, MySpace, Reddit, Ask.fm, and VK.

(=0) category. In my sample, 50.4% used at least one social media platform that employed an algorithm.

### *Control Variables*

I also include a set of control variables in the analysis. Specifically, these variables are *Group Membership*, *Intimate Social Group*, *Education*, *Foreign Fighter*, *Previous Criminal Activity*, *Islamist*, *Age*, *Male*, and *Year*.

I include *Group Membership*, as a measure of engagement with an extremist group, as a control. Group membership can facilitate the use of social media as a method of inter-group communication and can also influence engagement in violent extremism (Europarat, 2007; Hoffman, 2017; Weimann, 2016). This variable is recoded from its ordinal categories as a dummy variable, to represent if the individual was a member of either an informal group of extremists or a formal extremist organization/movement (=1) or if the individuals was not a member of an extremist group or was a member of non-extremist (i.e. legal) groups (=0). Those involved in above ground groups do not have the exposure to definitions that support illegal behavior in support of the ideology, thus differentiating them from those individuals with memberships to extremist organizations. Slightly less than two thirds of the sample (63.7%) report engagement with an extremist group.

I also control for whether an individual is engaged with a close group of extremist others, as these others can be a source of definitions favorable toward violent extremism. *Intimate Social Group* is a binary measure representing, “a close-knit, insular, and exclusive group of people containing at least two individuals” (PIRUS Codebook). Any individual who has a family member, friend or significant

other who also espouses an extremist ideology is coded as “yes” (=1) for this variable to represent the presence of extremist intimate social group and “no” (=0) for the absence of an extremist social group. Within the sample, 44.7% of extremists were engaged with an intimate social group.

The models also include a control for the individuals’ level of education. Research suggests that educational attainment is related to social media usage. Specifically, Greenwood et al. (2016) find that in 2016, individuals with a high school diploma or less are less likely to use social media platforms (Facebook, Twitter, Instagram and LinkedIn) than those with at least some college education. If individuals with lower levels of education are less likely to use social media, then they may be less influenced by it as well. Additionally, past literature has shown that education can either be protective or a risk factor for violent extremism (Borum, 2011b; Gartenstein-Ross, Grossman, 2009). *Education* is recoded as a binary measure representing if the individual has a high school education or less (=0) or at least some education past high school (=1). Slightly more than half of the sample (57.5%) report at least some education past high school.

I also include *Foreign Fighter* in the models to control for whether the individual is a foreign fighter. Foreign fighters are defined as those individuals who attempted to or successfully left the United States to join a foreign extremist group. According to Weimann (2016), foreign fighters are more likely to use social media than other extremists because it is their primary way of communicating with others and learning about extremist movements. This is a binary variable representing

foreign fighters (=1) or other political extremists (=0). Foreign fighters make up 35.2% of the sample.

As established through extant criminological research, past offending can predict future offending (Nagin & Paternoster, 1991; Blumstein, Farrington, & Moitra, 1985; Wolfgang, Figlio, & Sellin, 1972). I include an independent variable for *Previous Criminal Activity* to capture any previous non-ideologically motivated criminal behavior that the individual may have engaged in. This variable is measured on a scale from 0 to 3 to control for the relationship between past criminal history and extremist violence. This scale measures (0) no previous criminal activity; (1) previous non-violent minor criminal activity (i.e. misdemeanor); (2) previous non-violent serious criminal activity (i.e. felony); and (3) previous violent crime. Less than half of the sample report a criminal history (40.9%), with only 12.4% reporting a previous violent crime.

To account for the differences between ideological motives in their justifications for violence, all models include binary measures of *Islamist* and *Far Right*. Extant literature finds that acts motivated by an Islamist ideology are more likely to be violent than those by other ideologies (Piazza, 2009). *Islamist* is a binary measure coded as “yes” (=1) for those who espouse an Islamist ideology and “no” (=0) otherwise. Additionally, compared to single issue and Far Left ideologies, the Far Right ideology is also more highly supportive of extremist violence (Berlet and Lyons, 2000). Given this, I include *Far Right* as a binary measure coded as “yes” (=1) for those extremists who espouse a Far Right ideology and “no” (=0) for all other ideologies. The reference group includes individuals espousing either Far Left or

single issue ideologies. In this data, individuals following an Islamist ideology are 51.6% of the sample and those following a Far Right ideology are 33.1%.

The models also use additional demographic variables as controls. Due to a well-established relationship in the criminological literature between age and offending, *Age* is included to account for the changes in offending as individuals get older (Farrington, 1986; Blokland, Nagin, & Nieuwbeerta, 2005) and represents the individual's age at the time of engagement in extremist behavior. Additionally, I use a variable measuring the individual's gender in the model. *Male* is a binary measure where "yes" (=1) represents a male and "no" (=0) is a female. The majority of the sample (92.2%) is male with an average age of 33 ( $\sigma=13.7$ ).

I also use the variable *year* to represent the year in which the individual engaged in extremist behavior. *Year* represents the date of the violent or non-violent extremist behavior as reported in the sources. This is a continuous variable that controls for the change in social media exposure over time.<sup>9</sup>

### Missing Data

Table 1 also shows the prevalence of missing data in the variables in this analysis. A majority of the variables, specifically *Violent*, *Social Media*, *Algorithm*, *Group Membership*, *Islamist* and *Year* do not have any missing data given that complete information on these variables is required for inclusion into the dataset and my analytic sample. However, there is a range of missing data in *Intimate Social*

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<sup>9</sup> This time point was used in coding to ensure that all data that was collected represents the individual's behaviors before their engagement in the extremist behavior that led to their inclusion in the dataset.

*Group, Age, Previous Criminal Activity, and Education.* As shown in Table 1, *Education* and *Previous Criminal Activity* are missing over 30% of the cases, *Intimate Social Group* is missing less than 20% of the cases, *Age* is missing less than 1%.

### Methods

I first discuss strategies for handling missing data and then describe the bivariate and multivariate analyses that I use to test my hypotheses.

#### *Addressing Missing Data*

In this study I use multiple imputation through chain equations (MICE) to address the high degree of missing data in the PIRUS dataset (Graham, 2009; Graham, Olchowski, & Gilreath, 2007). When considering strategies for missing data, the first step is to identify the mechanism through which the missing values relate to other observed and unobserved variables, and the missing variable itself. According to Safer-Lichtenstein et al. (2017), it is imperative that researchers understand and discuss any assumptions they make when creating point estimates for a set of multivariate coefficients, as making any of these missing data assumptions comes with costs and, more importantly, implications for any conclusions.

The three mechanisms of missing values explained by Graham (2009) are missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). The second mechanism, MAR, explains the conditions where we can observe the ways in which those with missing data differ from those without missing data. In the presence of MAR, those with missing data are systematically different from those without missing data; however, including a set of predictors

(auxiliary variables) can make the MAR assumption more defensible. In these cases, the model should include variables that are correlated with the variables that are missing or that are predictive of the missingness. Given the extensive number of variables (162) available in PIRUS, I can use other variables related to the missing values to model the missing data mechanism, approach the assumptions of MAR and obtain a dataset without any missing values using MICE.

Past research using the PIRUS data has utilized multiple imputation methods to deal with the high amounts of missing data on some variables (Jasko, LaFree, & Kruglanski, 2017). Jasko et al. (2017) employ a multiple imputation strategy (MICE) as a solution to missing data problems. Similarly, I use MICE as a strategy to address missing data. This imputation method creates multiple datasets, using all variables from the analysis and a set of auxiliary variables to estimate values for the missing variables. Multiple iterations are run until the estimates converge (Graham, 2009). Based on Rubin (1987), each point estimate is the average of that parameter estimate in each of the imputed datasets. Multiple imputation allows parameter estimates to be unbiased and standard errors that are able to capture sampling variation and estimation variation (Graham et al., 2007). In MICE, a model for each variable is fit conditional on all other variables in the missing data model using the proper distribution for each variable (i.e. count, continuous, categorical). The number of imputations recommended is dependent on the amount of missing data. Graham (2009) discusses completing at least 40 imputations in cases of 50% missing data (see also, Graham, Olchowski, & Gilreath, 2007). Though Graham et al. (2007) identify computational challenges with estimating higher numbers of imputations, STATA



makes it easier to handle a large number of iterations. Given the prevalence of missing data, I use MICE to estimate 100 complete datasets and then Rubin's (1987) rules to create the point estimates to form a final dataset that I use for my analyses.

### *Analysis*

The analysis begins with a set of bivariate correlations between my independent variables and the dependent variable, *Violence*. After completing this analysis, I then conduct a multivariate analysis using logistic (logit) regression. Logit regression is appropriate for the proposed study because *Violent* is a binary measure.

To answer the research questions identified in this study, I estimate separate models using *Violent* as the dependent variable. The first model includes *Social Media* as the primary independent variable and all control variables. The second model includes *Algorithm* as the primary independent variable and all control variables. I estimate two versions of these models, where I first include only a set of basic controls and then add augmented controls to see how the relationships change<sup>10</sup>. Both models are clustered to account for any serial correlation that is attributable to the individuals in the sample knowing each other. Additionally, I estimate robust standard errors due to the heteroskedasticity associated with a binary dependent variable.

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<sup>10</sup> I distinguish age, foreign fighter and year as augmented controls because they are highly correlated with exposure to social media and personalization algorithms and engagement in violent extremism.

## Chapter 4: Results

In this chapter, I discuss the results beginning with the bivariate correlations between each explanatory variable and the dependent variable (*Violent*) to understand the associations between them. Following this discussion, I describe the findings from my multivariate models and then explain a set of post hoc analyses I undertake to further explore my findings.

### *Bivariate Results*

I present the bivariate statistics in Table 2. According to Table 2, both my hypotheses are supported at the bivariate level. Those individuals with social media exposure are significantly more likely to engage in violent extremism compared to those with no exposure to social media. Additionally, those individuals with exposure to social media platforms using personalization algorithms are also more likely to engage in extremist violence compared to other political extremists. I also find that foreign fighters, Islamists and males are significantly more likely to engage in violent extremism. Also, individuals espousing a Far Right ideology are significantly less likely to engage in violent extremism. The results also show that age is negatively correlated with violent extremism: younger persons are more likely than older persons to engage in violent extremism. Also, the results highlight that over time violence is increasing in the sample.

Table 2. Bivariate Correlations between Independent Variables and Dependent Variable (Violent)

<i>Variable</i>	<i>Correlation Coefficient</i>
Social Media	0.137*
Algorithm	0.150*
<i>Basic Controls</i>	
Intimate Social Group	0.089
Group Membership	-0.015
Education	-0.093
Male	0.113*
Previous Criminal Activity	0.015
Far Right	-0.163*
Islamist	0.253**
<i>Augmented Controls</i>	
Age	-.284*
Foreign Fighter	0.393**
Year	.140**

\*p<.05 \*\*p<0.01

### Multivariate Results

Table 3. H<sub>1</sub>: Logistic Regression with dependent variable (Violent)

Independent Variables	Model 1a (n=347)			Model 1b (n=347)		
	Beta	Odds Ratio	Robust SE	Beta	Odds Ratio	Robust SE
Social Media	0.478*	1.612	0.256	-0.359	0.698	0.33
<i>Basic Controls</i>						
Intimate Social Group	0.42	1.521	0.33	0.347	1.415	0.376
Group Membership	-0.182	0.834	0.316	-0.388	0.678	0.352
Education	-0.184	0.832	0.311	-0.128	0.88	0.347
Male	0.748	2.112	0.491	0.661	1.936	0.504
Previous Criminal Activity	0.222	1.248	0.149	0.296*	1.344	0.152
Far Right Islamist	0.11	1.117	0.364	0.5	1.641	0.38
	1.160**	3.19	0.369	0.006	1.006	0.406
<i>Augmented Controls</i>						
Age	-	-	-	-0.027**	0.973	0.011
Foreign Fighter	-	-	-	2.639**	13.993	0.475
Year	-	-	-	0.106**	1.112	0.045

\*p<.05 \*\*p<.05 Note: SE is the abbreviation for standard error. All p-values are reported for a one tailed test.

Table 3 presents the multivariate results from the logistic regressions I conducted to test H<sub>1</sub>. Model 1a only includes the basic controls and model 1b is the fully specified model, including the augmented control variables.

Considering the bivariate relationships highlighting that foreign fighters, younger individuals and year of extremist behavior are highly associated with violent extremism and knowing that historically these variables are also highly related to social media exposure, I decide to exclude them in model 1a. Extant research finds that foreign fighters are more likely to use social media compared to other political

extremists (Weimann, 2016). Also, literature supports that in general social media usage is more highly correlated with younger individuals and that since its inception in 2005 social media has become increasingly popular. Keeping in mind that these variables are not only highly associated with extremist violence but also social media, I exclude them from Model 1a. Model 1a highlights that, without the inclusion of these variables, there is a positive relationship between exposure to social media and engagement in violent extremism. The odds of violent extremism are 61.2% higher for extremists with exposure to social media compared to other extremists. Additionally, I find that the odds of violent extremism are 3.2 times higher for Islamists compared to extremists espousing single issue or Far Left ideologies.

However, in model 1b, I find that the inclusion of the augmented variables explains the relationship between social media exposure and violence and, though social media exposure is associated with violence at the bivariate level, the relationship is spurious. This means that the relationship between social media exposure and violence is driven by age, foreign fighters and year of the attack. In model 1b, I find that the odds of violent extremism are 14 times higher for foreign fighters compared to other political extremists. As age increases the odds of violent extremism decrease by 2.7%. I also find that over time the odds of violent extremism increase by 11.2%. Additionally, I find that the inclusion of the augmented variables explains the relationship between Islamists and violent extremism as well. Given that all foreign fighters are Islamist, the correlation between these two variables explains this finding. In this model, I also find that more serious previous criminal activity increases the odds of extremist violence 1.3 times.

Table 4. H<sub>2</sub>: Logistic Regression with dependent variable (Violent)

Independent Variables	Model 2a (n=347)			Model 2b (n=347)		
	Beta	Odds Ratio	Robust SE	Beta	Odds Ratio	Robust SE
Algorithm	0.604**	1.829	0.255	-0.183	0.833	0.328
<i>Basic Controls</i>						
Intimate Social Group	0.43	1.538	0.33	0.36	1.434	0.375
Group Membership	-0.16	0.852	0.318	-0.375	0.688	0.35
Education	-0.184	0.832	0.312	-0.128	0.88	0.346
Male	0.752	2.122	0.493	0.65	1.916	0.505
Previous Criminal Activity	0.225	1.252	0.15	0.292*	1.339	0.151
Far Right	0.111	1.117	0.368	0.458	1.581	0.377
Islamist	1.176**	3.24	0.37	-0.014	0.986	0.404
<i>Augmented Controls</i>						
Age	-	-	-	-0.026*	0.975	0.011
Foreign Fighter	-	-	-	2.608**	13.567	0.476
Year	-	-	-	0.095*	1.1	0.045

\*p<.05 \*\*p<.01 Note: SE is the abbreviation for standard error. All p-values are reported for a one tailed test.

Similarly, to the test of H<sub>1</sub>, in table 4 I first provide a model with only the basic controls (2a) and then a fully specified model, including the augmented controls (2b) testing the relationship between *algorithm* and *violence*.

In model 2a, I find that the odds of violent extremism are 82.9% higher for extremists with exposure to personalization algorithms compared to other extremists. I also find that, compared to those espousing Far Left or single issue ideologies, the odds of violent extremism are 3.2 times higher for Islamists. The findings in this model directly support my hypothesis (H<sub>2</sub>), however this model excludes three

variables that when included explain the relationship between personalization algorithms and violence.

Model 2b highlights how this relationship changes when controlling for age, foreign fighter status and year of extremist behavior. Adding these three controls to the model explains the relationship between personalization algorithms and violence, suggesting that the bivariate association between these two variables is spurious. I find that the odds of extremist violence are 13.6 times higher for foreign fighters compared to other political extremists. Additionally, as age increases the odds of violent extremism decrease by 2.5%. I also find that over time there is a 10% increase in the odds of violent extremism. The addition of these three variables also explains the relationship between Islamists and violent extremism. This is due to the high correlation between this variable and Foreign Fighter since all Foreign Fighters are Islamists. These findings do not suggest that algorithms do not matter when considering violent extremism, they suggest that any relationship between algorithms and violence is dependent on age, foreign fighter status and year of extremist activity. In this model I also find that previous criminal activity increases the odds of violent extremism by 130%.

### Post Hoc Analyses

Given the multivariate results, I further examine how each of the controls variables is related to social media exposure and algorithms. Considering the significant associations between exposure to social media and personalization algorithms with extremist violence that are explained by foreign fighter status, age and time, I am interested in further exploring what it is about these variables that are

important. To do this, I first explore the bivariate correlations between all the control variables and social media and algorithms, respectively. Then, I conduct a multivariate analysis considering how these variables are associated with exposure to social media and to platforms that employ personalization algorithms.

### *Bivariate correlations*

In Table 5, I provide the bivariate correlations between *Social Media* and the other independent variables. I find that extremists involved with intimate social groups are significantly less likely to be exposed to social media compared to other extremists. I also find that those extremists engaged in extremist groups are also significantly less likely to be exposed to social media when compared to extremists who do not report group membership. Islamists are also more likely to be exposed to social media compared to extremists with other ideological beliefs. Additionally, I find that the three augmented controls (year, foreign fighters and age) are all significantly correlated with exposure to social media. Older extremists are less likely to be exposed to social media, while foreign fighters are more likely to be exposed to social media. Also, I see that over time exposure to social media has significantly increased.



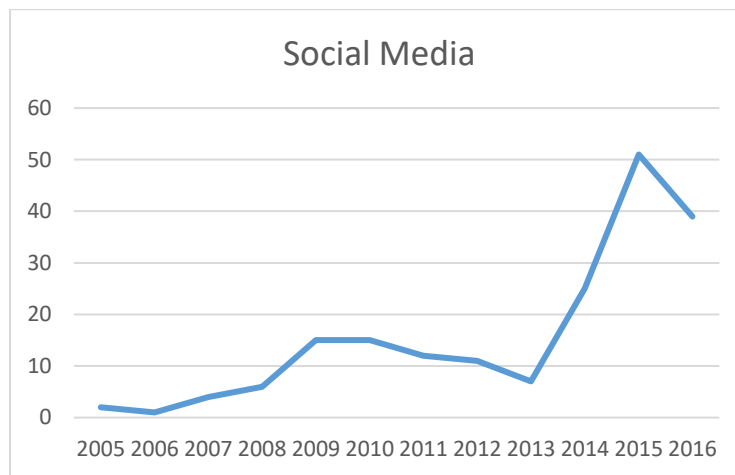
Table 5. Bivariate Correlations between Social Media and other Independent Variables

<i>Variable</i>	<i>Correlation Coefficient</i>
<i>Basic Controls</i>	
Intimate Social Group	-0.135*
Group Membership	-0.189**
Education	-0.097
Male	0.014
Previous Criminal Activity	-0.018
Far Right	-0.053
Islamist	0.1275*
<i>Augmented Controls</i>	
Age	-0.288**
Foreign Fighter	0.2169**
Year	0.5117**

\*p<.05 \*\*p<0.01

Comparing across the years in the sample, there is an increase in the frequency of exposure to social media over time. Figure 1 shows the change in the distribution of the sample exposed to social media, highlighting the increasing role of social media over the 12-year period in this sample. From 2005 to 2010, there is a continuous increase in exposure to social media and then in 2011, there is a decrease in the prevalence of social media exposure in the sample. The number of individuals exposed to social media increases again in 2012, drops slightly in 2013 and then increases again in 2014. Overall, from 2005 to 2016, more individuals are exposed to social media over time. The increased prevalence of exposure to social media in the sample is representative of an increased prevalence of social media in the US population generally. Duggan (2015) finds that in 2005 only 7% of the US adult population used social media, while in 2015 65% of the adult population was active on social media.

Figure 1. Prevalence of Social Media over time



The bivariate correlations, presented in table 6, highlight that *Algorithm* is significantly correlated to some of the other independent variables in my multivariate models. Those political extremists who are part of intimate social groups are significantly less likely to be exposed to social media platforms that employ algorithms. Similarly, political extremists who are members of extremist groups are also significantly less likely to be exposed to social media platforms that use algorithms compared to extremists with no group membership. I find that the three augmented controls that explain the relationship between algorithm and violence (Model 2) are significantly correlated with exposure to personalization algorithms. Older extremists are also significantly less likely to be exposed to algorithms compared to younger extremists. Foreign fighters are significantly more likely to be exposed to algorithms compared to other extremists. Also, I find that over time there is an increase in exposure to personalization algorithms.

Table 6. Bivariate Correlations between Algorithm and other Independent Variables

<i>Variable</i>	<i>Correlation Coefficient</i>
<i>Basic Controls</i>	
Intimate Social Group	-0.148*
Group Membership	-0.197**
Education	-0.08
Male	0.013
Previous Criminal Activity	-0.014
Far Right	-0.037
Islamist	0.089
<i>Augmented Controls</i>	
Age	-0.265**
Foreign Fighter	0.199**
Year	0.5417**

\*p<.05 \*\*p<0.01

### *Multivariate Analyses*

Given the multivariate results highlighting that age, foreign fighters and years explain the relationship between social media and violence and algorithms and violence, I decided to include a set of multivariate analyses to better understand how these three variables are directly associated with social media and algorithms.

Although I do find bivariate correlations between the other independent variables and exposure to social media, it is unclear how these other factors are associated with social media exposure. Model 4 below highlights the association between these variables and social media exposure (table 7). I find that membership in extremist groups decreases the odds of exposure to social media by 45.3%. Also, the odds of exposure to social media are 3.2 times lower for extremists with a Far Right ideology compared to extremists with Far Left or single issues ideologies.

Additionally, I find that the three variables that explain the relationship between social media exposure and violent extremism, are significantly associated to social media. Specifically, foreign fighters have 2.7 times higher odds of exposure to social media compared to other political extremists. Additionally, the odds of exposure to social media are 6.1% lower as extremists get older. It also appears that over time the odds of exposure to social media increase by 44.6%. Considering the previous results, I find that these three variables are all significantly related to violent extremism and now find that they are significantly related to social media exposure as well. These significant relationships offer insight into why their inclusion explains the relationship between social media and violent extremism (Table 3). It is not simply that social media exposure is not related to violent extremism, rather that foreign fighter status, age and the year of extremist behavior drive the relationship between these two variables.

Table 7. Logistic Regression with Dependent Variable (Social Media)

Independent Variables	Model 4 (n=347)		
	Beta	Odds Ratio	Robust SE
Intimate Social Group	-0.209	0.812	0.338
Group Membership	-0.604*	0.547	0.327
Education	-0.052	0.949	0.339
Male	0.267	1.306	0.47
Previous Criminal Activity	0.03	1.031	0.151
Far Right	1.167**	3.21	0.459
Islamist	0.439	1.552	0.5
Age	-0.053**	0.949	0.014
Foreign Fighter	1.007**	2.737	0.376
Year	0.369**	1.446	0.048

\*p<.05 \*\*p<.01 Note: SE is the abbreviation for standard error. All p-values are reported for a one tailed test.

Following this analysis, I also conduct a second analysis using personalization algorithms as my dependent variable. Given that the relationship between algorithms and violence is also explained by foreign fighters, age and the year of extremist behavior, I am interested in how these variables are related to my measure of whether individuals are using social media platforms that contain algorithms. Model 5 provides the results of this analysis looking at the association between the independent variables and personalization algorithms (table 8).

I find that membership in extremist groups is negatively associated with exposure to personalization algorithms. Specifically, membership in extremist groups decreases the odds of exposure to personalization algorithms by 44.9%. Additionally, the odds of exposure to personalization algorithms is 2.9 more likely for extremists espousing a Far Right ideology compared to Far Left or single issue ideologies.

Similarly to their significant relationships with exposure to social media (Table 7), foreign fighter status, age and year of extremist behavior are all significantly associated with exposure to personalization algorithms. The odds of exposure to personalization algorithms are 3.14 times higher for foreign fighters compared to other political extremists. Also, as extremists get older the odds of exposure to personalization algorithms decrease by 6.2%. I find that over time the odds of exposure to personalization algorithms increase by 49.2%. Understanding how these variables are related to personalization algorithms, allows for insight into why they explain the relationship between algorithms and violence (model 2). Given that these variables all predict the use of algorithms and extremist violence, I can identify why their inclusion drives the relationship between personalization algorithms and violence.

Table 8. Logistic Regression with Dependent Variable (Algorithm)

Independent Variables	Model 5 (n=347)		
	Beta	Odds Ratio	SE
Intimate Social Group	-0.247	0.781	0.344
Group Membership	-0.596*	0.551	0.328
Education	-0.047	0.954	0.339
Male	0.267	1.306	0.492
Previous Criminal Activity	0.02	1.02	0.139
Far Right	1.059*	2.883	0.476
Islamist	0.048	1.049	0.52
Age	-0.053**	0.948	0.014
Foreign Fighter	1.145**	3.141	0.393
Year	0.400**	1.492	0.05

\*p<.05 \*\*p<.01 Note: SE is the abbreviation for standard error. All p-values are reported for a one tailed test.

### Summary of Results

Overall, I do not find support for either of the hypotheses. However, I do find that both exposure to social media and personalization algorithms are positively associated with extremist violence, although both of these relationships are explained by foreign fighter status, age and the year in which the extremist behavior occurred<sup>11</sup>.

## Chapter 5: Discussion

Though multivariate results suggest that exposure to social media and personalization algorithms are not significantly related to violent extremism,

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<sup>11</sup> I used two additional missing data strategies (mean imputation and fixed value imputation), in addition to MICE, and find that the results are consistent across the three different methods used to estimate missing data.

additional analyses indicate that the relationship between these variables is more complex. Exposure to social media and personalization algorithms is positively and significantly correlated with violent extremism, however the inclusion of age, foreign fighter status, and year of extremist behavior explains this relationship. Given this finding, it is important to discuss why exposure to social media and personalization algorithms may not be related to violent extremism, but at the same time determine why the relationship is influenced by age, foreign fighter status and time controls. In the following section, I begin with an explanation of the theoretical considerations of why exposure to social media and personalization algorithms may not increase the likelihood of violent extremism, then transition into a discussion of how this may be different across age, foreign fighter status and time. I then discuss the limitations of this study, followed by a brief summary, and conclude with an explanation of future directions.

### *Theoretical Considerations*

When presenting my hypotheses, I posit that learning can occur in online environments and that exposure to extremist content on social media leads to an increased likelihood of engagement in violent extremism. I also argue that social media platforms allow for exposure to content that can reinforce an individual's ideas due to the use of personalization algorithms. Both of these hypotheses are in contrast to Sutherland's (1947; Cressey, 1965) classic statement that learning only occurs in face-to-face environments and more supportive of Akers' (2009) explanation of the influence of media on learning. Though this study uses social learning theory (SLT) as a framework for understanding how social media may be related to violent



extremism, it is not a perfect test of the theory. First, I was unable to do a direct test of the four elements of SLT (imitation, definitions, differential association, differential reinforcement), and second, SLT is a theory that contrasts criminal and non-criminal behavior. My data only allow me to distinguish between violent and non-violent behavior. Nevertheless, it is possible that learning does not occur over social media in a way that leads to behavioral changes offline.

Kenney (2010) argues that in recent years, researchers have focused too much on the internet as providing websites, chat rooms and other platforms for communication among terrorists. He challenges this understanding by arguing that the internet provides “abstract technical knowledge” and religious and ideological information but is unable to provide the “experiential situational knowledge” necessary for political violence (pg. 180). When specifically looking at the behaviors of Islamist militants in Spain and Britain, Kenney suggests that terrorists may be able to learn how to build a bomb, shoot a weapon, or how to engage in other types of violence from the internet but without practice they will not gain hands-on expertise. In order for an individual to fully become a successful terrorist they need these practical skills. While knowledge and practice are both important, the latter allows individuals to be able to use the knowledge in their specific circumstance. The internet cannot provide these practical skills and, according to Kenney (2010:181), they must be “shared among practitioners through face-to-face interactions, storytelling, apprenticeships, and hands-on demonstrations in building bombs, firing weapons, and other activities.” Considering this explanation, social media may not be able to provide the experiential knowledge necessary to engage in violence because it

lacks the face to face interactions that both Kenney and Sutherland explain as being important when it comes to learning.

Additionally, when considering SLT, the theoretical framework explains differential association as learning definitions favorable to engagement in criminal behavior as compared to definitions that view criminal behavior as unfavorable. However, in this study the dependent variable does not measure this dichotomy, but rather measures the difference between violent and non-violent illegal behavior. It is entirely possible that exposure to extremist content over social media may not be differentially related to violent and non-violent outcomes, but rather is related to engaging in extremist behavior irrespective of the severity of that behavior. Pauwels and Schils (2016) find that SLT is related to engaging in ideologically motivated crimes against both property and persons, lending support to the notion that social media exposure does not differentially impact violent and non-violent crimes. If this holds true, then the null findings in this study make sense, as social media should not be related to an increased likelihood of violent compared to non-violent extremism rather related to extremist behavior regardless of severity.

Though the findings suggest that Sutherland may be right and face-to-face interactions may be more important than interactions over media for learning, we cannot ignore Akers' (2009) argument that individuals may learn from the media through imitation and reinforcement. The findings do not suggest that social media is not important in the development of extremist violence, rather that there are other characteristics of individuals that are more important in explaining violent extremism. As Kenny (2010) discusses, the importance of social media may be overblown, but

not because the internet cannot provide hands on experiences, rather because other characteristics are more important when considering violent extremism. In the multivariate models, I find that the associations between social media and violence and algorithms and violence are explained by age, foreign fighter and time, suggesting that these variables may be more important than social media and algorithms when it comes to explaining violent vs. non-violent extremism.

When exploring this further, I find that not only are these three variables significantly associated with violent extremism, they are also significantly associated with exposure to social media and to algorithms. In the post hoc analyses, I find that foreign fighters are significantly more likely to be exposed to social media and to personalization algorithms. This finding aligns with extant literature where Hoffman (2017) explains how social media is relevant for foreign fighters because their points of contact with foreign groups mainly come from social media (see also, Weimann, 2016). Social media is the main way of communicating with other extremists and learning about a movement for foreign fighters because by definition they are geographically removed from the group (Hoffman, 2017; Weimann, 2012, 2016). Foreign fighters are a distinct group of extremists, suggesting that since these groups rely so much on social media to communicate we may assume that social media is relevant on a wider scale, when in reality it matters disproportionately for a specific subset of the population.

Additionally, traditional criminological theory has identified age as a main correlate of crime, explaining that younger individuals are more likely to engage in criminal behavior than older individuals and suggesting an overall negative

relationship between age and crime (DeLisi and Vaughn, 2016). My findings suggest that age is more important when explaining violent extremism, in part because exposure to social media and personalization algorithms follow the same pattern, where younger individuals are more likely than older individuals to be exposed to these platforms. Given that younger people have (typically) adapted to this new technology faster than older people, this relationship is also relevant over time. From 2005 to 2016, social media exposure in the sample increased dramatically, from a minority of the sample exposed in 2005 to the majority exposed in 2016. This change highlights that though social media is seen as a new technology and there is a concern surrounding its impact on extremism, this effect may not be present as society adapts to social media and it becomes more ubiquitous over time. In summary, it is important to consider that the effect of social media is time variant, that the impact of social media has changed since 2005 and that it will continue to change into the future.

### Limitations

There are several limitations to this thesis that warrant further discussion. First, there are some limitations that are unavoidable with the PIRUS dataset. The open source methodology of data collection has some important limitations related to the representativeness of the sample. The individuals included in PIRUS all must have engaged in some type of ideological behavior that is extreme enough for them to be included in the sources. Their behavior must have brought them to the attention of either the news media or the criminal justice system. Given the sampling procedures and the lack of a true random sample, these findings are not generalizable to those

outside the sample included in PIRUS. Also, given the cross-sectional nature of the data collection, coding is completed retrospectively, and thus it is hard to establish temporal ordering between the different antecedent variables coded before the dependent variable, *Violent*.

The data collection process also systematically excludes those individuals who hold strong ideological beliefs but fail to engage in any behavior in support of their beliefs. By excluding these individuals, the dataset cannot differentiate between individuals with extremist attitudes who have committed crime and those who have not. Without the presence of this group, it is inappropriate to use any findings to distinguish between decisions to engage in ideologically motivated behavior, rather we can only understand the differences between engaging in types of ideologically motivated behavior (violent vs. non-violent).

Additionally, researchers who collect PIRUS data use a multitude of different publicly available sources including news reports and court records to collect and code data. Due to the reliance on open sources for data, the reporting behaviors of the different news sources and court records moderates the presence of data in all the variables. It is entirely possible that more information will be present on those individuals who have engaged in some behavior that is of interest to the news and media sources and these will be the individuals who have more complete information. The news tends to pay more attention to more extreme cases and thus the cases that ended in violent behavior may have more data available than those with non-violent outcomes (Jensen et al., 2016). This process creates some concerns with missing data in this analysis. Furthermore, in the aftermath of 9/11 the media has paid increased

attention to individuals who follow an Islamist ideology as compared to those of other ideologies (Boyle et al., 2017). These reporting behaviors may increase the probability that those of an Islamist ideology will be overrepresented in the data.

Additional information related to social media usage would also have been useful to understand more completely the role of social media in the development of extremist behavior. For example, information about the frequency of social media usage and the types of behaviors engaged in over social media (i.e. viewing content vs. sharing content). With these measures it would be possible to identify those individuals who actively seek out extremist content compared to passively view content on social media. We could also then differentiate between those individuals for whom social media was the primary form of exposure to extremist content compared to those for whom it played an auxiliary role.

Additionally, while I posit that individuals will be influenced by echo chambers due to the structure of social media, I am unable to measure the extent to which the platforms actually served as echo chambers. It is entirely possible that the individuals in this sample, though exposed to social media and personalization algorithms, were not involved in echo chambers related to extremist content. I am assuming that due to algorithms everyone using social media is in an echo chamber, however I do not know if this is actually the case. Though I aim to address this assumption with *Algorithm* by differentiating between platforms that do and do not use personalization, there are some limitations related to the construction of this measure. When identifying the platforms that use algorithms compared to those that do not, I used multiple sources to find the most accurate date when they started using

algorithms to avoid a circumstance where an individual was using a platform before an algorithm was created and measuring them as using an algorithm. Though I made efforts to corroborate reports about the onset of algorithm usage on each platform there was still some discrepancy across sources. I used the earliest date that had the most support, but it is possible that by using publicly available information this measure may not be completely accurate.

### *Summary and Future Directions*

In this thesis, I aim to understand the relationship between exposure to social media and engagement in violent extremism. As social media develops and becomes more integrated into everyday life, a better understanding of the influence of social media on radicalization and engagement in violent extremism becomes increasingly important. The population targeted by this research is hard to study due to the constraints of reaching these individuals, so open source methods may be the best method available to study those who have engaged in ideologically motivated behavior. Though this thesis has limitations and does not find direct support for the main hypotheses, there are still some significant findings that lay the ground work for future research. I find that social media and algorithms are both significantly correlated with violent extremism, however these relationships are explained by age, foreign fighters and the year of extremist behavior. This is an important finding in itself as social media and content online may matter differentially for these groups as time goes on. We cannot rule out Akers' (2009) explanation of media as an important context for learning and place all our attention on face-to-face interactions as

Sutherland does, rather we need to further explore how social media may be important across different contexts and groups within society.

Given the findings from this study, there are a few different elements that should be explored in further research. It is important for researchers to consider how social media is important in the development of extremist behavior for younger individuals and foreign fighters, especially over time as social media becomes increasingly widespread. These groups are more likely to be exposed to social media and to engage in violent extremism, warranting further exploration into their use of social media as it relates to their behavior. If possible, researchers should try to monitor publicly available social media accounts of known political extremists to understand more about the frequency of their usage and their behaviors on these accounts. This will allow for a nuanced exploration of social media as it relates to extremism.

Additionally, research should also aim to understand whether social media exposure is related to more successful plots. It may be the case that social media exposure does not increase the likelihood of engaging in violence but increases the probability that the plot will be successful. Finally, if appropriate data can be collected on social media usage, researchers would be able to test the elements of SLT in social media and understand more appropriately whether learning can actually occur in online environments. Before we completely rule out any role social media may have in violent extremism, it is important that future research expand on this study as social media becomes more normalized into daily life. Researchers should use



different data, samples and methodologies to gain more insight into the nuanced role that social media plays in extremism.

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