UNDERSTANDING RADICALIZATION PROCESS IN ONLINE FAR-RIGHT EXTREMIST FORUMS USING SOCIAL INFLUENCE MODEL

By

Yi Ting Chua

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ABSTRACT

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The Internet serves multiple functions such as recruitment, networking, and information sharing, to many subcultural groups. Current literature on online criminal groups recognizes the role of online forums in the transfer of knowledge and socialization of members (Holt, 2007; Holt & Copes, 2010), but debates on the role of the Internet in the socialization and radicalization processes in the context of online extremist groups persist. This study aims to address one of the fundamental questions in radicalization and extremism – does radicalization occur in an online context. Through social learning theory and social network analysis, the study determines if interactions with other forum members contributes to the radicalization process. Findings suggest the occurrence of online radicalization at varying degrees in six of the seven forums, with lower level of expressed extremism after 2009. The study also found strong support of differential association and differential reinforcement, but showed the possibility of other mechanisms, such as self-radicalization and users' prior beliefs, at play. Findings from the study highlight the need to for theory integration, the inclusion of online peer association, and replication to address the complex phenomenon of online radicalization. Knowledge on these factors would enable law enforcement agencies to develop countermeasures and intervention tactics.

This dissertation is dedicated to mentors, friends and family.
Thank you for always believing in me and encouraging me to pursue my goals.

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CHAPTER 1: THE INTERNET AND SUBCULTURAL GROUPS

It is challenging to imagine a world without the Internet and technology as individuals, businesses, and governments increasingly rely on these platforms for all facets of communication (Holt, 2013; Newman & Clarke, 2003; Taylor, Fritsch, Liederbach, & Holt, 2011; Wellman, et al., 1996). The Internet affords us with convenience and opportunities for commerce. For example, online commerce in the United States amounted to roughly USD$340.4 billion in 2015, which accounted for 7.2% of total retail sales that year (Nicholson, 2017). Simultaneously, the Internet introduces vulnerabilities and criminal opportunities such as virtual attacks against computer systems by hackers and child pornography, to name a few (Taylor et al., 2011; Wall, 2001). All of these criminal activities result in serious economic and personal harms to Internet users, such as identity theft (Peretti, 2009; Symantec Corporation, 2018; Yip, Webber, & Shadbolt, 2013) and financial losses (Mikhaylov & Frank, 2016; Symantec Corporation, 2018).

Consequently, industries, governments and academia are increasing their focus and efforts on cybersecurity and cybercrime (Department of Homeland Security, 2018; Holt & Bossler, 2016; Holt, Freilich, Chermak, & McCauley, 2015; Hortin, 2017; Trump, 2017), some of which overlap with criminal justice concerns such as terrorism (Taylor et al., 2011; Wall, 2001). Terrorism demands our attention because research suggests that the Internet plays a role in the spread of extreme ideologies and the orchestration and encouragement of violent terrorist attacks (Gerstenfeld, Grant, & Chiang, 2003; Holt et al., 2015). Such violent terrorist attacks have dire consequences as evident in past events: a) the Oklahoma bombing which lead to the deaths of 168 individuals in 1995 (Hewitt, 2000), and b) the 9/11 attack which resulted in the deaths of 2,977 individuals (CNN, 2017). The ultimate goal across all of these stakeholders is to minimize risks and negative impacts of the Internet while securing the positive, especially with regards to cyberwarfare and terrorism (Hortin, 2017).

The purpose of this dissertation is to further current knowledge on the role of the Internet on individuals' radicalization process, where they develop and/or accept extreme ideologies (Borum, 2011), using social network analysis. This chapter will provide context for the dissertation, beginning with a brief history of the Internet and how individuals utilize this technology in the United States. This is followed by a discussion on the use of Internet by cybercriminals and subcultural groups, as well as the features of the Internet that contributed to such use. The chapter concludes by discussing the notion that far-right extremist groups constitute a subculture and merit scholarly attention given the process of radicalization and the popularity of the Internet.

Development of the Internet

To understand how the Internet became an essential resource in modern society, it is necessary to track its development overtime. The Internet is an evolution of a military project supported by the Advanced Research Projects Agency (ARPA), which began in the 1960s (Cerf, 1993; Ryan J. , 2010). Its initial purpose was to develop a centrifugal national communication network to address the possibility of nuclear attacks amid the Cold War. A feature of the network would be the lack of centralized hierarchy and a reliance on redundant control points (Ryan J. , 2010). The first transmission made over this network, coined ARPANET, happened in 1969 via leased telephone lines (Ryan J. , 2010, p. 30). Two years after its first transmission, the ARPANET grew to include 19 nodes located across 30 university sites with funding from ARPA (Cerf, 1993).

The development from ARPANET to the Internet was less linear. Breakthroughs were found by scholars and at multiple research institutes and businesses between 1970s and 1980s. Specifically, businesses and scholars worked on developing their own networks, communication software and tools after realizing ARPANET's value and potential for information and knowledge sharing (Ryan J. , 2010). The predecessor of online forums, the computer bulletin board system (BBS), was invented in the late 1970s and allowed individual users to share files and information on their board to whoever dials into it (Ryan J. , 2010). Within the ARPANET, discussion lists that allowed users to exchange opinions and information grew popular by the late 1970s.

By the 1990s, the ARPANET began to resemble to what we know as the Internet (Cerf, 1993). This transformation was aided with the development of the world wide web, which "puts a user-friendly face on the network" via graphic user-interface (Ryan J. , 2010, p. 115). The world wide web makes ARPANET accessible and welcoming to businesses and the public. The Internet gained popularity in the early 1990s as both businesses and the general public realize the benefits of the Internet in facilitating global communication; users can now share their knowledge and opinions globally via the Internet (Ryan J. , 2010).

In 1993, there were 3.8 million computers connected to the Internet, which was at the time owned and supported by the United States government. As the demand and popularity of the Internet increased, the National Science Foundation, which was operating the backbone of the connection at the time, took the initiative to privatize the Internet. By 1995, commercial activity was allowed on the Internet. Today, 49% of the world population and 8.4 billion devices are connected to the Internet, which marks the ultimate transformation of the Internet from a military communication network to a complex space of computers, mobile devices, and servers with data storage, and a global network of information and resources (Cerf, 1993; Rainie & Anderson, 2017; Ryan J. , 2010).

Individual Uses of the Internet

For most of the United States population, the Internet is a staple of life. According to the American Community Survey conducted by the United States Census Bureau, 86.8% of households in the United States have either a desktop, computer or a handheld device while 77.2% of households have Internet subscription (Ryan & Lewis, 2017). Only 11% of adults in the United States reported not using the Internet in 2018, compared to 48% in 2000 (Anderson, Perrin, & Jiang, 2018). When compared by age groups, two percent of individuals between the ages of 18 to 29 and three percent of individuals between the ages of 30 and 49 reported not using the Internet. The largest percentages of non-Internet users are individuals above the age of 65 (34%) (Anderson et al., 2018). In other words, most adults in the United States are users of the Internet.

The Internet plays the largest role in human connections and interactions. The typical use of the Internet by an overwhelming majority of the Internet users in the United States is social media (Pew Research Center, 2018). Specifically, 69% of adults in the United States reported using at least one social media site. When compared by age groups, 88% of adults between the ages of 18 and 29 reported using at least one social media site, followed by adults between the ages of 30 and 49 at 78%. Facebook and YouTube are respectively the top first and second sites among the top three most-visited social media pages between these two age groups. However, younger adults indicated more usage of Snapchat while adults between the ages of 30 and 49 used Instagram (Pew Research Center, 2018).

Similar patterns of Internet use are also found among youths in the United States. In 2015, 92% of teenagers between the ages of 13 and 17 reported going online daily (Lenhart, 2015). The report showed that the accessibility to smartphones was a contributing factor to high percentage of Internet use among this age group. Much like adults in the United States, 71% of teenagers reported using at least one social media sites, with Facebook, Instagram, and Snapchat being the top three most-visited sites (Lenhart, 2015).

With the increased use and popularity of online social networking sites, scholars become increasingly interested in the effects of these sites on both online and offline individual behaviors. One area of interest is on understanding how the absence of visual cues in online communications affects individual and group behaviors and communication styles (Christopherson, 2007; Dubrovsky, Kiesler, & Sethna, 1991; Spears & Lea, 1994). Subsequently, scholars found evidence of positive effects from using online social media. Ellison and colleagues (2007) found Facebook use among college students positively correlated with three types of social capitals – bridging, boding, and maintained. The bridging social capital, measured in terms of one's extent of integration into willingness to support the university, is especially worth noting since one's weak ties can in return provide them with resources and information (Ellison, Steinfeld, & Lampe, 2007; Granovetter, 1983). These studies, along with the high proportions of social media use among teenagers and adults suggest that the continuous role of the Internet in facilitating changes within human interactions and communications.

Internet, Cybercrime, and Subculture

Despite the positive effects of Internet and online social media use, the extremely high rate of Internet use among the general adult population raises concerns. One negative effect of such high rate of Internet use among the general adult population is an increase in their probability of becoming a victim of cybercrime. There are various types of cybercrimes, best encapsulated by Wall (2001) as four different forms of behaviors: cyber trespass, cyber deceptions/thefts, cyber pornography/obscenity, and cyber violence. Cyber trespass refers to behaviors that involve unauthorized access to computers or systems. Cyber deceptions/thefts involve behaviors such as credit card frauds and intellectual property thefts. Cyber pornography/obscenity can include the digital distribution of pornographic materials; only some materials such as child pornography are illegal (Wall, 2001). Lastly, cyber violence refers to behaviors on cyberspace that can result in violent outcomes to individuals or groups in the physical world (Wall, 2001).

Of all four types of cybercrime, cyber trespass and cyber deceptions/thefts receive more scholarly and commercial attention because these cybercrimes inflict a multitude of costs and damages on businesses and individuals. According to Norton Cyber Security Insights Report for 2017, cybercrime victims worldwide suffer a loss of USD$172 billion due to compromised password, phishing, credit and debit card fraud, etc. (Symantec Corporation, 2018). In addition to financial losses, seven percent of all United States resident above the ages of 16 were victims of identity theft and suffered from emotional distress as a result (Harrell, 2017). Similarly, data breaches can result in direct and indirect losses to businesses in terms of lower stock prices (Cashell, Jackson, Jickling, & Webel, 2004).

By contrast, cyber pornography/obscenity and cyber violence receive less attention. Most studies on cyber pornography/obscenity focus on sexual deviant behaviors such as prostitution, pedophilia, and zoophilia, and highlight the role of the Internet in the creation of social support network (Holt & Bossler, 2014; Maratea, Screwing the Pooch: Legitimizing Accounts in a Zoophilia On-line Community, 2011; Milrod & Weitzer, 2012). Within the category of cyber violence, most scholars concentrate their efforts on topics such as online harassment and cyber bullying as opposed to the role of Internet in extremism and terrorism (Holt & Bossler, 2014). This may be a function of the increased prevalence of online harassment and cyberbullying among teenagers and young adults resulting from the connectedness afforded by the Internet and social media (Hinduja & Patchin, 2007; Li, 2007; Reyns, 2010). Such connectedness increases the convergence of potential offenders and victims (Reyns, 2010). In addition, cyber bullying causes an array of negative consequences, ranging from delinquicies (Hinduja & Patchin, 2007) to suicides (Hassan, 2016). These two factors contribute to the growth in scholarly attention on direct interpersonal form of cyber-violence.

Other sub-topics of cyberviolence such as online extremism and cyber-terrorism remain understudied. Earlier literature on online extremism and cyber-terrorism were theoretical or hypothetical and the discussions revolved around the impacts of cyber terrorists' attack on critical infrastructures, such as launching a denial-of-service attacks against government websites for the purpose of inducing terror, harm, or violence (Foltz, 2004; Furnell & Warren, 1999; Taylor et al., 2011). As current literature finds support for the role of the Internet in the organization of terrorist acts (Gerstenfeld et al., 2003; Gill et al., 2017; Holt et al., 2015) and the emergence of lone-wolf terrorists (McCauley & Moskalenko, Toward a Profile of Lone Wolf Terrorists: What Moves an Individual From Radical Opinion to Radical Action, 2014), there is an increasing need to focus on the simple communication of cyberviolence. Particularly, there is a need for research to further our knowledge on radicalization, which refers to the process through which an individual develops and/or accepts extreme ideologies and beliefs, because it marks the first stage in the transgression from extremism to terrorism (Borum, 2011).

One approach to understand radicalization is to consider extremist groups, especially online extremist groups, as subcultures. This approach is common in literature on understanding the development of values and norms in other subcultures such as various forms of sexual deviance (Holt, Blevins, & Kuhns, Examining Diffusion and Arrest Avoidance Practices Among Johns, 2014; Maratea, Screwing the Pooch: Legitimizing Accounts in a Zoophilia On-line Community, 2011; Milrod & Weitzer, 2012) and hacking (Holt, 2007; Jordan & Taylor, 1998; Kinkade, Bachmann, & Smith-Bachmann, 2013; Thomas, 2002). The reason for the subcultural approach is twofold. First, extremist groups, much like these subcultures, hold beliefs and norms that go against the broader society's norms and values (Freiburger & Crane, 2008; Gerstenfeld et al., 2003; Gill et al., 2017; Holt et al., 2015; Koehler, 2014, Weimann, 2004). Second, studies have shown that extremists use the Internet for similar functions as other subcultures. These functions include education, distribution of materials, research, and recruitment of new members (Freiburger & Crane, 2008; Gerstenfeld et al., 2003; Gill et al., 2017; Weimann, 2004).

Because of non-mainstream norms and values, individuals in subcultures rely on the Internet and cyberspace to develop communities and support network that would otherwise be impossible to do in the physical world (Maratea & Kavanaugh, 2012).These online communities serve as platforms for information sharing, recruitment, development of unique languages (Holt et al., 2014; Holt, 2007; Jordan & Taylor, 1998; Kinkade et al., 2013; Maratea, 2011; Milrod & Weitzer, 2012; Thomas, 2002). Several features of the Internet contribute to its popularity as a platform for subcultural groups. The first feature is the anonymous nature of the Internet, which is a result of the inherent lack of authentication needed to access to the Internet (Newman & Clarke, 2003). Anonymity greatly reduces the risks of detection by law enforcement agencies since online identities are not always tied to real offline identities. Additionally, social media and the Internet increase the diversity of the audience who can receive messages. Individuals can communicate with anyone around the world with no filter or engagement with traditional media.

Overall, similarities between online extremist groups and other online subcultural groups demonstrate the applicability of the subcultural approaches in understanding radicalization in the online context. However, extremism and radicalization differ from the process of socialization in other online subcultural groups. For one, a small portion of members who participate in online extremist groups undergo radicalization and accept ideologies that encourage the use of violence against others in the real world. This is known as the radicalization of action, which is distinct form the radicalization of opinion, since not all individuals who are radicalized act in violence and vice versa (McCauley & Moskalenko, Toward a Profile of Lone Wolf Terrorists: What Moves an Individual From Radical Opinion to Radical Action, 2014). In this sense, radicalization poses not only threats of violent terrorist acts, but also the spreading of extreme ideological beliefs. Such differentiation adds complexity to examining the role of the Internet in the radicalization process and calls to questions what factors contribute to the process both in terms of online and offline contexts.

Current studies on radicalization of jihadists and right-wing terrorists suggest variations in contributing factors to online radicalization. For example, Holt and colleagues (2015) found that victim videos and jihad videos played a role in leading to violent actions in their case studies. Gill and colleagues (2017) argued that there is a false dichotomy with online and offline radicalization processes since right-wing extremists who engaged in non-virtual network activities and interactions were more likely to use the Internet. In addition, right-wing extremists who associated with a wider network and attempted to recruit were more likely to use the Internet. When compared to jihadists, the authors found that right-wing extremists were significantly more likely to use the Internet (Gill et al., 2017). These results suggest variations in the functionality of the Internet among right-wing extremists. However, it is unclear the role of the Internet within the radicalization process.

These studies point to the need for further empirical studies on the radicalization process. Current literature on the role of the Internet among online extremist groups place an emphasis on how online extremist groups use the Internet, but it does not inform on the Internet's role in the radicalization process (Bowman-Grieve, 2009; Freiburger & Crane, 2008; Gerstenfeld et al., 2003; Gill et al., 2017; Hale, 2012; Holt et al., 2015; Koehler, 2014, Weimann, 2004). Given what we have known about the Internet and subcultural groups, it would be insightful to examine the radicalization process in online extremist groups given the similarities in the Internet's functions for subcultural groups such as hacker communities and online extremist groups. Such studies would allow us to determine whether radicalization occurs in online extremist groups, and if so, identifying the contributing factors and specific dynamics of the process.

Conclusion

Information and technology introduce us to convenience while simultaneously expose governments, businesses, and individual users to risks and threats (Holt, 2013; Newman & Clarke, 2003; Taylor et al., 2011; Wellman, et al., 1996). As society incorporates the Internet for individual, commercial, and national uses, the higher the probabilities of individuals becoming involved with or victims of cybercrime. This is especially true with the increased popularity of the Internet across subcultural groups due to the anonymous and far-reaching nature of the Internet (Holt, 2010; Newman & Clark, 2003). To many subcultural groups, the Internet serves the functions of recruitment, networking, and information sharing (Holt, 2007; Holt et al., 2014;

Jordan & Taylor, 1998; Kinkade et al., 2013; Maratea, 2011; Milrod & Weitzer, 2012; Thomas, 2002).

In the context of cyberiolence, specifically radicalization and extremism, online extremist groups are of interest. Online extremist groups are arguably like other subcultural groups, especially with regards to their use of the Internet. At the same time, some members of online extremist groups undergo an unique process known as radicalization (Borum, 2011; Conway, 2017; Ducol, Bouchard, Davies, Ouellet, & Neudecker, 2016; Mandel, 2009; Neumann, 2013). There are still debates on the role of the Internet in the radicalization process; specifically, 1) does radicalization occur in online contexts, and 2) what are the specific mechanisms and differences of violent online radicalization (Conway, 2017, p. 82). The purpose of this study is to provide insight on both questions through analyzing 27,404 posts collected between 2014 and 2015 from online extremist web forums, as well as social networks structures of these web forums.

To address these questions, this study utilizes the influence model of social network analysis. This study uses quantitative social network analyses because web forums function as online communities for members of the communistic nature of these online extremist web forums (Bowman-Grieve, 2009; De Koster & Houtman, 2008; Hale, 2012; Koehler, 2014). An influence model is appropriate for this study because it allows for a statistical model to identify changes in individuals' attitudes or behaviors as an outcome of social interactions among other possible predictive factors (Frank & Fahrbach, 1999). Findings from multiple forums will provide insight on factors that contribute to the process of radicalization and social learning experienced by online members. Knowledge on these factors would enable law enforcement agencies to develop countermeasures and intervention tactics.

CHAPTER 2: LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Recently, the far-right movement and extremist groups have gained media attention in the United States. One of the most notable events was a series of riots that occurred in 2017 in Charlottesville, Virginia. On August 11, 2017, supporters of white nationalists, neo-Nazis, and Ku Klux Klan (KKK) members came together at the University of Virginia for a white nationalist rally, “Unite the Right”, in response to a decision to remove a Confederate monument from a park (Park, 2017). However, the rally turned violent when rally attendees clashed with counter-protestors and a vehicle drove into a crowd marching through downtown and killed one protestor (Heim, Silverman, Shapiro, & Brown, 2017). These riots and subsequent violence brought to light the continued existence of right-wing extremism in the United States since the emergence of the KKK during the Civil War era (Mudde, 2018).

This link between the far-right movement and violent acts is not a new occurrence. Between 1955 and 1998, Hewitt (2000) found a total of 501 victims of domestic terrorist attacks. Of those victims, 176 individuals were victims in cases involving White Racist ideology and this count excluded 168 victims from the 1995 Oklahoma bombing (Hewitt, 2000), which is “the most lethal act of domestic terrorism ever perpetrated on American soil” (Michael, 2003, p. 107). Although the masterminds behind the Oklahoma bombing were not affiliated with any specific far-right groups, they were supporters of anti-government beliefs common among the Christian Identity and Militia movement within the far-right movement in the United States (Michael, 2003). With the recent events and political climate in the United States, the possibility for domestic terrorist act motivated by far-right ideologies is of concern.

To understand the link between far-right ideologies and domestic terrorist act, it is necessary to understand definitions of terrorism in the United States. The Federal Bureau of

Investigation (FBI) differentiates between international and domestic terrorism (Federal Bureau of Investigation, n.d.). The distinction between the two types of terrorism lies in the perpetrators; international terrorism involves individuals and/or groups related to foreign terrorist organization or nations whereas domestic terrorism involves individuals and/or groups related to movements based in the United States (Federal Bureau of Investigation, n.d.). The United States Department of Defense, on the other hand, defines terrorism as “the unlawful use of violence or threat of violence, often motivated by religious, political, or other ideological beliefs, to instill fear and coerce governments or societies in pursuit of goals that are usually political” (United States Department of Defense, 2017). These definitions differ in scope and emphasis, which may be reflective of the distinct missions of the government agencies. Nonetheless, these variations illustrate the severity and complexity of the threat of domestic terrorism.

Despite such variations, there are some commonalities across most formal definitions of terrorisms such as the use of illegal force and political motivations (Martin, 2006; United States Department of Defense, 2017). Martin (2006) suggests a comprehensive definition for terrorism based on existing definitions from various government agencies in the United States:

> Terrorism is a premeditated and unlawful act in which groups or agents or some principal engage in a threatened or actual use of force or violence against human or property targets. These groups or agents engage in this behavior intending the purposeful intimidation of governments or people to affect the policy or behavior with an underlying political objective. (p. 48)

This definition highlights the two components essential to defining a terrorist attack: the unlawful behavior and the intent of groups or agents with an underlying political objective. This definition accounts for the connection between political ideologies and violent acts, and the second component particularly highlights the role of the political ideologies in terrorism. In this context, current definition suggests the key in understanding the connection between far-right movement and domestic terrorism is understanding the development and acceptance of relevant political ideologies.

Given the recent connection between movement and violent acts in the United States, there is an increased effort to understanding the far-right political movement in the United States. One specific area of focus is the movement's dependence on and usage of the Internet and technology. This is a growing concern that the Internet allows for these groups to propagate their ideological belief to mass audiences (Newman & Clarke, 2003) and organizing terrorist acts (Gill, et al., 2017). Current literature focuses far-right extremist groups and their use of the Internet to create virtual communities for various purposes such as recruitment (Hale, 2012; Koehler, 2014; Lamberg, 2001; Levin, 2002) and networking (Bowman-Grieve, 2009; Futrell, Simi, & Gottschalk, 2006; Hale, 2012; Levin, 2002). These studies, however, do not address how the Internet plays a role in radicalization, which is the unique process through which one comes to accept and adopt ideologies (Borum, 2011; Conway, 2017; Ducol et al., 2016; Neumann, 2013). Thus, to minimize and prevent the possibilities of future violent events, it is essential that we understand the impacts of technology and the Internet on radicalization in the context of far-right extremism and terrorism in the United States.

Far-Right Extremism in the United States

Prior to discussing the relationships between the Internet and radicalization, it is necessary to understand the far-right extremist movement in the United States. At its core, extremism refers to non-mainstream opinions and ideologies, which includes a system of beliefs and ideas that range across political, social, economic, racial, and/or religious perspectives (Borum, 2011; Martin, 2006). The general categorizations of ideologies are right-wing, center, or left-wing, although the categories can be further broken down into seven categories: left fringe, far left, liberalism, moderate center, conservatism, far right, and fringe right (Martin, 2006). Based on this spectrum, ideologies from the left tend to include some Marxist ideologies, class and/or national components. Liberalism emphasizes on the governments play a positive role and that policies need to be made for the benefits of the societies. Moderate center is considered the middle point on the spectrum and is marked by consensus rather than change. Ideologies on the right side of the spectrum tend to focus on defending existing social order and traditional values with possible roots in race, nationality, and/or religion (Martin, 2006). The far-right movement is considered an extremist movement due to the categorization of their political ideologies and beliefs as well as intolerance towards opposing interests and ideologies (Martin, 2006).

These categories and spectrum, although common in academic discussion, do not fully reflect the variations and heterogeneity in real-world extremist movements. For example, Martin (2006) highlights the differences in far-right political movements in the United States and European countries, with movements in the former country having a stronger presence of grassroots organizations and the latter have a stronger representation and involvement in the government (pp. 39-40). In addition, far-right political movements in European countries seek different outcomes such as anti-welfare agenda and more open markets whereas far-right political movements in the United States have cultural, religious and/or racial undertones (Martin, 2006; Michael, 2003).

The far-right extremist movement has a long history in the United States. One of the earliest movements that gained substantial influence is the Know-Nothings movement (Michael, 2003; Mudde, 2018). This movement is characterized by its anti-immigration and xenophobic beliefs and ideologies against Irish and German Catholic immigrants (Michael, 2003; Mudde, 2018). The movement gained political influence, with 52 supporters of the movement in the House of Representatives (Mudde, 2018).

Another well-known group within the movement is the Ku Klux Klan (KKK). The KKK is an American right-wing organization founded in 1865 with emphasis on several extreme ideologies related to race and Protestant Christianity (Bowman-Grieve, 2009; Martin, 2006; Mudde, 2018). Its original intention was to target "African Americans, Northerners, and Southern collaborators" in the post-Civil war era (Martin, 2006, p. 457). Eventually, anti-Klan laws and the Union Army led to the dismantle of the organization (Martin, 2006). However, the organization continued to exist and underwent went several eras of changes. For example, in the 1920s, the KKK re-emerged after a film that romanticized the first era Klan as protectors of the White (Martin, 2006; Mudde, 2018). During this period, the organization was involved or inspired violent events around the nation resulting in the deaths of thousands of people (Martin, 2006). Currently, the KKK operates at regional and local level, and condones violent acts (Bowman-Grieve, 2009; Martin, 2006).

Despite similarities in racial undertones in ideological beliefs between the Know-Nothings movement and the KKK, the far-right movements in the United States have grown to be far more heterogenous and diverse. Several ideologies fall under the movement, with at least eight sub-groups present: 1) Christian identity, 2) holocaust denial, 3) Ku Klux Klan, 4) Militia, 5) neo-Nazi, 6) Posse Comitatus, 7) Skinhead, and 8) White Nationalist (Bowman-Grieve, 2009; Gerstenfeld et al., 2003; Michael, 2003).

The Militia and Posse Comitatus groups' ideologies are more focused on government and law (Michael, 2003). The Posse Comitatus views the county level government as the highest level and has a general distrust towards other government agencies and financial institutes (Michael, 2003). The Militia movement believes that the federal government is a threat to the Constitution and views the stocking and practice of military-grade weapons and training as appropriate protection measures (Michael, 2003).

By contrast, the Christian identity movement, the KKK, neo-Nazis, and the Skinheads hold the belief in the superiority of the White race with variations in origins (Bowman-Grieve, 2009; Michael, 2003). The Christian Identity and the neo-Nazi traced the superiority back to religious beliefs that Whites are the descendants of Adam and therefore the true chosen people of God (Bowman-Grieve, 2009; Martin, 2006). The Skinhead also hold similar beliefs on race, but do not share the same religious background and are more likely to engage in violent acts (Michael, 2003).

Despite ideological differences, there are some fundamental similarities across the far-right extremist groups in the United States. Bowman-Grieve (2009) identifies the following ideologies as common across the eight sub-groups: 1) emphasis on racial pride and protecting the White race from extinction, 2) belief in Zionist occupation government (ZOG), which is a belief that the Jews are in powerful positions to target the White race, 3) perception of non-White races as inferior, and 4) the inevitableness of a Racial Holy War (RAHOWA) (p. 995).

In addition to shared ideological beliefs and values, use of the Internet is another common feature among the far-right extremist groups. Much like other online subcultural groups, the Internet appeals to the far-right extremist groups because of its anonymous nature and capability to reach diverse and large audiences (Holt, 2010b; Newman & Clarke, 2003).

Studies have shown far-right groups' use of the Internet for various purposes ranging from recruitment to revenue generation (Bowman-Grieve, 2009; Futrell et al., 2006; Gerstenfeld et al., 2003; Hale, 2012; Lamberg, 2001; Lennings, Amon, Brummert, & Lennings, 2010). The Federal Bureau of Investigation (FBI) has also identified the Internet as a contributing factor to the changing landscape of terrorism (Federal Bureau of Investigation, n.d.). Of these identified purposes, three purposes merit further discussions as it pertains to the growth and sustainability of the movement: 1) recruitment, 2) information sharing, and 3) social network and online communities.

Recruitment. One of the major purposes of the Internet for far-right extremist groups in the United States is recruitment. In 1980s, a neo-Nazi publisher George Ditz created the first bulletin board system (BBS) dedicated to the movement and provided pro-Nazi and anti-Jewish messages and writings to users (Levin, 2002). One of the groups, Aryan Nations, specifically used BBS to assist with recruitment and communication. This suggests that right-wing extremists in the United States are aware of the benefits of the Internet and are early adopters of the technology for recruitment.

Today, these far-right extremist groups can easily use the Internet to reach out to teenagers and younger adults. Both sub-sets of the population are highly connected to the Internet (Koehler, 2014; Lenhart, 2015; Pew Research Center, 2018). As part of the recruitment effort, these groups offer age-appropriate resources; coloring books for children, and video games and hate music for teenagers (Lamberg, 2001). These extremist groups target such young audiences with the hope of achieving long-term persuasion effect through exposure to graphical or stereotypical information (Lennings et al., 2010)

In addition, the Internet is a platform for current supporters to aid potential recruits in identifying the motivation and recognizing the necessity for further engagement in the movement. For example, potential recruits can read about current supporters' awakening, or stories on how an individual became involved with movement, which help potential recruits relate to the process of developing a movement-related identity (Bowman-Grieve, 2009). The Internet also allows current supporters to coordinate efforts in offline recruitment efforts. An example is an offline campaign named "Project Schoolyard USA" where CD sampler with hate-music was distributed across locations such as schools, university campuses, shopping malls and parties (Hale, 2012).

Information sharing. The Internet also provides the movement with the benefit of information in a diffuse environment, which often overlaps with other purposive uses of technology. In the context of recruitment, potential recruits are exposed to their ideology and views in a simple fashion through online social media sites (Bowman-Grieve, 2009; Hale, 2012; Weimann, 2004). In terms of networking, potential recruits and current members access online communities that contain information, resources and personal stories (Bowman-Grieve, 2009; Hale, 2012; Holt et al., 2015; Koehler, 2014).

In the 1980s, information and messages were shared via BBS, and anyone with a computer and dial-up modem can access them (Levin, 2002). With the Internet, it also become easier to share a larger quantity of information as well as non-textual information such as videos and music (Costello, Hawdon, Ratliff, & Grantham, 2016; Futrell et al., 2006; Hale, 2012; Holt et al., 2015; Pauwels & Schils, 2016). Costello and colleagues (2016) found that of a sample of 1034 youth and young adult Internet users, 65% of were exposed to online extremism through sites such as Facebook, YouTube, and Twitter.

Compared to traditional text-based information and knowledge, the influences of these new media types on individuals are more powerful. Holt and colleagues (2015) found that videos play a role in the violent radicalization process while reviewing two case studies from the jihadist movement. Specifically, victim videos show emotional outrage and injustice to potential recruits, while jihad videos provide motivation and a sense of hope to viewers (Holt et al., 2015). When combined, these videos serve as great pull factors for individuals since it demonstrates both problem and solution to viewers.

Music also plays a prominent role in the far-right movement. Specifically, a music genre known as "hate rock" has been gaining popularity around the world and is used by right-wing extremists to introduce radical ideologies and beliefs to teenagers and adolescents (Hale, 2012). For supporters, various music festivals serve as offline gatherings and focal points at the local and national level (Futrell et al., 2006). Through the music and relevant festivals, supporters and recruits "articulate, materialize, reaffirm, and experience their commitment to the movement" (Futrell et al., 2006, p. 294). Within this scene, various stakeholders utilize the Internet – the fans use it for communication, the artists and record companies use it for advertisement and marketing (Futrell et al., 2006). With the Internet, groups within the far-right movement can appeal to a wider audience using information of various formats.

Social networks and online communities. Beyond information sharing, the Internet provides a platform for like-minded individuals to find one another. Bowman-Grieve (2009) argued that virtual spaces, despite the physical distance and lack of face-to-face interactions, allow for the growth of communities that create and sustain social relationships. Social network sites, forums, and other communications medias, like communities in the real world, have shared common values norms, and a sense of identity (Maratea & Kavanaugh, Deviant Identity in

Online Contexts: New Directives in the Study of a Classic Concept, 2012). They can also have profound influence on individuals' real-world behaviors.

An example of such a virtual community in the far-right movement is Stormfront, which was launched as a forum for planning and formation of political and social groups in April 1995 (Levin, 2002). Online forums are popular online platforms for virtual communities (Bowman-Grieve, 2009). Forums can be divided into various sub-section, with each sub-section comprised of threads (Holt, 2007; Mann & Sutton, 1998). Each thread contains a topic, and users, including the thread starter, can respond to it with posts. Forums also allow users to communicate via private messages (Yip, Webber, & Shadbolt, 2013). These features and structures make online forums an ideal location to facilitate the formation of social relationships and interactions among members.

Virtual communities serve as a platform that allows potential recruits and active members to create and solidify movement-related identities (Maratea & Kavanaugh, Deviant Identity in Online Contexts: New Directives in the Study of a Classic Concept, 2012). First, they allow users to share their personal stories of involvement, which include personal stories and perceived grievances or movement literature (Bowman-Grieve, 2009; Wojcieszak, 2010). Many users discuss their "awakening", which are personal stories where individuals share their process of involvement and commitment to the movement (Bowman-Grieve, 2009). These stories and literature can then serve as an inspiration or bonding moment for other users. Additionally, these stories may prompt others to reflect upon their own experiences and identify similarities between their experiences, which can further encourage potential and new users.

Other aspects of the communities also contribute to the process of formation and reinforcement of the sense of group identity. Individuals involved in the movement use specialized language when communicating online to refer to identity-related values and beliefs. In some forums, individuals use the number “18” to refer to Adolf Hitler since the letter “a” is the first in the alphabet and the letter “h” is the eighth. The purpose of such language is to create a sense of in-group identity (Hale, 2012); only individuals who are part of the movement and community can understand and therefore participate. This is very common to most other online subcultural groups such as online communities for johns (Blevins & Holt, 2009) and hackers (Holt, 2010a; Thomas, 2002). The use of such language act as a facilitator for self-identity and a source of network and social support for potential recruits or active members in the right-wing extremist movement.

Furthermore, Stormfront users discuss and share knowledge on integrating the movement with other aspects of life. For example, the community contains a dating section for White singles (Bowman-Grieve, 2009). By encouraging users to date others who are like-minded, the community assist users in developing a network and community of far-right extremists and movement supporters. Users also exchanged conversations on topics such as education, home-schooling, and music. In many ways, these online conversations and interactions dictate the offline interactions users have by encouraging interactions only with like-minded individuals. Such selective interactions reinforce a sense of group identity (Bowman-Grieve, 2009).

The Internet plays an undeniable role in the growth and continuance of far-right movement in the United States. It allows various subgroups to reach out to the general public, network with current and potential recruits, and creates group identities for active followers (Maratea & Kavanaugh, Deviant Identity in Online Contexts: New Directives in the Study of a Classic Concept, 2012). The benefits of the Internet bring to the movement are undeniable.

Despite the wealth of knowledge on the movement's use of the Internet, current studies do not address the fundamental question on the role of the Internet in the process of radicalization.

Radicalization: Theories and Framework

Understanding radicalization is essential given its role as pathways into extremism and terrorism. The connection between extremism and terrorism has shifted in the research community from extremism being a precursor to terrorist activity to a more non-linear relationship between the two (Borum, 2011; Martin, 2006). It is now acknowledged that there are other stages and processes between one's transition from extremism and terrorism, with specific attention being paid to radicalization, or the process through which an individual develops and/or accepts extreme ideologies and beliefs (Borum, 2011; Conway, 2017; Holt, Freilich, & Chermak, 2017; Mandel, 2009; McCauley & Moskalenko, 2008).

At the individual level, Martin (2006) recognized some common characteristics among individuals who hold extreme ideas and are violent: 1) intolerance, 2) moral absolutes, 3) broad conclusions, and 4) new language and conspiratorial beliefs. Intolerance refers to individuals' perceptions of the cause as being absolute good and just, and those in opposition of the cause is immediately perceived as being evil and bad. The second characteristic, moral absolutes, refers to one's view and approach to morality. Extremists tend to draw broad conclusions about their cause that often include simplified reasonings of the cause. They also do not allow for exceptions to the reasonings behind their cause. Lastly, new language and conspiratorial beliefs refer to the use of language and conspiracies to create a distinct in-group/out-group identities and conflicts between the extremists and their oppositions (Martin, 2006, pp. 43-45).

In general, there are multiple paths to extremism and violence for individuals. McCauley and Moskalenko (2008) identified twelve mechanisms of radicalization operating at three levels:

individual, group, and mass. At the individual level, individuals can become radicalized towards violence via personal victimization, political grievances, or joining a radical group. At the group level, radicalization towards violence occurs because of group polarization, isolation and threat, and various forms of competition. At the mass level, radicalization is seen as a result of conflict with an outgroup (McCauley & Moskalenko, 2008).

Borum (2011) also identified three promising theories of radicalization. Social movement theory (SMT) proposes that any organization's or movement's primary task is to maintain its survival, which is achieved through collecting and maintaining a body of collectors. Within SMT, there are two theories that influence the study of radicalization: a) new social movement (NSM) theory and b) resource mobilization (RM) theory. The NSM theory focuses on structural and macro-level processes, whereas the RM theory focuses on contextual processes. The second theoretical framework, social psychology, takes the group-level approach to understand the behaviors of extremists as a group. The last theoretical framework, conversion theory, focuses on the process of beliefs and ideologies transformation at the individual level. This theory is rooted in the sociology and psychology of religion. These proposed mechanisms and theories of radicalization illustrate the complexities of the process.

When examining radicalization, scholars need to decide at which level they wish to examine radicalization and which variables need to be considered. In addition, scholars need to decide the types of radicalization. McCauley and Moskalenko (2014), in their studies of lone wolf terrorists, found distinction between radicalization of opinions and radicalization of actions. The distinction points to the possibility for individuals to hold radicalized or extreme opinions but never engage in violent acts. Furthermore, it is possible for individuals involved in violent terrorist to act but hold no radicalized opinions (Holt et al., 2015). This distinction adds complexities in addressing the mechanisms and theories of radicalization.

Current research finds support for some of these mechanisms and theories in the far-right movement. Bowman-Grieve (2009) found accounts of awakening stories on Stormfront where users identified personal experiences and grievances as a pulling factor. This coincides with McCauley and Moskalenko’s (2008) individual-level mechanisms of radicalization of personal grievances. In an experiment, Warner (2010) found that respondents’ attitudes became more polarized in moderate and conservative conditions during which they were exposed to different media sources such as written articles, blogs, and videos on a political topic. The analyses controlled for variables such as political party affiliation and sex of respondents (Warner, 2010).

To some extent, the results from Warner’s (2010) experiment suggest that exposure to extreme materials in online environments can potentially lead to radicalization, However, the applicability of the experiment is limited given the level of exposure and the swiftness of the evaluation after exposure (O'Hara & Stevens, 2015). Even so, it is undeniable that the Internet affects the radicalization process as evident in research on far-right movements. Holt and colleagues (2017) suggested that the Internet acts a point of convergence for extremists’ radicalization process regardless of their initial start point, given the easy access and constant availability of the Internet.

Overall, the Internet affects the radicalization process by creating an environment that allows for polarization. This is due to the Internet being an echo chamber, which refers to an environment where individuals surround themselves with information that confirm their own beliefs, opinions, and views (Sunstein, 2007). According to Sunstein (2007), the Internet creates an online echo chamber for individuals and has detrimental effects for a democratic society because it undermines two main requirements: 1) the society must expose its citizens to various materials they would not otherwise choose, and 2) citizens of the society must share common experiences that enable mutual understanding and sympathy.

More specifically, Sunstein (2007) argued that it is the capacity for individuals to filter and personalize information and interactions online that is the root cause. Individuals are exposed to like-minded information and materials, which subsequently results in the creation of echo chamber (Sunstein, 2007). Within an echo chamber, groups consist of like-minded individuals mostly talk and listen to one another are likely to form (Sunstein, 2007). These homogeneous interactions are then likely to increase one's level of extremism due to group polarization where opinions tend to become more extreme in the original direction that group member favored after they participate in group discussions. Group polarization are more likely to occur with exacerbated effects if the members perceive themselves as "part of a group having a shared identity and a degree of solidarity" (Sunstein, 2007, p. 67).

Although the main objective of the argument pertains to oversight and regulation of the Internet, Sunstein (2007) recognized the danger of the echo chamber that is enabled by the Internet. It is even argued by some that echo chamber is a given in cyberspace (O'Hara & Stevens, 2015). This danger coincides with other radicalization mechanisms discussed in the context of extremism and terrorism. For example, McCauley and Moskalenko (2008) listed group polarization as one of the twelve mechanisms that addresses the radicalization process. Costello and colleagues (2016) also found that 31.8% of their sample of 1034 Internet users sought out extremist materials online and 14% of the sample encountered such material via the referral of a friend or acquaintance. In this sense, the danger of echo chamber participation and polarization is more prominent in online far-right groups.

The danger of echo chamber is further supported in current literature on the Internet and the far-right movement. Wojcieszak (2010) found that participants experienced increased positive feelings and support towards Hitler and racial violence after participation in an online neo-Nazi forum. Pauwels and Schils (2016) also found that active online exposure, such as engaging in discussions, was a stronger predictor of self-reported political violence towards property and persons compared to passive consumption of materials. These findings show support on the effects of online exposure to movement-related information and media and suggest that the Internet is an effective echo chamber for far-right movement in the United States.

Even with the supportive findings of the Internet as an effective echo chamber, the need to identify mechanisms through which online radicalization remains. Bouchard and Nash (2015) highlighted the lack of empirical evidence on the occurrence of online social networks for terrorists. Ducol and colleagues (2016) suggested that the Internet has differential effects on one's radicalization process. More importantly, in a review of current literature on violent radicalization, Conway (2017) stated that most current research on the relationship between the Internet and violent radicalization were descriptive in nature and mainly focused on the jihadist movement, and undermines the "what" and "why" approach to understanding the relationship.

In order to expand on current knowledge on the relationship between the Internet and the radicalization process, Conway (2017) puts forth two fundamental questions. The first question involves determining the possibility for radicalization to occur in an online context, and if such a possibility exists, does it contribute to violent radicalization (Conway, 2017, p. 82). The second question addresses the need to examine the mechanisms through which violent online radicalization, if it is proven to occur (Conway, 2017, p. 82). In this regard, any insight on these two questions would allow researchers to understand the specificities of the impact Internet has on extremism and terrorism and develop better counter-terrorism policies and agenda.

Of these two questions, the first question is easier to address as studies have shown partial evidence and support to the possibility of online radicalization (Bowman-Grieve, 2009; Gerstenfeld et al., 2003; Hale, 2012; Koehler, 2014; Lennings et al., 2010; Levin, 2002; Pauwels & Schils, 2016; Warner, 2010; Wojcieszak, 2010). Koehler (2014), via interviews with eight former German right-wing extremists, found that some of these extremists view the Internet as creating the perception that the movement is of critical mass and progressing towards its goals. This perception then increases members' sense of pride and activeness in the movement since it provides them with a sense of hope via participation (Koehler, 2014). In other words, participation in the movement via the Internet facilitates one's identification with and connection to the movement.

The current literature on this first question primarily attempts to distinguish between types of radicalization (McCauley & Moskalenko, 2014). Some studies illustrate support for correlation between the use of Internet and radicalization of actions (Koehler, 2014; Pauwels & Schils, 2016), while some shows support for correlation between the use and radicalization of opinions (Warner, 2010; Wojcieszak, 2010). Only Suttmoeller and colleagues (2018) found that the use of the Internet is a significant predictor of deaths for both violent and non-violent far-right groups. The findings demonstrate the importance of the Internet in both radicalization of opinions and violence at the group level. It is arguable that further empirical support on both is necessary since radicalization of opinions is crucial to the survival of the movement while radicalization of actions is crucial in understanding domestic terrorist act.

As for the second question on mechanisms of online radicalization, the literature is less certain. Qualitative analyses of online far-right forums suggest that awakening stories on these online forums are influential in one's decision of involvement (Bowman-Grieve, 2009; Wojcieszak, 2010). Wojcieszak's (2010) analysis of posts in online neo-Nazi forums found that individuals against the movement or on the fence were more likely to become a White nationalist after reading awakening stories and well-referenced discussions on White nationalism:

> Members mention reading 'the intelligently expressed posts' and refer to them as educational ('Thanks for the education ... I am proud to be associated with such astute White Nationalists', StormFront). (p. 644)

This fits well with McCauley and Moskalenko's (2008) individual radicalization by political grievance construct where individuals become radicalized due to political trends or events. McCauley and Moskalenko (2008) posited that it is likely for these individuals to be associated with a larger movement. Sunstein (2007) also suggested that members' perception of themselves within the group is likely to have an impact on the magnitude of group polarization's effects. Thus, it is necessary to take the group membership and dynamics into consideration when examining the mechanisms of online radicalization.

Another relevant radicalization mechanism is joining a radical group due to "the power of love" (McCauley & Moskalenko, 2008, p. 421). McCauley and Moskalenko (2008) suggested that individuals join radical groups because of social relations such as friendships with members in those groups, and those relations tend to intensify after group involvement due to common goals and threats. In his study, Wojcieszak (2010) examined the moderating effects of offline ties with similar and dissimilar political views. The results showed that both types of offline ties increase the effects of participation in online neo-Nazi forums, although the effects were weaker for politically similar offline ties. In other words, the effects of participation in online neo-Nazi forums were exacerbated for those exposed to offline ties with dissimilar political views. These findings lend support to the concept of echo chamber yet simultaneously illustrate the necessity to examine the processes that occur in online far-right forums that contribute to radicalization.

Applying Traditional Criminological Theory to Radicalization

The extremism and terrorism literature have merit in understanding the radicalization process, but it is relatively new and requires greater elaboration to address gaps in current literature. One gap in current radicalization theories appears to not account for the role of the Internet in the radicalization processes (Bouchard & Nash, 2015; Conway, 2017; Ducol et al., 2016). The traditional criminology theories may be able to provide the expansion, because of their use in accounting for various types of offenses. In addition, criminology theories have been consistently tested with deviant and offending behaviors in online settings (Holt & Bossler, 2014). Since terrorism is legally considered a crime (Federal Bureau of Investigation, n.d.; United States Department of Defense, 2017), the application of criminological theories can bring new perspectives to current knowledge on the role of the Internet in the radicalization process.

A theoretical framework from criminology that encompasses online group membership, group dynamics, and social relations is the social learning theory (SLT). The general proposition of the theory is that any behavior, whether criminal or non-criminal, is learned. Specifically, an individual is more likely to commit a criminal behavior when they associate with others who is favorable towards a behavior and commit the behavior. There are four main concepts to this theory: differential association, definition, differential reinforcement, and imitation (Akers, 2009).

Differential association refers to social ties through which one is exposed to norms, values and beliefs. These social ties can be one's primary group of family and/or friends, or it can be secondary and reference groups such as neighbors and authority figures (Akers, 2009, p. 60). Akers (2009) viewed differential association as the strongest component in the theory since it encompasses "other behavioral effects that go beyond and are not fully captured by reinforcement, modeling, and definitions … it can serve as a kind of summary or global index of all other unmeasured behavioral processes." (p. 65) This is true since differential association provides the social contexts for the other three components.

Differential association varies on four dimensions: frequency, duration, priority, and intensity. The first two dimensions are straightforward: priority refers to the temporal order of exposure to offenders. Interactions and ties from childhood carry more weight compared to later ones, and shape future associations. Intensity, on the other hand, refers to the prestige or significance of the associations to an individual (Akers, 2009). In other words, the more impactful associations on one's future behavior are those that one deems important, occur earlier, for more time, and more often.

Definitions encompass one's perceptions and attitudes towards a learned behavior. There are three different types of definitions: positive, negative and neutral. With criminal behavior, positive definitions are beliefs or attitudes that are favorable towards the behavior. Negative definitions are values, norms, and beliefs that discourage the criminal behavior. Lastly, neutral definitions refer to attitudes or beliefs that justify the criminal behavior (Akers, 2009). In addition to perception and attitudes, definitions also include techniques, motives, and rationalizations of a behavior (Akers, 2009). This component, along with differential association, appear to have the largest mean effect sizes in meta-analysis of studies using the theory (Pratt, et al., 2010).

The other two components, differential reinforcement and imitation, address the main learning processes. Differential reinforcement refers to the consequences, either real or perceived, that are associated with the learned behavior. This learning mechanism is modeled after operant conditioning from behavioral psychology (Akers, 2009). Rewards, or positive reinforcement, can increase the likelihood of one committing a behavior. Negative reinforcement, on the other hand, encourages a behavior because it allows one to avoid or escape from an unpleasant situation. Differential reinforcement can occur in social and non-social contexts. With social reinforcement, it refers to both rewards from others and rewards that are deemed valuable by the society. For example, money is seen as social reinforcement despite it being a non-social reward because we learned from the society and others that money is valuable. As for non-social reinforcement, it is limited to the physiological reactions that one experienced when committing a behavior. An example would be the physiological responses associated with the use of drug (Akers, 2009).

Lastly, imitation addresses the learning process through observation of others' behaviors (Akers, 2009). Akers (2009) posited that imitation is more relevant to learning about a new behavior as opposed to maintaining or ending the behavior. Imitation with the most impact on one’s learning process is most likely to occur with others within a person’s primary group. Recent advances in technology led Akers (2009) to suggest that the mass media can be a source for imitation, but the effects are considered weaker because the effects of imitation is weaker than differential reinforcement. In this sense, mass media can be conceptualized as a reference group.

Although the SLT hypothesizes about one's probability of engaging in a behavior, it is a suitable theory for examining radicalization. With the radicalization of action, the SLT accounts for one's social interactions and the impacts these interactions have on one's behaviors. The theory has been suggested as a framework for understanding the recruitment process of terrorist groups (Freiburger & Crane, 2008). Specifically, Freiburger and Crane (2008) discussed how the four components of the SLT interact with each other to draw individuals into a terrorist group. For example, terrorist groups often reach out and establish relationships with second-generation individuals. To recruit these individuals, terrorist groups then use the Internet to create positive and favorable images of themselves and the cause (Freiburger & Crane, 2008). Although the study did not provide empirical support, the authors' use of the SLT as a framework for the recruitment process of terrorist groups suggests the suitability of the theory in studies of terrorism and extremism.

In addition, Pauwels and Schils (2016) tested the SLT on the relationship between exposure to extremist content in new social media and self-reported political violence among Belgian teenagers. The findings showed that active search for violent extremist content, participating in online discussions about extremism, and exposure to violent extremist content were predictive of self-reported violence towards property and persons. These predictors remained significant after controlling for strains, individual traits, and peer influences. This study suggests the applicability of the SLT to understand the process of radicalization in the online context (Pauwels & Schils, 2016). Altogether, both studies suggest that the theory can be used to examine one's radicalization process while taking learning processes, social relationships, and network dynamic into account.

The theory seems less relevant to the radicalization of opinions as the theory emphasizes on behaviors. To examine one's changes in attitudes, definitional acceptance must be used as an outcome variable rather than an independent variable. Although unconventional, it is a plausible dependent variable given Akers's (2009) discussion on differential association providing the social contexts for the other three theoretical components. In this sense, the theory is suitable for examining the radicalization of opinions for two reasons. First, it allows scholars to isolate the impacts of a specific group of individuals and reference groups. For example, it enables scholars to test several mechanisms, such as the slippery slope and the power of love, proposed by McCauley and Moskalenko (2008). This allows for network dynamics to be taken into consideration.

Second, the theory is compatible with the views that the Internet is an echo chamber. The Internet and current technology allow individuals to expose themselves to and interact with like-minded others. The theory accounts for such autonomy and agency by recognizing that one's choice of association dictates one's exposure to definitions, reinforcement, and models for imitation. This is evident in the digital piracy literature where peer association is a consistent and significant predictor across studies (Holt & Copes, 2010; Miller & Morris, 2016; Skinner & Fream, 1997). Furthermore, Miller and Morris (2016) found that the influence of online peers operate in similar manners as offline peers. Thus, the SLT allows for the examination of the effects of online social ties on changes in attitudes. In particular, the theory allows for assessing the effects of one's participation and interactions in the cyberspace and online forums on the radicalization of opinions.

Research Question

Conway's (2017) call for further studies on violent radicalization highlights the necessity to focus on two fundamental questions: 1) do online radicalization occurs and 2) how online radicalizations occur. This study aims to address both questions in the context of online far-right extremists forums. Specifically, the current study examines if participation in online far-right forums contributes to the radicalization of opinions using the SLT.

This study makes two assumptions as to human behavior and the radicalization process. First, this study takes the approach that radicalization is a gradual and dynamic process. This is evident in the case studies by Holt and colleagues (2015). Individuals from two case studies began with exposure to extremist beliefs, experienced change in self-identities, and ultimately decided to act on behalf of the movement (Holt et al., 2015). Current literature also indicates the possibility for individuals to de-escalate from the process (Koehler, 2014). By viewing the radicalization process as a gradual process, it allows for studies to understand the specific factors and mechanisms that facilitate or halt the process.

The second assumption is that users who participate in online far-right extremism communities have already begun their radicalization process. This is rooted in the echo chamber and fragmentation theses (Sunstein, 2007; Warner, 2010). Individuals who are registered users and participate in online extremist forums are assumed to have made the choice to surround themselves with such materials. This assumption is also rooted in studies that suggest variations in users' purposes for joining online communities (Bowman-Grieve, 2009). For example, new users come to online extremist forums for information and support (Bowman-Grieve, 2009), while current movement supporters utilize the online platform for information sharing and revenue generation (Bowman-Grieve, 2009; Hale, 2012). All of these studies propose that users on online far-right extremist forums are potentially at various stages of the radicalization process. Given that radicalization is defined as the process through which an individual develops and/or accepts extreme ideologies and beliefs (Borum, 2011; Mandel, 2009; McCauley & Moskalenko, 2008), it is highly likely for users in these online forums to have substantial difference in ideological beliefs and commitment to the movement.

With these two assumptions, we can address Conway's (2017) questions by focusing on the online radicalization of opinions since it allows us to view the Internet as a tool and a space where social connections do develop. This potential difference does not hinder our ability to understand online radicalization process. The current study aims to determine whether radicalization occurs, and if it does, the mechanisms of the process, in online far-right extremist forums. To address the question, we used the main theoretical concepts from the SLT as the guiding theoretical frameworks for understanding the online learning process and the effects of social influence. With data from seven online far-right extremist forums, this study determines if users' changes in ideological beliefs is a function of social interactions with other members in the forums, as well as other SLT variables, using social network analysis.

CHAPTER 3: METHODOLOGY

Description of the Dataset

Data for this analysis was based on a set of 27,404 posts derived from online web forums operated by and for individuals with an interest in the ideological far-right both in the United States and other nations. Web forums are a form of computer mediated communication that allow individuals to connect and discuss their resources and needs. Forums are composed of threads, which begin when an individual creates a post where they describe a product or service, ask a question, give an opinion, or simply share past experiences. Others respond to the initial post with posts of their own to create a thread that running conversation or dialogue. Thus, threads are composed of posts that center on a specific topic under a forum's general heading. Since posters respond to other users, the exchanges present in the threads of a forum may "resemble a kind of marathon focused discussion group" (Mann & Sutton, 1998, p. 210).

The forums included in this dataset were selected on the basis of their population size and tie to offline real-world groups. Forums with both large and small user populations were identified to represent the range of forums currently operating online. Similarly, forums that were explicitly linked to a real-world group were selected as were ideologically expressive, but non-affiliated sites. Five forums were identified via google searches whose names were the same as prominent national or international groups that have physical meetings offline, such as the Ku Klux Klan, and stated they were operated by these groups.

Three forums were also identified that had no specific group link but whose names or keywords were linked to far-right ideologies. Specifically, a google search was conducted using common key terms used within the far right including "white power 1488 forum." The principal investigators of the grant actively selected the resulting forums on the basis that the content focused solely on white nationalism and traditional far right ideologies rather than a single thread within a larger unrelated forum. Choosing these sites enabled a way to compare the presence or absence of expression of ideological ideas based on ties to a real-world group (see Table 3.1).

Table 3.1. Description of Forums

Forums	Relations to Real World Groups	Sub-forums	Date of First Post	Date of Last Post	No. of Threads	No. of Users
Forum 1	Yes	Yes	02/12/2008	02/03/2015	131	293
Forum 2	Yes	Yes	11/08/2008	09/16/2015	1454	927
Forum 3	Yes	Yes	11/24/2005	02/26/2015	303	443
Forum 4	No	No	10/29/2010	03/05/2015	130	45
Forum 5	Yes	Yes	01/10/2010	04/29/2015	906	250
Forum 6	No	Yes	10/26/2001	03/20/2015	1331	829
Forum 7	No	No	04/01/2011	04/22/2015	103	65

In addition, the researchers gathered threads from various subforums within each forum site. Subforums are specialized sections within a given forum that focus on a specific topic of interest, such as humor, technology, or science. This study specifically oversampled on subforums related to technology, gender, or general interest content so as to understand the extent to which ideological expression is present in posts that may not have a direct link to an ideological agenda. This would enable an examination of the degree to which ideological beliefs are always promoted by participants, even when discussing issues that are potentially removed from ideological concerns.

All data were collected during 2014 and 2015, with all threads from each selected forum and subforum saved as html files for analysis. The content of each post was then read and coded by hand by undergraduate and graduate students in order to determine the extent to which ideological messaging was present in each post. The unit of analysis for this study is at the level of users as we are evaluating their changes in attitudes over time. This is achieved by coding the content of each post and aggregating the information for each user during specified time period. Table 3.2 provides the breakdown for each forum's time points and average post per year. Although the time points varied across forums as the dates of collected threads differed across forums, the length between each time point was set to one year. This length was chosen because it allows for aggregation of content for each user.

Table 3.2. Time Points and Annual Average Posts by Forums

Forums	No. of Time Points	Total No. of Posts	Average Posts (per Year)	Total No. of Posts with Ideological Content	Average Post with Ideological Content (per Year)
Forum 1	7	936	117	625	78.12
Forum 2	8	10192	1132.44	7622	846.89
Forum 3	11	1947	177	1438	130.72
Forum 4	6	1378	229.67	771	128.5
Forum 5	7	6544	934.86	3199	457
Forum 6	15	6113	407.53	2625	175
Forum 7	5	297	49.5	269	44.83

Data from seven far-right forums are included for this study. Of the seven forums, two forums have no sub-forums, and four forums have no ties to real world far-right groups. Dates of the collected posts range between 2001 and 2015. These forums also varied in the number of threads, with the Forum 2 having the largest number (1454) and the Forum 7 having the smallest (103). With regards to the number of users, the Forum 2 again have the highest (927) while the

Forum 4 has the smallest number of users (45) during this time period. Please see Table 3.1 for further information on all seven forums.

The dataset has two limitations due to its format. First, the dataset captures public interactions on the forums via threads and posts. It does not account for interactions via private messages or offline interactions and therefore cannot address dynamics beyond those observed from the threads. This dataset does capture public display of attitudes and therefore allows for examination on the radicalization process in the forums. Second, the dataset does not examine social network and dynamics from the users' perspective. There can potentially be discrepancies between users' identifications of friends and frequency of interactions in general versus the public interactions captured by the dataset. Despite these limitations, the dataset is still suitable for the study because it contains information on social network, dynamics, and interactions among users within each forum.

Data Entry and Coding

Data for this study were coded by trained undergraduate and graduate students. Posts from each thread were read and coded into the database. For each post, coders enter information on its ideological content and social dynamics. For the ideology dataset, each post is coded for the number of times the following beliefs were mentioned: 1) conspiracy, 2) xenophobic, 3) anti-government, 4) anti-tax, 5) survivalist, 6) anti-gun control, 7) anti-lesbian, gay, bisexual, transgender, and queer (anti-LGBTQ), 8) anti-African American, 9) anti-Latino, 10) anti-immigrant, 11) anti-Jewish, 12) anti-Catholic, and 13) anti-Islamic.

In addition, the coders coded for users' indication of offline participation, the use of movement-related usernames, the use of movement-related signatures, and self-claiming statements of being supporters of the movement. All these variables were entered as binary. Dates of the posts and respective thread titles are also entered into this dataset.

With the social network dataset, coding also occurred at the post-level. For each post, the coder determines if the post is a “seeker” or a “helper”. A “seeker” post is an inquiry post where a user asks a question or for help from fellow members. It is given the annotation of “i”. A helper post is a content post where information is shared, and it is given the annotation of “i'”. The shared information can be general content, such as a link to a news article, or response to another user’s post. When the helper quoted another user (User A) directly, the interaction is coded between the helper and User A. If the helper’s post is a general post to the thread, then the interaction is coded between the helper and the original thread poster because it is impossible to determine the number of posts read by the helper prior to his/her response. Although the helper is potentially influenced by other posts in the thread, it is challenging to identify the specific post(s) without direct quotes. This approach captures active interactions and exchanges between users, as well as the frequencies of interactions between specific pair of users. Dates of posts and respective thread titles are also entered into the dataset.

Three user attributes were coded in addition to interactions. Users’ status in the forum was captured in multiple aspects - administrator, moderator, common member, and guest – and all of these are coded as binary measures. For users with any named or ranked status, the actual name or status is coded under “Special Status”. Users’ activities in the forum were measured in terms of the number of threads users had started and their joining dates. The former is also recoded into a binary variable to determine if the user has started a thread in the forum. Users’ demographic information included geographic location and gender when available. Gender was coded based on username and user’s interactions with fellow members. For example, if User B praises User A's abilities with raising her children, then User A's gender is coded "0" for females.

Once coded, the ideology and social network datasets were then merged to create a complete dataset for each forum. To do so, we aggregated the ideological beliefs for each user across time and entered the aggregated value as one measure under an individual's attributes. This was achieved through the matching of usernames. The coded information on dates and posts allow for aggregation of ideological beliefs for specific time periods. Please refer to Table 3.2 for the total number of points within each forum.

Analytic Strategy

To address the two proposed research questions, repeated measures analysis of variance (RM-ANOVA) and social network analysis was chosen to analyze the collected content from online extremist web forums. RM-ANOVA is highly suitable for measuring within-subject changes, especially when multiple measurements on one specific variable were taken from the same group of subjects (Howell, 2004; Lix & Keselman, 2010). Since ideological beliefs were aggregated by each year, RM-ANOVA is suitable for determining if there is any significant change in the mean level of ideological beliefs within each forums between time points. The results provide preliminary evidence on the occurrence of radicalization of opinions in online forums.

To explore changes at the user-level, social network analysis is utilized. Social network analysis has evolved from methods to a discipline that focuses on understanding the relationships between social structures and allocation of resources within them (Wellman, 1988). It is often applied to understand a specific social structure over a given period using statistical models, and thus encompasses characteristics commonly associated with qualitative and quantitative methods

(Breiger, 2004). Social network analysis was chosen because these web forums are virtual communities that allows for active participation and social interactions between members (Bowman-Grieve, 2009). This specific feature meets a critical assumption of social network analysis – interdependency between members (Breiger, 2004). In other words, users' interactions with others embedded in the online social structures have an impact on their far-right ideological beliefs and involvement in the movement.

Social network analysis is increasingly being applied to understand social science research questions. Borgatti and colleagues (2009) discussed how various types of social network theories and concepts can be applied to social science research. For example, it is possible to understand one's social capital by examining their ties to others and positions in their social networks (Borgatti, Mehra, Brass, & Labianca, 2009). In the context of terrorism and extremism, Bouchard and Nash (2015) proposed that the social network approach adds to current literature by: 1) adding to current knowledge on the impact of social ties and networks on the radicalization process; 2) allowing researchers to explore the organizational structures and dynamics of terrorist networks without any presumption; and 3) identifying possible points for intervention and assessing effects of counter-terrorism measures.

Researchers in the field of terrorism and extremism have been using social network analysis to advance current knowledge on organization structures and dynamics of terrorist groups. Burris and colleagues (2000) studied the interconnections between 80 White supremacist sites and found that the websites were relatively decentralized and isolated from mainstream political and religious groups. Xu and colleagues (2009) found that the Global Salafi Jihad (GSJ) network underwent three distinct stages in the evolution of the network: emerging, maturing, and disintegrating. They identified the stages by examining the network's average degree and degree distribution over time; degree is a network concept that refers to the number of ties an actor has. Sullivan (2015) utilized two-mode social network analysis and network cluster analysis to understand behaviors and network dynamics of far-right extremists involve in the anti-tax movement. The results indicated that two-thirds of financial schemes linked to the anti-tax movement were committed by lone wolves, and most of these schemes were motivated by far-right ideologies. The cluster analysis showed that there were six cohesive groups within his sample, and two of these subgroups had ties to larger anti-tax organizations. All three studies illustrate the compatibility of social network analysis in identifying organizational structures and dynamics of online terrorist and extremist groups.

With the current study, it is necessary to incorporate other existing models of social network analysis as the aim is to understand the radicalization of opinions in online contexts. One possible approach is examining patterns of interactions and influences. Frank and Fahrbach (1999) utilized two models, influence and selection, to understand the relationship between individual-level interactions and the formation of organization culture. The model of influence addresses the changes in an individual's attitude or behavior as a result of interactions with others. The changes can occur because of accumulation of information, or conformity to group norms (Frank & Fahrbach, 1999). The model of selection, on the other hand, addresses an individual's choice on who to interact with, which can be based on the motivation to seek new information or based on similar attitudes (Frank & Fahrbach, 1999).

For this study, the model of influence is utilized as the research question pertains to the effects of interactions on users' attitudinal changes in online far-right forums. The social influence model is highly suitable for three reasons. First, the model of influence allows us to examine the impact of participation in online far-right extremis forums on radicalization process.

Second, the influence model is consistently employed by scholars from various fields to examine the effects of social networks on behaviors and attitudes. Frank and colleagues (2004) used the social influence model to understand the adoption of computer technology among teachers. Using social capital as the guiding framework, the authors found that informal access to expertise (i.e. other teachers) and perceived social pressure are significant predictors of teachers' decisions on technology use in classrooms (Frank, Zhao, & Borman, 2004). Although the study focused on behavioral changes, it demonstrates the applicability of the social influence model in understanding the effects of social influences on individuals.

Third, the social influence model allows us to address each theoretical concept of the social learning theory (SLT). This is true since the social influence model is a regression model with the inclusion of a network factor (Frank & Fahrbach, Organization Culture as a Complex System, 1999). The network factor in the model corresponds to differential association and definition of the SLT since it captures the number of interactions between user pairs, as well as the definitions of the user that one had interacted with. This allows us to determine if and how active interactions with users in online extremist web forums affects one's far-right ideological beliefs. Furthermore, the SLT is highly compatible with proposed mechanism of change through the accumulation of information (Frank & Fahrbach, 1999).

Thus, to address the second research question on the mechanisms of online radicalization, the analytic strategy is to analyze the within- and full-forum datasets using the social influence model. Given the heterogeneity of far-right ideologies (Bowman-Grieve, 2009; Gerstenfeld et al., 2003; Michael, 2003), multiple variable structures are used for analyses within each forum. Since the social influence model measures changes in attitudes and/or behaviors over time (Frank & Fahrbach, 1999; Frank et al., 2004), it is necessary to establish different timepoints for analysis (See Table 3.2). Despite the difference in timepoints, the basic social influence model for all analyses can be represented as a multivariate regression model:

$$EI_{it} = \rho \sum_{i'=1}^{n} DA_{ii'_{t-1 \to t}} EI_{i'_{t-1}} \times RK_{i'_{t-1}} + \gamma_1 DR_{i_{t-1}} + \gamma_2 IM_{i_{t-1}} + \gamma_3 PT_{i_{t-1}} + \gamma_4 EI_{i_{t-1}}$$
$$+ \gamma_5 TS_{i_{t-1}} + \gamma_6 SC_{i_{t-1}} + \gamma_7 NE_{i_{t-1}}$$

The first variable in the equation ($\sum_{i'=1}^{n} DA_{ii'_{t-1 \to t}} EI_{i'_{t-1}} \times RK_{i'_{t-1}}$) is the network term unique to the social influence model. This model aims to identify factors that contribute to the attitudes of user i at time t. The variables are discussed in detail in the following section.

The model is applied to time frames within each forum and across all forums. A total of 46 models were conducted. The reason for the lower number of models compared to the total number of time frames is twofold. First, there was an absence of data in two forums. In Forum 1, there were no data from year 2012 and therefore it is impossible to predict users' attitudes for year 2013. Instead, data from year 2011 was used. In Forum 6, there were no social interaction from year 2001 and no data from year 2002. As a result, the multivariate regression model was not performed for those two years. Second, there were lack of variations in users' attitudes in year 2008 for Forum 1 and Forum 2. Variables from the 48 models were then compiled together to create an full-forum data file and the social influence model was performed using this file.

In addition to the social network analysis, sensitivity analyses were conducted for all social influence models within this study. The purpose of sensitivity analysis is to understand the level of biases that needed to have occurred to invalidate findings (Frank, Maroulis, Duong, & Kelcey, 2013). This is expressed as the percentages or numbers of cases from the sample that needed to be replaced to invalidate findings. If a significant effect requires a large number of case replacement to invalidate, it is safe to conclude that the finding is fairly robust.

Dependent variable. The dependent variable for this study is expressed extremist ideology at time t (EI_{it}). The content in each post was coded using content analysis techniques to quantify the appearance of key terms, phrases, and imagery using a modified version of typology derived from Kerodal, Freilich and Chermak (2016) to assess ideologies of far-right groups. Multiple variable structures are used given the results of reliability and factor analyses. The Cronbach's alpha of the original 13 items is 0.413, which suggests the items are not highly correlated. Factor analysis was then performed to determine if there are dimensions among the 13 items at the post-level (See Table 3.3). The results indicated five components, but only two of the five components fit with the current literature on far-right ideologies within the United States.

Table 3.3. Factor Analysis for Dependent Variable

	Component				
	1	2	3	4	5
Conspirational		.544	-.379		
Xenophobic	.770				
Anti-Gov't	.304	.597			
Anti-Tax		.327	.332		
Survivalist				.515	.365
Anti-Gun Control		.419			
Anti-African American	.439	-.397		.419	
Anti-Latino	.458		.409		
Anti-Immigrant	.429		.424	-.432	
Anti-LGBTQ					-.718
Anti-Jewish Sentiment	.478		-.569		
Anti-Catholic					.547
Anti-Islamic				-.455	

The first component included the following items: xenophobic, anti-Latino, anti-African American, anti-immigrant, and anti- Jewish. These items clustered around racial beliefs that are common in some far-right extremist groups such as the Ku Klux Clan (Bowman-Grieve, 2009; Michael, 2003). The second component included three items: conspirational, anti-government, and anti-gun control. The second component contained core ideological beliefs that complement the Militia and Posse Comitatus groups. However, the remaining three components do not fit well with any far-right extremist sub-groups. For example, the fifth component included anti-LGBTQ and anti-Catholic but the correlation for anti-LGBTQ was negative.

Given that the social influence model is conducted at the user-level, reliability test was reconducted after aggregating ideological posts for all users. The Cronbach's alpha is relatively high (α = 0.803), indicating a high reliability of this measurement for the dependent variable. As such, all 13 items were used to measure users' extreme far-right ideological beliefs for all analyses.

Independent variables. There are four independent variables for this study. Each of the independent variable corresponds to the four theoretical components of the SLT. The first component is differential association ($\sum_{i'=1}^{n} DA_{ii'_{t-1} \to t} EI_{i'_{t-1}} \times RK_{i'_{t-1}}$), which is also referred to as the exposure term. Since there are various modalities to differential association (Akers, 2009), this variable is measured as the number of interactions between user pairs during the specified time frame weighted by the ranking of the user i' ($RK_{i'_{t-1}}$). This measurement accounts for the frequency and intensity of association (Akers, 2009). In other words, the attitudes of users with higher ranking and more frequently interacted with would exert more influence on user i.

The number of interactions refer to instances where user *i* has responded to another user's post. The response can occur in one of the following manners: 1) a direct response where user *i* quoted the post of another user, 2) a response where user *i* did not directly quote but is responding to the topic of the thread, and 3) a response to another user within a thread but did not use direct quote. With the second instance, the interaction is attributed to the thread starter. These interactions are conceptualizations of social ties between users since they capture the flow of information, in this case far-right ideological beliefs and values, between specific pairs of users.

With differential association, it is necessary to account for the unique nature of online communication. Not only does online communication transcends physical boundaries, it also transcends over temporal limits due to the asynchronous nature of online communication (Wellman, 1997). Most of the coded social interactions between users occur during time *t-1*. In other words, both users posted during time *t-1*. Nevertheless, there were interactions during which a user responded to content posted in earlier time frames, such as time *t-2*. For example, during time *t-1*, User C responded to User A's post from time *t-2*. As a result, the ideological coding for User A's post from time *t-2* is included in the analysis for time *t-1* because User C was exposed to that post during time *t-1*.

Definition ($EI_{i'_{t-1}}$) is measured as the extreme far-right beliefs of user i' with whom user i had interacted with during the specified time frame. This variable is measured in the same manner as the dependent variable, but during time *t-1*. This allows us to take the peer group's definitions into consideration when examining their influence.

The ranking of the user i' ($RK_{i'_{t-1}}$) is measured as categorical variable to account for variations in forums' hierarchical structures. For example, Forum 4 has five levels of ranks: administrators, approved members, probationary members, no title, and banned. On the other hand, Forum 1 included German military ranks such as Oberstleutnant and Obergrenadier in addition to common web forum rank status such as administrators and moderators. As a result, Forum 1 had 15 rank levels. Across all seven forums, administrator is measured the highest rank across all seven forums and the ranking starts with "1", which indicates the lowest rank. The lowest rank for five forums is "Banned", while it is "Guest" for Forum 5 and "On Leave, Gone" for Forum 7.

Differential reinforcement ($DR_{i_{t-1}}$) is measured as the in-degree of user i. The in-degree is defined as the number of in-coming connections and/or nominations from other users and is a partial component of degree centrality (Wasserman & Faust, 1994). Differential reinforcement refers to the consequences, either real or perceived, that are associated with the behavior at question (Akers, 2009). In this context, responses from other users are seen as positive reinforcement because it is a proxy for understanding social support within these online communities. This is due to the nature of online forums where most social interactions are carried out via public posts or private messages (Bowman-Grieve, 2009; De Koster & Houtman, 2008). Thus, receiving responses from other users are an indicator of how well users are integrated into the communities (Bowman-Grieve, 2009; De Koster & Houtman, 2008). Specifically, the more responses received by users, the higher the chance of the individual to experience radicalization.

Imitation ($IM_{i_{t-1}}$) is measured with two items: movement-related username and movement-related signature imagery. Both items are binary variables. Movement-related username measures if a user has a username that contains symbols, words, and/or phrases related to the far-right movement. For example, usernames such as "John1488" would be coded as "1" because it contains movement-related symbols: "88" is generally known as "Hail Hitler" as "h" is the eighth alphabet (Hale, 2012). As for movement-related signature imagery, it measures if a user included movement-related pictures as part of his/her signature. A signature on a forum post functions much like a signature in real-life, where it appears at the end or bottom of a post.

These two items are appropriate measures for imitation because it reflects users' attachment to far-right ideologies, which is an indicator of their online identities within these forums (De Koster & Houtman, 2008). Moreover, images used by far-right movement are directly linked to the core ideologies (Chambers, 2015). Users' inclusion of such images can then be seen as attempts to mimic other members' expression of ideologies in forums. Both aspects address Akers's definition of imitation - the learning process through observation of others' behavior (Akers, 2009). As such, both measurements are included for the variable of imitation.

Control variables. The study has five control variables for the model within each forum: 1) users' length of participation, 2) number of threads started by users, 3) users' claim as supporter 4) user's prior attitude and 5) if user i experienced exposure.

Users' length of participation ($PT_{i_{t-1}}$) is measured by the number of months between the user's registration date to time *t*. For users who did not have a registration date, such as guests, the date of the first post was used as a proxy for determining length of participation. Users who registered at time *t-1* are including in subsequent models from time *t* and onward.

This variable accounts for users' length of exposure and interaction within a forum. It is likely that the longer a user has been a member of a forum, the more in-degree he/she will receive given the user's assumed seniority. For newer members, they are encouraged to ask questions and seek out new information while the older members provide knowledge (Bowman-Grieve, 2009).This distinction between old and new members is a feature of online communities that highlight the importance of active involvement and participation (Bowman-Grieve, 2009). In addition, the longer length of participation can be correlated with an increased integration of movement-related beliefs into one's online identity as radicalization happens gradually (Borum, 2011; Holt, Freilich, Chermak, & McCauley, 2015; Koehler, 2014; McCauley & Moskalenko, 2008). Thus, by controlling for length of participation, it ensures that any found effect of the theoretical components is not residual of other factors.

The second control variable is the number of threads started by user i ($TS_{i_{t-1}}$). This variable measure one's willingness to take actions after deciding to become a registered member on online far-right forums. This is measured as the number of threads started by user i at time *t-1*. This variable is a proxy measure for racial awakening because users are encouraged by the forums to be involved in the communities (Bowman-Grieve, 2009; De Koster & Houtman, 2008). In addition, users who had experienced stigmatization offline are drawn to the anonymity and freedom of expression on these forums (De Koster & Houtman, 2008). Thus, measuring the number of threads started are appropriate for users' investment and attachment to far-right ideologies and movement.

The third control variable is users' claim as supporter of the movement($SC_{i_{t-1}}$). This control variable is included to account for the possibility of variations in users' experiences of radicalization. This is one of the two assumptions of the current study and is rooted in the echo chamber and fragmentation theses (Sunstein, 2007; Warner, 2010). Users who publicly claim to be a supporter on far-right extremist forums may have distinct reasons and purposes for participating in the forums (De Koster & Houtman, 2008). Another reason to control for users' self-claiming behavior is because users who made such claims may be less likely to be impacted by social learning processes. Differential associations, differential reinforcement and imitation have stronger impacts on the obtainment of new belief compared to the maintenance of an existing belief (Akers, 2009). Controlling this variable allows us to better identify the effects of social learning theory on online radicalization process.

The fourth control variable is the attitude of user i at time *t-2* ($EI_{i_{t-1}}$), or users' prior beliefs. An exception to this measurement is for the first model within all forums. Rather than using the attitude of user *i* at time *t-1*, these models include the attitude of user *i* at time *t* due to the lack of data from time *t-1*. It is necessary to control for prior definition because it controls for the effects of prior associations within differential association (Akers, 2009). Akers (2009) suggests that earlier associations with family members or peers can condition future associations. For example, individuals exposed to law-abiding definitions during their childhood are less likely to meet those who hold non-law-abiding definitions (Akers, 2009). In addition, controlling for prior definition accounts for dependencies that result from an individual's decision to interaction with similar-others (Steglich, Snijders, & Pearson, 2010). Thus, to assess the influence of participation in online far-right forums, it is necessary to control for user's initial attitude.

The fifth control variable measures the exposure experienced by user *i* during time *t-1* ($NE_{i_{t-1}}$). This is a binary variable where "1" indicates that user *i* has not experienced any exposure at time *t-1*. In other words, users who had posted in a thread or responded directly to another user's post during time t-1 id coded as "0" because they were exposed to content in the forums. The inclusion of this control variable is to distinguish between two types users with an exposure term of zero. The first type of users included users who had posted but was exposed to non-ideological content. The second type refers to users who did not post at all during time *t-1*. This binary variable allows us to measure if passive involvement in forums contribute to radicalization.

For the full-forum models, additional control variables were included to control for fixed-effects. These variables are binary variables for years and forums were included. The year of 2009 and Forum 5 were chosen as reference groups. The year of 2009 was selected because it was the second year with models from all seven forum. As for Forum 5, it was chosen as the reference group because it is the medium on the number of users and threads compared to other forums. Forum 5 also has a well-known offline association. By using Forum 5 as the reference group, it provides some insight on the online and offline dynamics between forums. Lastly, there is a binary variable that measures whether a forum has offline associations ($RL_{i_{t-1}}$). As a result, the social influence model for the full-forum model is represented as follow:

$$\begin{aligned} EI_{it} = {} & \rho \sum_{i'=1}^{n} DA_{ii'_{t-1} \to t} EI_{i'_{t-1}} \times RK_{i'_{t-1}} + \gamma_1 DR_{i_{t-1}} + \gamma_2 IM_{i_{t-1}} + \gamma_3 PT_{i_{t-1}} + \gamma_4 EI_{i_{t-1}} \\ & + \gamma_5 TS_{i_{t-1}} + \gamma_6 SC_{i_{t-1}} + \gamma_7 NE_{i_{t-1}} + \gamma_8 RL_{i_{t-1}} + \gamma_9 Year2003_{i_{t-1}} \\ & + \gamma_{10} Year2004_{i_{t-1}} + \gamma_{11} Year2005_{i_{t-1}} + \gamma_{12} Year2006_{i_{t-1}} \\ & + \gamma_{13} Year2007_{i_{t-1}} + \gamma_{14} Year2008_{i_{t-1}} + \gamma_{15} Year2010_{i_{t-1}} \\ & + \gamma_{16} Year2011_{i_{t-1}} + \gamma_{17} Year2012_{i_{t-1}} + \gamma_{18} Year2013_{i_{t-1}} \\ & + \gamma_{19} Year2014_{i_{t-1}} + \gamma_{19} Forum1_{i_{t-1}} + \gamma_{20} Forum2_{i_{t-1}} + \gamma_{21} Forum3_{i_{t-1}} \\ & + \gamma_{22} Forum4_{i_{t-1}} + \gamma_{23} Forum6_{i_{t-1}} + \gamma_{24} Forum7_{i_{t-1}} \end{aligned}$$

CHAPTER 4: ANALYSIS AND FINDING

A total of seven forums were included for the analyses. Across all seven forums, there were a total of 2,851 users and 27,407 posts spanning from 2001 to 2015. Of the total posts, 60.3% of the posts, or 16,531 posts, contained far-right ideological content. See Table 4.1 for breakdowns on posts with far-right ideological content for all forums. It is worth noting that of the 2,851 users, there were 44 users with the same name across all forums. Within this group of 44 users, three appeared in three forums, while the remaining users appeared in two forums. Since no identifiable information regarding participants was collected, it is impossible to determine if these accounts were made by the same individual or if they were simple coincidences in naming conventions related to the far-right movement (i.e. Bob1488).

The discussions of analysis results are divided into two sections. In the first section, the discussion is based on models within forums. The second section focuses on results from the full-forum models. There are two issues to note regarding the analyses and results. The first is that in order to examine the effects of the independent and control variables, cases with missing information on any of the variables were excluded from each model. This resulted in smaller sample populations included in the analysis than the total number of users present at each time point because users who had yet to join the forum were excluded. For example, if User C and User D joined the forum at time T2, they would be excluded from the model at T1. Second, variables were transformed using the natural log function. For repeated-measures analysis of variance (RM-ANOVA), users' ideological beliefs were transformed due to their skewness. For all social influence models, the exposure term was transformed due to skewness as well.

Table 4.1. Breakdowns of Ideological Beliefs across Forums

Forum	Total No. of Posts	No. of Posts with Ideological Content	Percentage
Forum 1	936	625	66.8
Forum 2	10192	7622	74.8
Forum 3	1947	1433	73.6
Forum 4	1378	767	55.7
Forum 5	6544	3189	48.7
Forum 6	6113	2626	43.0
Forum 7	297	269	90.6

Within-Forum Models

Forum 1. Forum 1 was one of the four forums with links to real-world groups. It contains sub-forums and a total of 293 users. Figure 4.1 illustrates all social interactions that took place between 2008 and 2015. Each circle represents a user in the forum. The size of the circle represents their ideological beliefs; the larger the circle, the more radicalized a user is. Users that did not post any far-right content are represented with no circle. It is important to note that in this context, radicalization can refer to a user diversifying in their far-right ideological beliefs or becoming more extreme within one specific belief such as anti-Jewish sentiment. The mean of user-level aggregated ideological beliefs was 0.99, with a standard deviation of 2.33 and maximum value of 19. For this forum, there was some dispersion with ideological beliefs, but most users expressed a minimal level of extreme ideological beliefs.

To determine if extreme ideological beliefs differed between time points, a repeated-measures analysis of variance (RM-ANOVA) was utilized. The results of the RM-ANOVA, with a Greenhouse-Geisser correction due to violation of sphericity assumption, determined that the mean of extreme ideological beliefs for Forum 1 differed statistically significantly between time points ($p < 0.01$). Post hoc tests using the Bonferroni correlation indicated that the mean of far-right ideological beliefs was significantly higher at T1 compared to all other time points. This suggests a general decreasing trend in extreme far-right ideological beliefs for Forum 1.

Figure 4.1. Social Interactions among Users in Forum 1 (2008 – 2015)

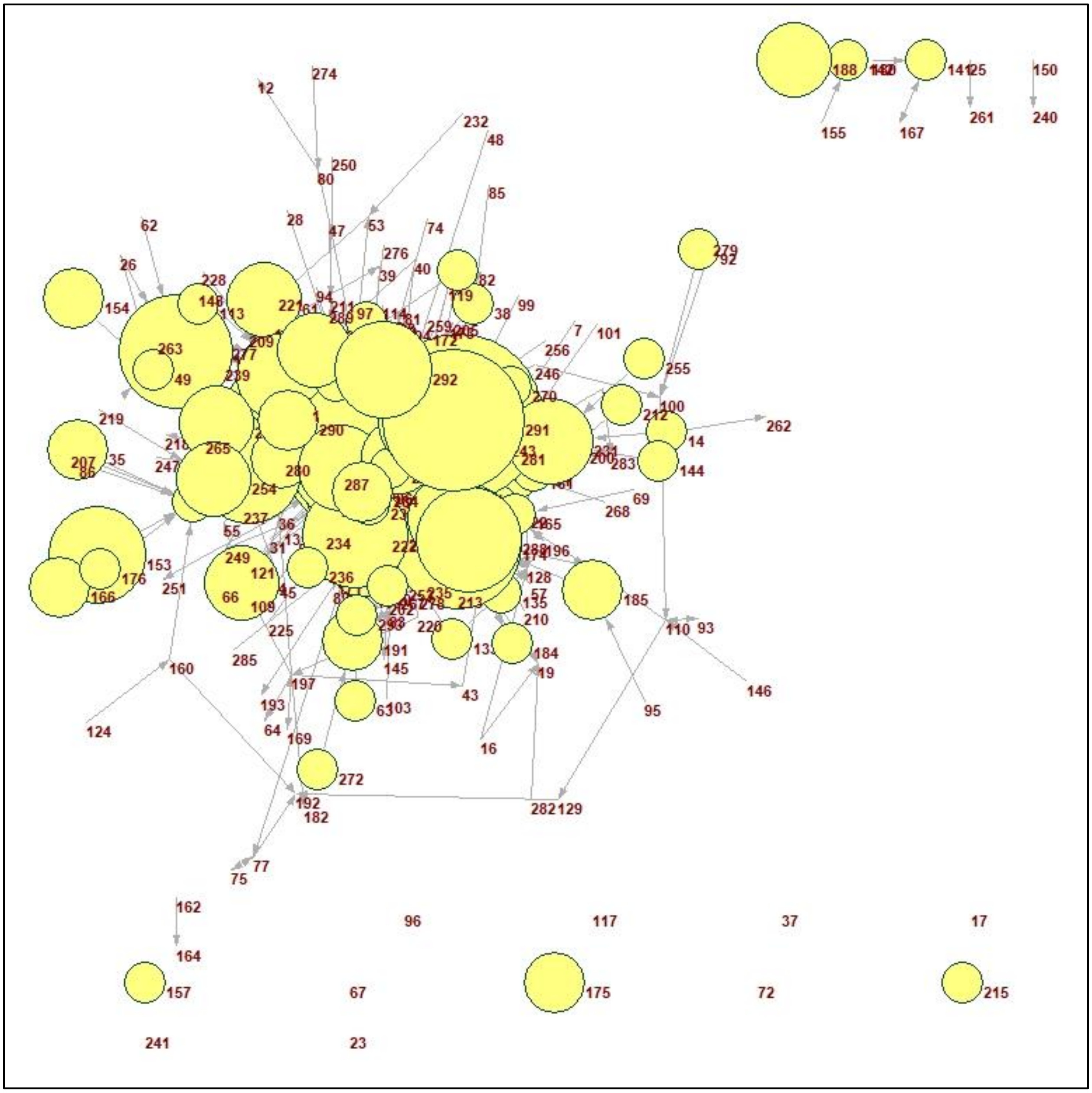


Table 4.2. Social Influence Models for Forum 1

	Model T1			Model T2			Model T3		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.056	0.046	1.773	0.002	0.011	1.633			
In-Degree	-0.02	0.019	2.215	0.001	0.006	1.548	0.008	0.025	3.136
Movement Image	-0.267	0.167	1.138	-0.005	0.035	1.618	0.024	0.08	5.292
Movement Name	0.005	0.167	1.168	0.003	0.036	1.411	0.022	0.072	5.67
Control									
Length	-0.002	0.007	1.121	-0.002	0.001	1.07	-0.001**	0	1.248
No. Thread Started	-0.310*	0.132	1.516	-0.004	0.023	1.378	-0.045	0.042	3.804
Self-Claim	-0.145	0.251	1.378	0.001	0.074	1.226			
Prior Beliefs	0.199**	0.045	1.571	-0.002	0.007	1.048	-0.001	0.002	1.003
No Exposure	0.264	0.197	1.375	0.024	0.033	2.005	-0.007	0.03	1.656
Constant	0.154	0.137		0.026	0.034		0.038	0.032	
R-Square	0.38			0.114			0.168		
N	196			263			275		

Note. *$p < 0.05$, **$p < 0.01$

Table 4.2. (cont'd)

	Model T4			Model T6		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure				0.307	0.354	7.218
In-Degree	-0.003	0.021	4.423	0.37	0.506	6.587
Movement Image	-0.006	0.04	2.573	-0.172	0.553	4.491
Movement Name	-0.009	0.05	1.355	-0.222	0.569	2.392
Control						
Length	-0.001*	0	1.131	-0.001	0.003	1.438
No. Thread Started	-0.004	0.047	3.612	0.344	0.426	2.663
Self-Claim						
Prior Beliefs	-0.005	0.02	1.007	-0.081	0.524	1.017
No Exposure	0.008	0.031	2.331	0.669	0.725	9.606
Constant	0.026	0.033		-0.56	0.736	
R-Square		0.133			0.129	
N		277			286	

Note. *$p < 0.05$, **$p < 0.01$

A total of six models were ran for this forum (see Table 4.2). There was one model where the time span was two years instead of one due to the lack of posts from 2005. The last model (T7-T8) was excluded from Table 4.2 because there was no post with far-right ideological content during T8. For all models, collinearity diagnostics were performed. All VIF values were under 10, which is the acceptable threshold for multicollinearity diagnostics (Myers, 1990).

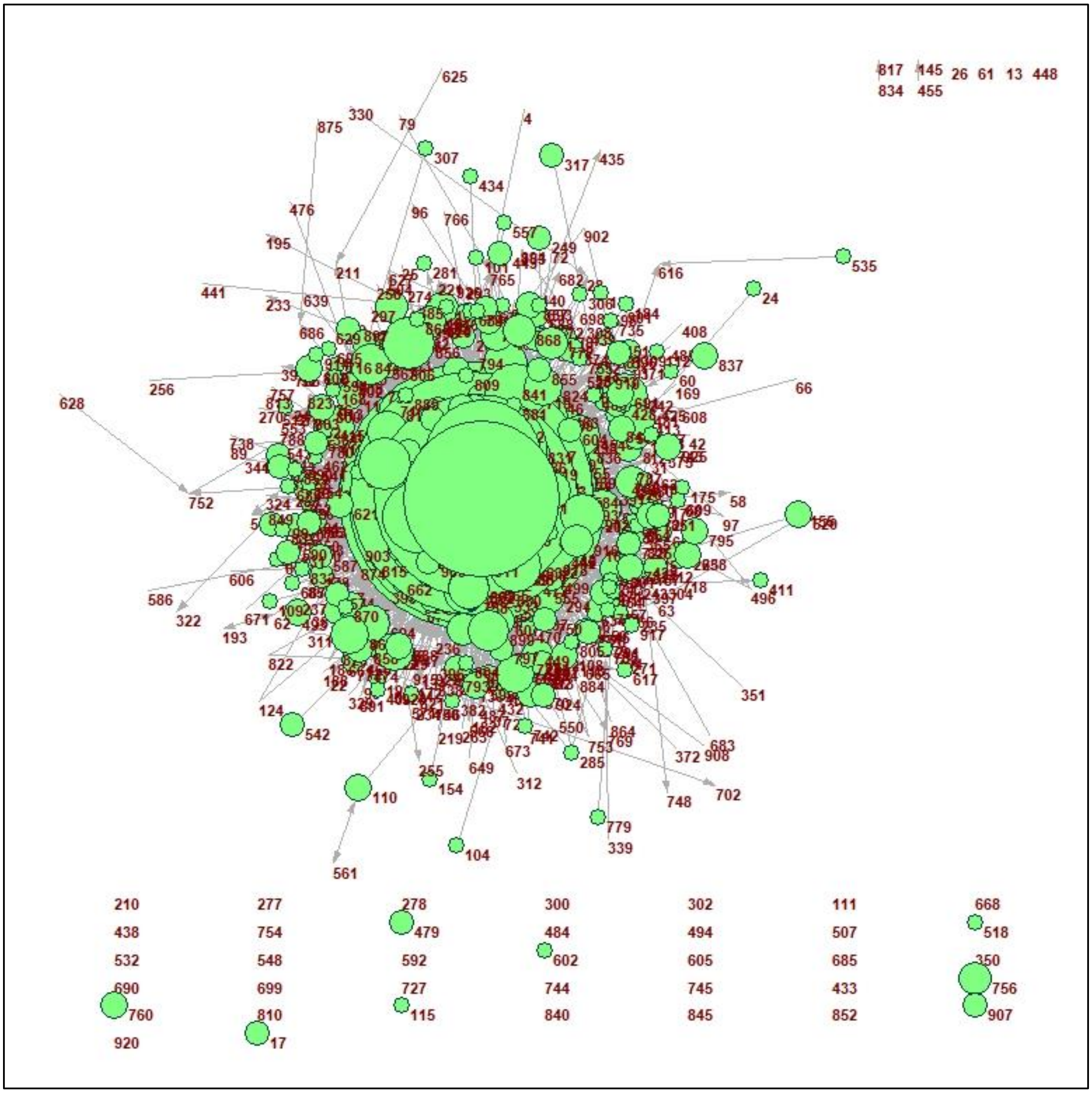
Across all models, none of the independent variables were statistically significant. For Models T3 and T4, differential association was excluded from the analysis due to the lack of correlations. This showed that social interaction and learning was not a contributing factor to predicting users' ideological beliefs during those time points.

As for control variables, length of participation, number of threads started, and users' prior beliefs were statistically significant at different time points. In Model T1, the correlation for the number of threads started was in the opposite direction. Another control variable that was significant in Model T1 was users' prior beliefs. The significant results of these variables indicated that users with higher prior beliefs and started less threads were more likely to have higher extreme ideological beliefs in T2. The third control variable, users' length of participation, was significant in Models T3 and T4, indicating that users who participated longer in the forum expressed less extreme ideological beliefs during those years.

Forum 2. Forum 2 was also tied to a real-world group, contained sub-forums, and had the highest number of users and threads. Figure 4.2 illustrates all social interactions that took place between 2008 and 2015. The mean of the user-level aggregated beliefs was 5.22, with a standard deviation of 17.103 and a maximum value of 250. This indicates a high level of dispersion in the data. In other words, users with high levels of extreme ideological beliefs and users with no or minimal expressed beliefs frequented this forum. In addition, Forum 2 had the highest mean, which indicates that this forum was more extreme in their expression of far-right ideological beliefs.

To determine if extreme ideological beliefs differed between time points, RM-ANOVA was utilized. The results of the RM-ANOVA with a Greenhouse-Geisser correction determined that the mean of extreme ideological beliefs for Forum 2 varied statistically and significantly between time points ($p < 0.01$). Post hoc tests using the Bonferroni correlation indicated that the mean of extreme far-right ideological beliefs was significantly lower at T1 when compared to time points T2 to T7. Time point T8 was the exception; the mean far-right ideological beliefs at T8 was significantly lower than T1. This suggests that online radicalization occurred within Forum 2 during the eight-year period.

Figure 4.2. Social Interactions among Users in Forum 2 (2008 – 2015)



A total of seven models were ran for this forum. The last model was excluded for this forum due to lack of variation in extreme ideological beliefs at T8 (see Table 4.3). For all models, collinearity diagnostics were performed. The VIF values for differential reinforcement in Models T2 and T5 were greater than 10, indicating potential multicollinearity issues.

The statistical correlations may be a result of the exposure term and users' in-degree, which was a proxy measure for differential reinforcement. Users' in-degree refers to the number of in-coming connections and/or nominations from users. Exposure, on the other hand, includes the number of interactions users have with others as part of its calculation. It is possible for both measures to be correlated with each other since individuals with higher in-degree are likely to have more frequent interactions with other users. For Models T2 and T5, separate analyses were performed where the number of threads started was excluded from the model to correct for the issue of multicollinearity in the models (see Table 4.3a). The modified models yielded similar results except for Model T5a where users' prior beliefs became significant.

The results across models showed support for the social learning theory (SLT). Differential association was significant in two of the five models, demonstrating that users' changes in attitudes were influenced by users they interacted with. In Model T3, differential association had the highest beta value while it had the third highest beta value in Model T6. The support for differential reinforcement was stronger; it was significant across all five models. With Forum 2, the correlations for both variables were positive, which indicated that users who interacted with more radical individuals and received more responses were more likely to hold extreme beliefs in the following year.

Table 4.3. Social Influence Models for Forum 2

	Model T1			Model T2			Model T3		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	-1.169	1.922	2.278	0.614	0.330	2.976	0.727**	0.252	4.264
In-Degree	1.935**	0.715	3.755	0.348**	0.114	13.742	0.160**	0.059	5.787
Movement Image	-4.772	6.254	1.633	-0.785	1.584	1.373	3.240**	1.033	1.486
Movement Name	1.477	5.820	1.414	0.478	1.456	1.226	-0.782	0.979	1.280
Control									
Length	2.323	5.334	1.418	-0.074	0.147	1.199	-0.224**	0.060	1.278
No. Thread Started	-10.062*	4.185	2.96	0.05	0.641	13.38	-0.310	0.237	4.236
Self-Claim	-9.745	17.658	1.072	-2.999	3.951	1.027	-2.465	2.822	1.021
Prior Beliefs	0.651	1.138	1.512	0.766	0.534	1.167	0.029	0.064	1.786
No Exposure	-3.510	5.627	1.438	2.844	2.291	2.870	4.654**	1.521	3.592
Constant	7.159	4.760		-1.939	2.240		-0.882	1.463	
R-Square	0.436			0.655			0.378		
N	57			221			451		

Note: *$p < 0.05$, **$p < 0.01$

Table 4.3. (cont'd)

	Model T4			Model T5			Model T6		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.078	0.08	4.345	-0.101	0.065	6.483	0.159**	0.032	3.14
In-Degree	0.118**	0.024	6.048	0.147**	0.026	13.432	0.135**	0.017	3.403
Movement Image	1.700**	0.396	2.112	0.213	0.23	2.069	0.468**	0.146	2.431
Movement Name	-0.969**	0.367	1.575	-0.119	0.208	1.464	-0.055	0.13	1.72
Control									
Length	-0.02	0.012	1.277	-0.003	0.005	1.283	-0.006**	0.002	1.226
No. Thread Started	-0.173	0.135	5.306	-0.265**	0.053	11.757	-0.536**	0.08	2.946
Self-Claim	0.294	0.576	1.092	-0.438	0.46	1.053	-0.202	0.671	1.024
Prior Beliefs	0.035*	0.015	1.217	0.015	0.009	1.242	-0.020*	0.009	1.083
No Exposure	0.421	0.515	4.584	-0.392	0.318	5.444	0.506**	0.136	3.228
Constant	0.04	0.498		0.576	0.311		-0.212	0.135	
R-Square	0.489			0.285			0.44		
N	614			751			856		

Note: $*p < 0.05$, $**p < 0.01$

Table 4.3a. Modified Social Influence Models for Forum 2

	Model T2a			Model T5a		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	0.616	0.329	2.966	0.008	0.062	5.765
In-Degree	0.356**	0.035	1.281	0.024**	0.008	1.209
Movement Image	-0.796	1.575	1.362	0.218	0.234	2.068
Movement Name	0.484	1.451	1.222	-0.062	0.212	1.46
Control						
Length	-0.074	0.147	1.197	-0.001	0.005	1.278
No. Thread Started						
Self-Claim	-3.032	3.919	1.015	-0.49	0.467	1.052
Prior Beliefs	0.757	0.521	1.117	0.028**	0.009	1.155
No Exposure	2.851	2.284	2.866	-0.142	0.319	5.31
Constant	-1.94	2.235		0.266	0.309	
R-Square		0.655			0.223	
N		221			751	

Note: *$p < 0.05$, **$p < 0.01$

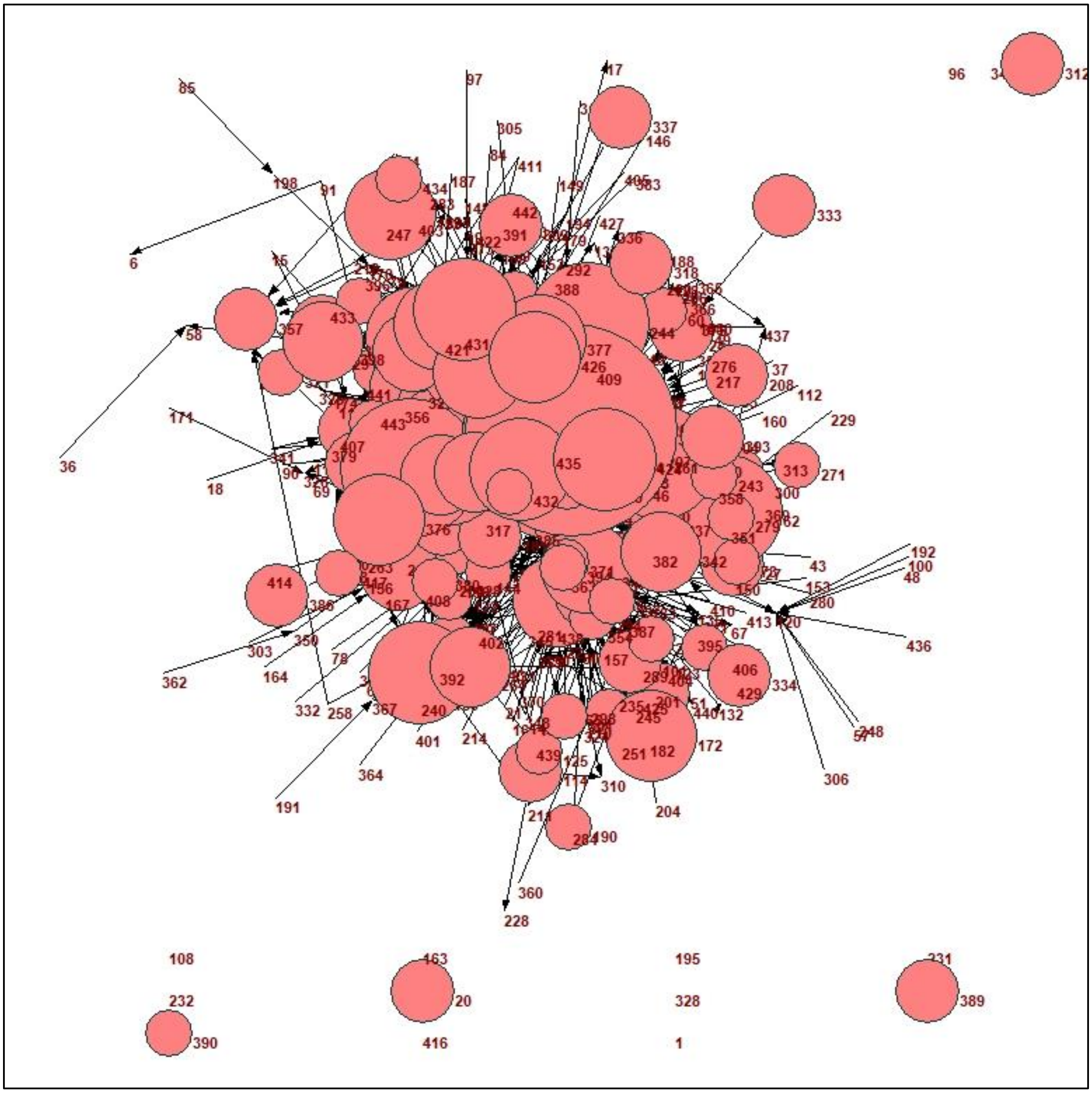
Imitation, measured as the use of movement-related images and usernames, was also significant in Models T3, T4 and T6. The results demonstrated that users with movement-related imagery in their posts were more likely to have extreme ideological beliefs. The use of movement-related usernames was, however, significant in the opposite direction in Model T4, suggesting that users with movement-related usernames at T4 were less likely to hold extreme ideological beliefs. For the modified models, the use of movement-related image and username did not reach significance.

As for control variables, four of the five control variables were significant in at least one model. The number of threads started by users was significant in three models, but with mixed direction. Users' prior beliefs was significant in three models; the correlation was negative in one model while positive in the remaining two models. On the other hand, users' length of participation was negative and significant in two models. The findings showed that older members of the forum experienced less radicalization. As for the absence of exposure, it was significant in Models T3 and T6. In both models, users who were not exposed to other users' content were significantly more likely than those who did to express more extreme beliefs in the following year.

Forum 3. Forum 3 was also associated with real-world groups, contained sub-forums, and had 443 users and 303 threads. Figure 4.3 illustrates the social interactions of all users between 2005 and 2015. For extreme ideological beliefs, the mean was 1, with a standard deviation of 2.552 and a maximum value of 21. This indicates some level of dispersion in the data. Despite the forum having a fairly large number of users, most users appeared to hold comparable level of extreme ideological beliefs.

The results of the RM-ANOVA with a Greenhouse-Geisser correction determined that the mean of extreme ideological beliefs for Forum 3 differed statistically significantly between time points ($p < 0.01$). Post hoc tests using the Bonferroni correlation indicated that the mean of extreme far-right ideological beliefs was significantly lower at T1 when compared to time points T2 to T4; there was an upward trend in the mean level of expressed ideological beliefs during this time period. The peak occurred at time point T4, followed by a sharp decrease at time point T5. The decrease in expressed ideological beliefs persisted from T5 onwards, with the mean far-right ideological beliefs at T8 being significantly lower than T1. This suggests that online radicalization occurred within Forum 3, but over a shorter period of time.

Figure 4.3. Social Interactions among Users in Forum 3 (2005 – 2015)



A total of nine models were conducted for this forum (see Table 4.4). Collinearity diagnostics indicated multicollinearity issues with Model T1, Model T9 and Model T10 where the VIF values for differential reinforcement were greater than 10. For all three time points, the model was modified and re-ran. The results are included in Table 4.4a. There were minor differences between results from the two models. Differential association was significant at the

0.01 level in Model T1 but only at the 0.05 level in Model T1a. There was also a decrease in R-squared value in Model T1a, which suggested that the modified model is a poorer fit compared to Model T1. In Model T9a, the exclusion of the number of threads started by users resulted in all other variables reaching statistical significance but the direction of correlations in Model T9a were the same as Model T9. There was also a decrease in R-squared. With Model T10, two different modifications were made. Model T10b fits the data better given its high R-squared values ($R^2 = 0.993$). In this model, both measures of imitation were no longer significant.

Results of the nine models showed general support for the SLT as a framework for radicalization. Differential association was overall a positive and significant predictor in five models and negatively significant in three models, including Models T9a. These significant findings tended to occur at later time points and regardless of the findings of other SLT and control variables. The results lent some support on the effect of differential influence within the forum, despite the contradiction in the direction of correlation from year to year.

Different reinforcement, on the other hand, was overall negatively correlated to the dependent variable, with two exceptions of significant positive correlation in Model T3 and Model T9a. This indicated that as users' number of received responses increased, their expressed extreme ideological beliefs decreased. The correlation did not correspond to the existing literature on social interactions within online far-right forums (Bowman-Grieve, 2009; De Koster & Houtman, 2008). This result may be affected by the content of the received posts. If users in this forum receive more negative responses, they may be less likely to experience an increase in extreme ideological beliefs due to the lack of social support received.

As for imitation, the use of movement-related images and usernames were significant predictors for models beyond T6. There were two exceptions. First, the use of movement-related usernames did not reach significant in Model T7. Second, both items for imitation failed to reach statistical significance in Model T10b. The results showed that users who included movement-related imagery in their post tended to express higher extreme ideological beliefs in the following year. The opposite effect was true for the use of movement-related usernames. In other words, users with usernames containing movement-related terminology such as “88” or “14” were less likely to express higher extreme ideological beliefs in the following year.

Users’ prior beliefs were almost consistently and positively correlated to extreme ideological beliefs in cases where the correlation was significant. This provided partial support for self-radicalization (McCauley & Moskalenko, Mechanisms of Political Radicalization: Pathways Toward Terrorism, 2008) since individuals with higher ideological beliefs in the previous year expressed higher extreme ideological beliefs in the following year. One exception to this pattern occurred in Model T8, where the correlation was in the opposite direction. Nonetheless, these results showed support for Akers’s (2009) proposition that individuals’ learning and maintaining of behavior is conditioned by their prior definitions and self-radicalization (McCauley & Moskalenko, Mechanisms of Political Radicalization: Pathways Toward Terrorism, 2008).

Table 4.4. Social Influence Models for Forum 3

	Model T1			Model T2			Model T3		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.701**	0.227	2.412	-1.122	0.616	1.381	0.013	0.053	1.91
In-Degree	-0.36	0.179	19.417	-0.172	0.102	1.371	0.077**	0.025	1.701
Movement Image	0.723	0.578	2.579	-0.180	0.262	1.101	0.146	0.188	1.789
Movement Name	-0.276	0.504	3.536	0.096	0.264	1.169	0.175	0.186	1.375
Control									
Length	-0.007	0.184	1.994	0.000	0.031	1.176	-0.032**	0.01	1.431
No. Thread Started	0.863	0.558	14.363	0.177	0.108	1.19	-0.307	0.157	1.537
Self-Claim	1.475	1.105	2.643	-0.198	0.936	1.017	0.235	0.448	1.078
Prior Beliefs	-0.193	0.323	2.385	1.815**	0.533	1.509	-0.032	0.073	1.082
No Exposure	0.029	0.457	3.295	-0.174	0.285	1.128	0.403	0.217	2.916
Constant	0.232	0.351		0.224	0.263		0.328	0.21	
R-Square		0.646			0.272			0.276	
N		29			197			294	

Note: **p* < 0.05, ***p* < 0.01

Table 4.4. (cont'd)

	Model T4			Model T5			Model T6		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.046	0.026	2.979	0.000	0.031	3.027	0.150**	0.041	1.683
In-Degree	0.002	0.012	1.897	-0.013	0.016	4.115	-0.085**	0.031	1.878
Movement Image	0.126	0.079	2.091	0.087	0.069	1.93	0.412**	0.095	2.433
Movement Name	0.057	0.083	1.499	0.050	0.067	1.449	-0.269**	0.084	1.766
Control									
Length	0.000	0.002	1.279	-0.003*	0.001	1.365	0.001	0.001	1.293
No. Thread Started	0.109	0.071	1.578	0.082	0.086	3.136	0.124	0.096	1.445
Self-Claim	0.011	0.079	1.171	0.006	0.027	1.929	0.021	0.068	1.48
Prior Beliefs	-0.102	0.171	1.031	0.051**	0.012	1.074	0.218**	0.038	1.065
No Exposure	0.135	0.092	3.398	0.118	0.084	3.468	0.069	0.091	2.438
Constant	-0.121	0.097		0.009	0.085		-0.083	0.091	
R-Square	0.234			0.277			0.432		
N	350			393			412		

Note: **p* < 0.05, ***p* < 0.01

Table 4.4. (cont'd)

	Model T7			Model T8			Model T9			Model T10		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning												
Exposure	0.157**	0.026	2.807	-0.078**	0.025	2.426	-0.003	0.036	5.021	-0.011**	0.003	2.861
In-Degree	-0.052**	0.012	2.152	-0.024	0.02	4.530	-0.139**	0.021	16.966	-0.056**	0.003	4.307
Movement Image	0.201*	0.085	3.774	0.274**	0.043	4.743	0.331**	0.038	4.444	-0.063**	0.011	10.413
Movement Name	0.086	0.073	2.316	-0.234**	0.05	4.899	-0.546**	0.038	1.847	0.029**	0.008	3.183
Control												
Length	-0.001	0.001	1.237	0.000	0.000	1.115	0.000**	0.000	1.129	-1.26E-05	0	1.111
No. Thread Started	0.108**	0.034	5.699	0.023	0.028	7.427	0.645**	0.051	11.567	0.242**	0.002	1.966
Self-Claim	-0.135	0.08	6.053	-0.083*	0.042	3.25	0.016	0.057	2.072	-0.034*	0.014	1.839
Prior Beliefs	0.063	0.034	1.205	-0.048**	0.012	1.319	0.038**	0.014	1.057	0.000	0.004	1.032
No Exposure	0.178*	0.078	3.967	-0.161**	0.038	3.146	-0.052	0.035	3.849	-0.09**	0.009	8.017
Constant	-0.120	0.077		0.152	0.039		0.017	0.036		0.091**	0.009	
R-Square	0.463			0.465			0.813			0.994		
N	432			434			439			440		

Note: $*p < 0.05$, $**p < 0.01$

Table 4.4a. Modified Social Influence Models for Forum 3

	Model T1a			Model T9a		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	0.561*	0.216	2.030	-0.281**	0.034	3.182
In-Degree	-0.099	0.060	2.039	0.107**	0.010	2.679
Movement Image	0.715	0.597	2.579	0.169**	0.042	3.941
Movement Name	-0.035	0.496	3.197	-0.407**	0.043	1.694
Control						
Length	-0.035	0.190	1.974	0.001**	0.000	1.109
No. Thread Started						
Self-Claim	0.541	0.956	1.851	0.429**	0.055	1.396
Prior Beliefs	-0.299	0.326	2.278	0.040*	0.016	1.057
No Exposure	0.114	0.469	3.248	-0.188**	0.039	3.492
Constant	0.198	0.362		0.131**	0.041	
R-Square		0.587			0.732	
N		29			439	

Note: *$p < 0.05$, **$p < 0.01$

Table 4.4a.

	Model T10a			Model T10b		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	-0.126***	0.022	2.685	0.008**	0.003	1.600
In-Degree	0.136***	0.019	3.469	-0.054**	0.003	4.275
Movement Image	-0.083	0.079	10.412	-0.005	0.01	7.029
Movement Name	-0.079	0.061	3.160	0.002	0.009	2.798
Control						
Length	0.000**	0.000	1.099	0	0	1.093
No. Thread Started				0.244**	0.002	1.935
Self-Claim	-0.374***	0.103	1.793	0.05**	0.012	1.109
Prior Beliefs	0.01	0.026	1.032	-0.001	0.004	1.032
No Exposure	-0.269***	0.069	7.890			
Constant	0.235***	0.069		0.004	0.003	
R-Square		0.605			0.993	
N		440			440	

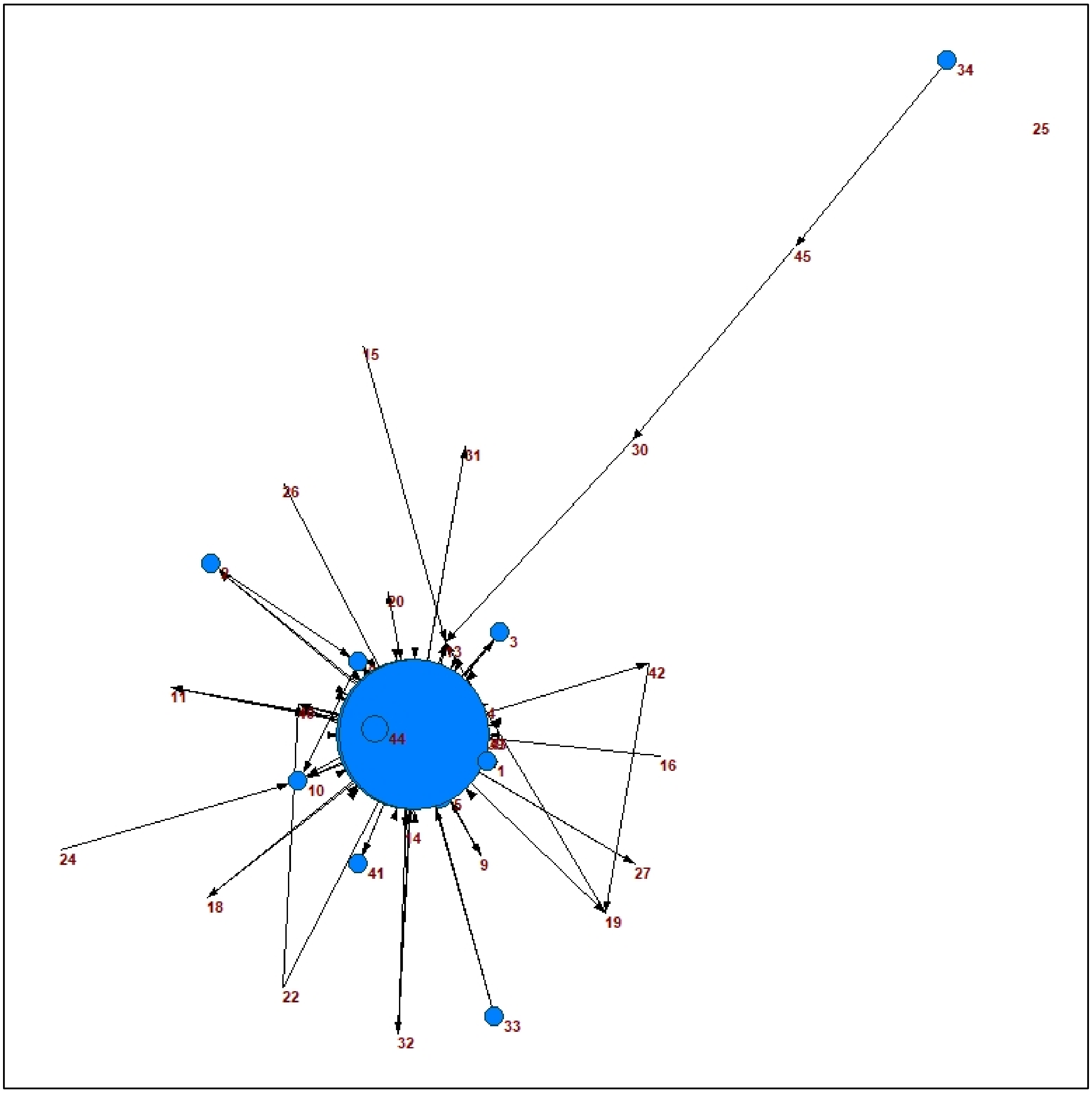
Note: *$p < 0.05$, **$p < 0.01$

The remaining control variables were significant in at least one of the nine models. Users' length of participation, users' claiming to be a supporter and users' lack of exposure were significant in three models. Users with longer participation at T3 and T5 expressed less extreme ideological beliefs in T4 and T6, respectively. One possible explanation is that experienced users were more likely to have identified and accepted extreme ideological beliefs, and therefore less likely to experience changes in attitudes. In Model 9a, users who participated longer on the forum, who claimed to be supporters of the movement, and experienced exposure to other users' posts were more likely to expressed extreme ideological beliefs. For users' length of participation, correlation from this model was an exception. For the other two variables, similar pattern of correlation was found in other models.

The number of threads started by users was significant in Models T7 and T10b, which meant that users who started more threads during these time points expressed more extreme ideological beliefs in the following year. As users displayed increased interest in far-right ideology and took actions after joining far-right online forums, they were more likely to experience radicalization at T7 and T10.

Forum 4. Forum 4 was one of the three forums with no relations to real-world groups and no sub-forums. This forum had the smallest number of users (45) and second lowest number of threads (130). Figure 4.4 illustrates the social interactions of all users between 2011 and 2015. For extreme ideological beliefs, the mean was 4.64, with a standard deviation of 12.419 and a maximum value of 56. This indicated high level of dispersion in the data.

Figure 4.4. Social Interactions among Users in Forum 4 (2011 – 2015)



To determine if extreme ideological beliefs differed between time points, RM-ANOVA was utilized. The results of the RM-ANOVA with a Greenhouse-Geisser correction determined that the mean of extreme ideological beliefs for Forum 4 differed statistically significantly between time points ($p = 0.01$). When examining the changes between specific years, time point

T4 showed the highest mean level of expressed ideological beliefs. However, the post hoc tests using the Bonferroni correlation did not identified significant differences between any pair of time points.

For this forum, a total of four models were conducted, ranging from 2011 and 2015 (see Table 4.5). This forum suffered from multicollinearity issues, as the VIF values for differential association, differential reinforcement and number of threads started were greater than 20 for all four models. As a result, data from Forum 4 were re-conducted with the modified models (see Table 4.5a).

The first modified model excluded the number of threads started by users, which resolved the multicollinearity issue in Model T1. For the remaining models, more modifications were needed. For Model T2b, differential reinforcement was excluded in addition to the number of threads started by users. For Models T3 and T4, users' lack of exposure was excluded in addition to the number of threads started by users. Overall, the results of the modified models were comparable to the results from the original models apart from the SLT variables.

The analyses based on this forum showed strong support for one SLT variable despite the lack of significant findings in the original models. In the modified models, differential association reached statistical significance in one model while differential reinforcement reached statistical significance in three models. None of the measurements for imitation was significant in the original and modified models. One possible explanation for the lack of stronger support is the small sample size of Forum 4.

Table 4.5. Social Influence Models for Forum 4

	Model T1			Model T2		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	0.552	0.408	2.793	-0.068	0.153	13.542
In-Degree	0.149	0.601	26.505	0.042	0.029	15.896
Movement Image	-1.143	1.305	2.538	0.169	0.378	2.185
Movement Name	-0.88	0.963	1.243	0.357	0.272	1.455
Control						
Length	0.116	0.128	1.69	-0.036*	0.017	1.994
No. Thread Started	-1.561	2.155	25.327	0.192	0.148	13.927
Self-Claim				-3.912	2.521	22.385
Prior Beliefs	1.116	0.8	2.672	0.643**	0.208	2.326
No Exposure	1.931	1.432	1.717	0.32	0.506	7.027
Constant	-0.671	1.328		0.293	0.511	
R-Square		0.688			0.805	
N		18			31	

Note: $*p < 0.05$, $**p < 0.01$

Table 4.5.

	Model T3			Model T4		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	1.33	1.367	30.701	-0.189	0.14	53.953
In-Degree	0.426	0.321	34.604	0.021	0.011	54.03
Movement Image	-1.597	1.756	1.978	0.194	0.293	3.54
Movement Name	0.834	1.252	1.589	0.1	0.181	1.441
Control						
Length	-0.088	0.048	1.608	0.008	0.005	1.424
No. Thread Started	0.219	1.281	20.973	-0.111**	0.031	21.542
Self-Claim	15.559**	5.278	4.898	2.394**	0.386	4.473
Prior Beliefs	0.23	0.484	2.566	0.224	0.121	1.39
No Exposure	4.619	3.153	14.194	-0.816	0.639	22.174
Constant	-2.202	2.769		0.502	0.649	
R-Square		0.938			0.944	
N		35			44	

Note: $*p < 0.05$, $**p < 0.01$

Table 4.5a. Modified Social Influence Models for Forum 4

	Model T1a			Model T2a			Model T2b		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.419	0.356	2.23	-0.028	0.152	12.991	0.103	0.111	6.781
In-Degree	-0.266	0.18	2.495	0.036	0.029	15.44			
Movement Image	-0.628	1.068	1.784	0.17	0.384	2.185	0.296	0.375	2.034
Movement Name	-0.904	0.939	1.242	0.246	0.261	1.308	0.184	0.26	1.262
Control									
Length	0.11	0.125	1.683	-0.035	0.017	1.988	-0.031	0.017	1.919
No. Thread Started									
Self-Claim				-1.338	1.572	8.444	0.44	0.68	1.545
Prior Beliefs	1.038	0.774	2.624	0.716**	0.203	2.154	0.762**	0.202	2.085
No Exposure	1.448	1.236	1.344	0.318	0.513	7.027	0.628	0.455	5.396
Constant	-0.257	1.17		0.273	0.518		-0.101	0.429	
R-Square		0.665			0.787			0.770	
N		18			31			31	

Note: *$p < 0.05$, **$p < 0.01$

Table 4.5a. (cont'd)

	Model T3a			Model T3b			Model T4a			Model T4b		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning												
Exposure	1.326	1.341	30.692	-0.546	0.542	4.786	0.237*	0.088	15.921	0.106*	0.044	3.749
In-Degree	0.474**	0.151	8.015	0.614**	0.123	5.065	-0.017**	0.003	3.631	-0.016**	0.003	3.302
Movement Image	-1.697	1.624	1.756	-1.91	1.656	1.743	-0.231	0.311	2.965	-0.251	0.318	2.961
Movement Name	0.796	1.209	1.539	0.579	1.229	1.518	0.148	0.209	1.433	0.143	0.214	1.433
Control												
Length	-0.089	0.047	1.591	-0.059	0.044	1.302	0.008	0.006	1.423	0.009	0.006	1.416
No. Thread Started												
Self-Claim	14.913**	3.618	2.391	17.865**	3.126	1.702	3.371**	0.318	2.266	3.467**	0.321	2.193
Prior Beliefs	0.229	0.475	2.566	0.256	0.486	2.562	0.295*	0.139	1.353	0.332*	0.14	1.319
No Exposure	4.676	3.076	14.031				0.858	0.509	10.47			
Constant	-2.225	2.714		1.578	1.077		-1.186*	0.521		-0.389*	0.224	
R-Square	0.938			0.932			0.921			0.915		
N	35			35			44			44		

Note: $*p < 0.05$, $**p < 0.01$

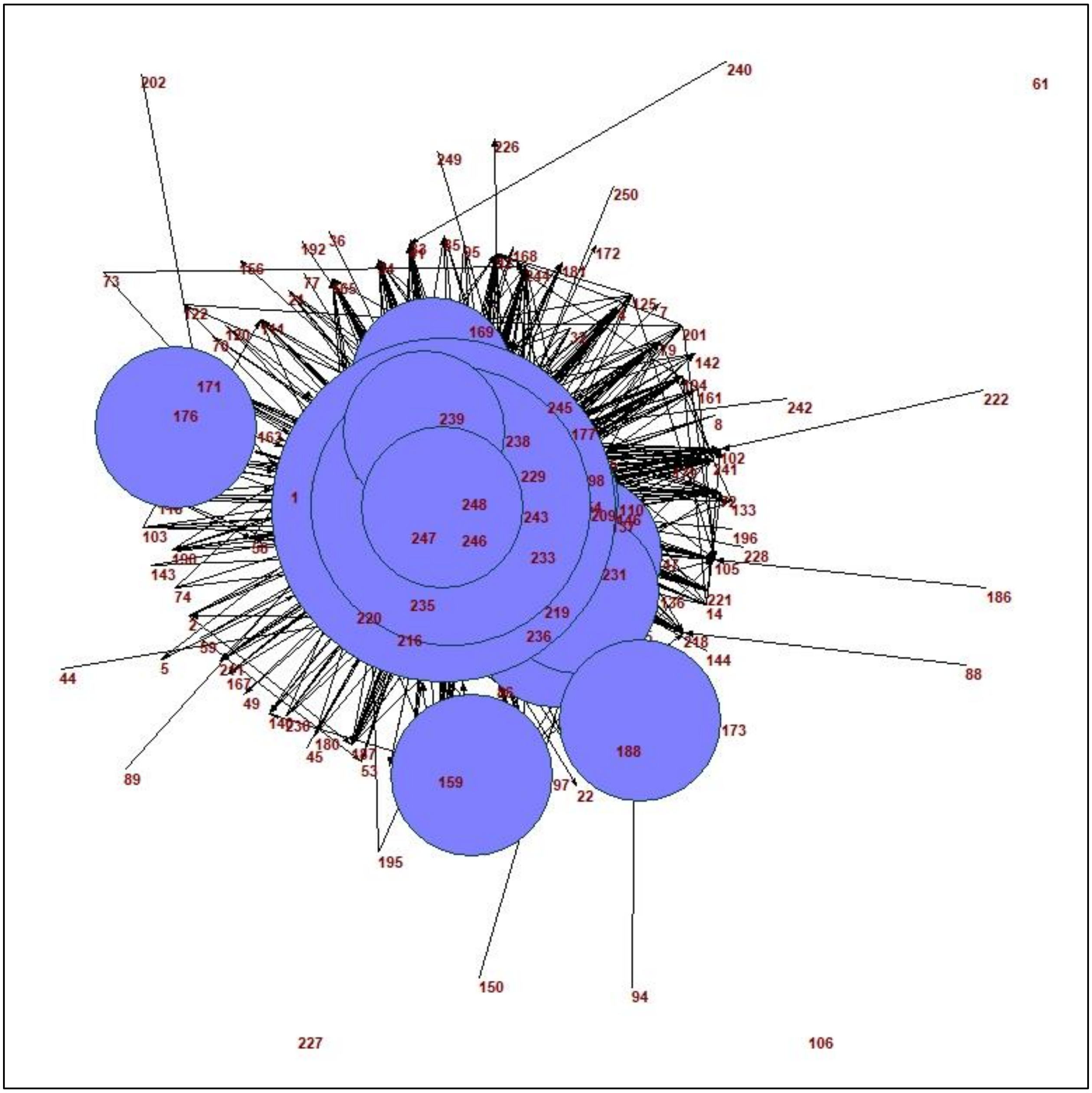
Results from sensitivity analyses confirmed this finding. Sensitivity analyses for Model T4a indicated that to invalidate the inferences for differential association and differential reinforcement, 25% and 64% of cases would have to be replaced respectively with cases for which there is an effect of zero. Similarly, for Models T3a and T3b, to invalidate the inferences for differential association and differential reinforcement, 35% and 59% % of cases would have to be replaced respectively with cases for which there is an effect of zero (Frank et al., 2013).

Two control variables, users' prior beliefs and users' claims to be supporters, also consistently reached statistical significance in both the original and modified models. Users with higher expressed extreme ideological beliefs in the previous years and claimed to be supporters were more likely to have higher level of extreme ideological beliefs in the following year.

When interpreting the results from this forum, there are two issues to consider. First, one needs to be cautious when interpreting the findings from Forum 4 due the issue of multicollinearity. Second, the sample size for each model was small and therefore likely to produce biased estimates. It is possible for Forum 4 have features and dynamics that were inherently different from other forums.

Forum 5. Forum 5 was the fifth forum with real-world group affiliations and included sub-forums. The total population was 250 users and 906 threads, which was the third highest number of threads across the forums. Figure 4.5 illustrates the social interactions of all users between 2010 and 2015. For extreme ideological beliefs, the mean was 0.34, with a standard deviation of 1.134 and a maximum value of 9. This indicated some level of dispersion in the data. Despite the forum having a fairly large number of users, most users appeared to hold comparable level of extreme ideological beliefs.

Figure 4.5. Social Interactions among Users in Forum 5 (2010 – 2015)



To determine if extreme ideological beliefs differed between time points, RM-ANOVA was utilized. The results of the RM-ANOVA with a Greenhouse-Geisser correction determined that the mean of extreme ideological beliefs for Forum 5 were not statistically different between time points (p = 0.231). Despite the lack of difference in mean across years, it is possible for changes in extremist ideology to occur at the individual level.

Thus, a total of five social influence models were conducted to determine if SLT is a possible mechanism for online radicalization (see Table 4.6). For all models, collinearity diagnostics were performed. Only Model T5 had multicollinearity issue. For this model, the VIF value for the number of threads started by users was 12.489. As a result, it was removed from the model (see Table 4.6a). A modified model was also conducted for Model T3. This is because the VIF value for the number of threads started by users was very close to 10.

Results from the five models showed moderate support for SLT. Differential association was significant in the last two models, indicating that as users interacted with others who were more radicalized, their beliefs and attitudes became more extreme. In Model 4, sensitivity analysis suggested that to invalidate the inference, 16% of the cases would have to be replaced with cases for which there is an effect of zero. In Model 5a, the percentage increases to 36% (Frank et al., 2013).

Differential reinforcement was significant in Models T3, T3a, and Model T5 but failed to reach significance in Model T5a. As users received more incoming connections, they expressed more extreme ideological beliefs in the following year. Sensitivity analyses for Model T3a showed that to invalidate the inference, 86% of the cases would have to be replaced with cases for which there is an effect of zero (Frank et al., 2013). As for imitation, neither movement-related imagery in posts nor movement-related usernames were significant for this forum.

Table 4.6. Social Influence Models for Forum 5

	Model T1			Model T2			Model T3		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	-0.03	0.027	1.993	-0.018	0.022	1.519	-0.013	0.027	1.711
In-Degree	-0.002	0.005	3.541	0.001	0.003	6.481	0.020**	0.003	9.515
Movement Image	0.077	0.099	1.919	0.012	0.059	2.912	-0.149	0.080	3.125
Movement Name	-0.046	0.088	1.179	0.083	0.047	1.295	0.113	0.072	1.243
Control									
Length	-0.016	0.018	1.202	0.003	0.003	1.134	0.000	0.002	1.279
No. Thread Started	0.007	0.02	3.368	-0.005	0.015	6.365	-0.034*	0.016	9.346
Self-Claim	-0.011	0.062	1.511	-0.002	0.014	1.625	-0.007	0.008	1.071
Prior Beliefs	0.004	0.036	1.310	-0.015	0.025	1.832	0.025	0.087	1.028
No Exposure	0.024	0.115	1.936	-0.011	0.057	2.607	0.025	0.076	2.868
Constant	0.181	0.15		-0.043	0.069		-0.035	0.078	
R-Square		0.23			0.229			0.72	
N		86			118			171	

Note: *$p < 0.05$, **$p < 0.01$

Table 4.6. (cont'd)

	Model T4			Model T5		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	0.059*	0.025	1.950	0.128**	0.034	2.636
In-Degree	0.001	0.003	2.697	0.035**	0.007	12.474
Movement Image	-0.041	0.098	2.462	-0.074	0.118	2.737
Movement Name	0.019	0.120	1.260	-0.276	0.166	1.097
Control						
Length	0.003	0.002	1.204	0.000	0.002	1.198
No. Thread Started	0.015	0.019	2.874	-0.109**	0.025	12.489
Self-Claim	-0.022	0.033	1.060	0.748**	0.115	1.183
Prior Beliefs	0.009	0.110	1.018	-0.016	0.078	1.026
No Exposure	0.003	0.104	2.738	0.142	0.122	3.426
Constant	-0.093	0.101		-0.130	0.122	
R-Square		0.296			0.57	
N		203			234	

Note: $*p < 0.05$, $**p < 0.01$

Table 4.6a. Modified Social Influence Models for Forum 5

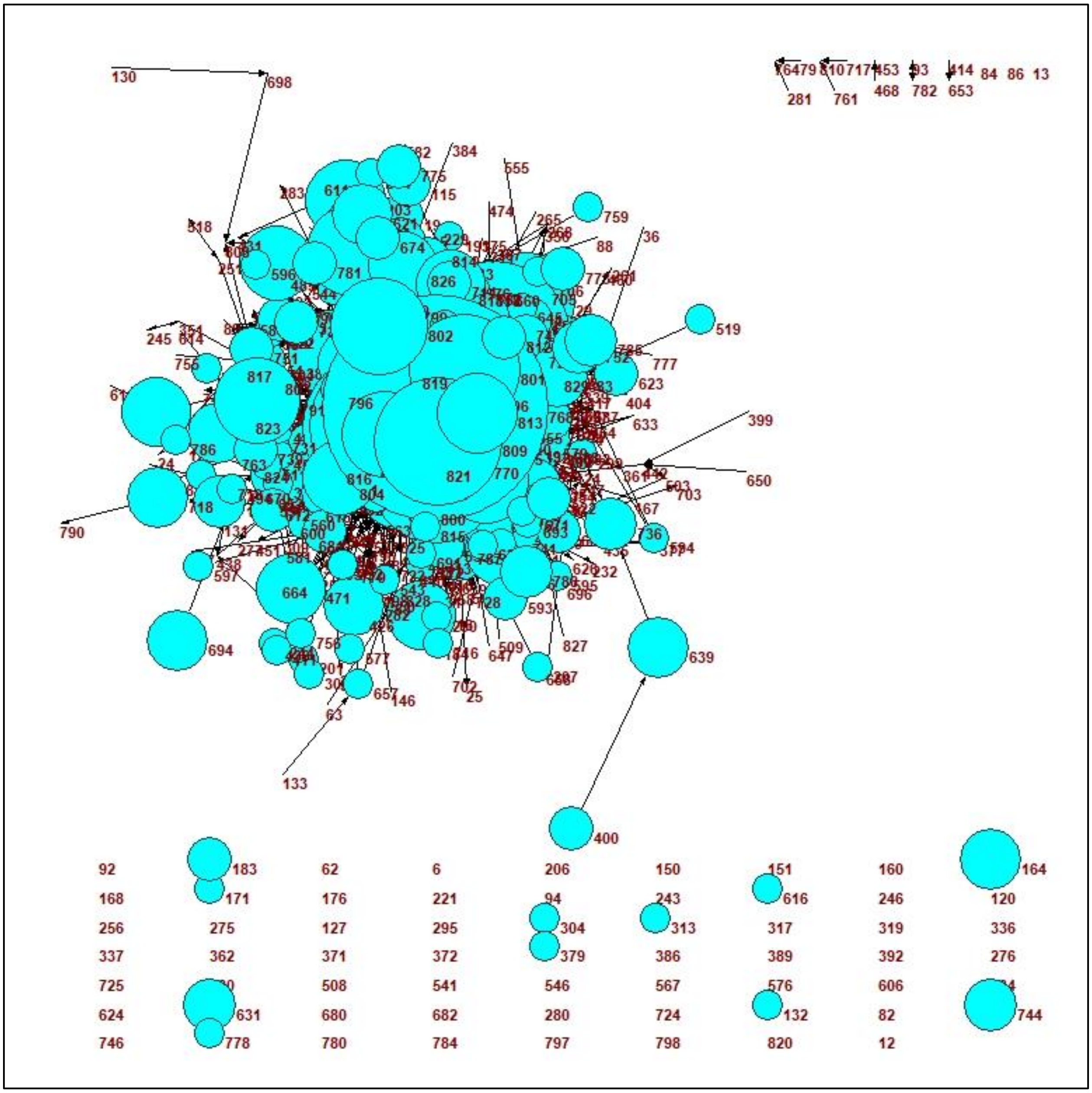
	Model T3a			Model T5a		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	-0.023	0.027	1.663	0.107*	0.035	2.583
In-Degree	0.014*	0.001	1.396	0.004	0.003	1.395
Movement Image	-0.126	0.080	3.066	0.044	0.119	2.595
Movement Name	0.090	0.072	1.216	-0.327	0.172	1.092
Control						
Length	-0.001	0.002	1.248	0.000	0.002	1.197
No. Thread Started						
Self-Claim	-0.004	0.008	1.045	0.765*	0.119	1.182
Prior Beliefs	0.031	0.087	1.027	-0.036	0.081	1.022
No Exposure	0.023	0.077	2.868	0.192	0.126	3.396
Constant	-0.014	0.078		-0.188	0.126	
R-Square	0.71			0.516		
N	171			234		

Note: $*p < 0.05$, $**p < 0.01$

As for control variables, users' claims to be supporters was the sole variable to reach statistical significance in both the original and modified models for T5. In both models, users who claimed to be supporters of the movement expressed more extreme ideological beliefs. It is important to note that differential association was also significant in the same model. In other words, users who claimed to be supporters were at the same time influenced by social interactions with others in the forum between T5 and T6.

Another control variable that was significant was the number of threads started by users. It was significant in Model T3 but not in Model T3a where the variable was excluded to correct for the issue of multicollinearity. Results from sensitivity analyses suggested that the significant results in Model T3 was strong, as 70% of the cases would have to be replaced with cases for which there is an effect of zero to invalidate the inference (Frank et al., 2013).

Figure 4.6. Social Interactions among Users in Forum 6 (2001 – 2015)



Forum 6. Forum 6 was the second forum with no relations to real-world groups but contained sub-forums. This forum had the second largest number of users (829) and threads (1331). Figure 4.6 illustrates the social interactions of all users between 2001 and 2015. The mean of extreme ideological beliefs was 0.72, with a standard deviation of 2.597 and a maximum value of 26. This indicated a high level of dispersion in the data.

To determine if extreme ideological beliefs differed between time points, RM-ANOVA model was utilized. The results of the RM-ANOVA with a Greenhouse-Geisser correction determined that the mean of expressed ideological beliefs for Forum 6 differed statistically significantly between time points ($p < 0.01$). Post hoc tests using the Bonferroni correlation indicated that the mean was statistically significantly lower for T1 when compared to the rest of the time points, apart from time point T13. When Using T13 as the point of reference, the post hoc test indicated that the mean was significantly lower than all but T1. The highest mean level of expressed ideological beliefs occurred at time point T3 but it was only significantly higher compared to time point T5. Furthermore, the test showed a lack of significant differences between any time point from T2 to T12. As such, Forum 6 experienced a gradual decrease in the mean level of extreme ideological beliefs between 2003 and 2015.

For this forum, a total of 12 models were ran, ranging from 2003 and 2015. Data from 2001 and 2002 were excluded from analyses because there were no social interactions in the dataset in 2001 and there were no data collected for 2002 (see Table 4.7). For all models, collinearity diagnostics were performed and only one model had multicollinearity issue. For Model T10, the VIF values for differential reinforcement and the number of threads started by users were respectively 13.618 and 12.71. To correct for this, the number of threads started by users was remove. The results from this modified model were similar to the results from the original, full model (see Table 4.7a).

The results from the 12 models showed moderate support for SLT. Differential association were significant and positive in five of the 12 models, with the exception of one negative correlation. In three of the five models, differential association was significant while other independent and control variables were also significant. For example, in Model T11, the use of movement-related usernames and the absence of exposure were the only two non-significant variables.

Results from sensitivity analyses for each model also showed these effects to be moderate. Sensitivity analyses for differential association suggested that to invalidate the inference, 77% of the cases would have to be replaced with cases for which there is an effect of zero (Frank et al., 2013). The weakest effect for differential association was from Model T12 where 7% of the cases would have to be replaced with cases for which there is an effect of zero (Frank et al., 2013). Nonetheless, these results showed that differential association played a role in the changes of users' extreme ideological beliefs.

Differential reinforcement was significant and positive for five of the 12 models: the higher the number of incoming connections a user received, the more extreme ideological beliefs a user expressed. Sensitivity analyses showed that to invalidate the inference for these five instances, more than 50% of cases within each model would have to be replaced (Frank et al., 2013). Differential reinforcement also had the most consistent effect within this forum throughout different years.

The findings were less consistent regarding imitation. The use of movement-related imagery in posts was significant in five models, but the direction of correlation was inconsistent. In three of the five models, users who included movement-related imagery in their posts were less likely to expressed extreme ideological beliefs in the following years. In the other two models, the correlation was positive. The use of movement-related usernames, on the other hand, was significant and positive in Models T6 and T9.

Table 4.7. Social Influence Models for Forum 6

	Model T3			Model T4			Model T5		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.063	0.494	2.687	0.349	0.149	2.158*	0.058	0.075	4.225
In-Degree	-0.129	0.415	5.403	0.044	0.081	3.115	0.021	0.024	3.220
Movement Image	0.562	0.944	1.521	0.488	0.579	1.208	1.220**	0.290	1.293
Movement Name				-0.276	0.643	1.074	0.219	0.307	1.231
Control									
Length	-0.016	0.053	1.110	0.021	0.039	1.042	-0.017	0.010	1.109
No. Thread Started	0.127	0.980	2.636	0.125	0.266	2.550	0.228**	0.084	2.312
Self-Claim				-1.779	1.444	1.085	0.280	0.223	1.219
Prior Beliefs	-0.101	0.627	1.743	-0.529	0.873	1.049	-0.056	0.060	1.098
No Exposure	0.361	0.593	2.280	0.521	0.417	1.587	0.207	0.290	3.088
Constant	0.204	0.565		-0.163	0.462		0.157	0.283	
R-Square	0.18			0.293			0.471		
N	62			209			330		

Note: *$p < 0.05$, **$p < 0.01$

Table 4.7. (cont'd)

	Model T6			Model T7			Model T8		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.051	0.029	2.878	-0.078	0.069	2.082	-0.056	0.061	2.482
In-Degree	-0.009	0.017	4.327	0.003	0.031	2.406	0.036**	0.009	1.474
Movement Image	0.012	0.104	1.407	0.354*	0.159	1.548	-0.014	0.183	1.402
Movement Name	0.386*	0.150	1.198	0.162	0.255	1.280	0.115	0.407	1.261
Control									
Length	0.004	0.002	1.046	-0.006*	0.003	1.026	0.001	0.002	1.056
No. Thread Started	0.068	0.045	3.389	-0.047	0.063	1.820	0.328**	0.053	1.265
Self-Claim	-0.088	0.096	1.082						
Prior Beliefs	0.018	0.012	1.137	-0.016	0.030	1.097	0.047	0.071	1.094
No Exposure	0.055	0.091	2.329	-0.113	0.124	1.896	-0.263	0.152	2.131
Constant	-0.058	0.095		0.387**	0.131		0.335*	0.165	
R-Square	0.272			0.179			0.399		
N	419			500			549		

Note: $*p < 0.05$, $**p < 0.01$

Table 4.7. (cont'd)

	Model T9			Model T10			Model T11		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	-0.151**	0.052	4.071	0.077	0.056	1.904	0.213**	0.044	2.258
In-Degree	0.136**	0.023	3.765	-0.031	0.043	13.618	0.147**	0.026	3.710
Movement Image	-0.333*	0.141	1.531	-0.366*	0.184	1.369	-0.536**	0.131	1.348
Movement Name	0.757*	0.372	1.110	-0.368	0.550	1.051	-0.250	0.295	1.031
Control									
Length	-0.002	0.002	1.094	-0.003*	0.001	1.091	-0.002*	0.001	1.103
No. Thread Started	-0.009	0.060	3.159	0.029	0.038	12.710	-0.044**	0.012	2.770
Self-Claim				2.516**	0.473	1.037	-3.167**	0.761	1.376
Prior Beliefs	0.005	0.039	1.042	0.024	0.043	1.099	0.066*	0.028	1.109
No Exposure	-0.394*	0.158	3.802	-0.417**	0.140	1.927	0.141	0.118	2.523
Constant	0.551**	0.160		0.727**	0.143		0.052	0.122	
R-Square	0.396			0.314			0.398		
N	601			664			702		

Note: **p* < 0.05, ***p* < 0.01

Table 4.7. (cont'd)

	Model T12			Model T13			Model T14		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning									
Exposure	0.273**	0.057	2.729	-0.073	0.037	2.775	0.039**	0.010	2.329
In-Degree	0.037	0.030	3.148	0.114**	0.012	1.797	0.030**	0.006	3.350
Movement Image	-0.207	0.187	1.281	-0.063	0.137	1.399	0.016	0.030	1.227
Movement Name	-0.458	0.623	1.018	-0.348	0.295	1.158	0.014	0.074	1.046
Control									
Length	-0.001	0.001	1.148	0.001	0.001	1.162	0.000	0.000	1.122
No. Thread Started	0.117	0.075	2.717	0.009	0.024	1.232	-0.013**	0.005	2.964
Self-Claim				-0.010	0.534	1.266			
Prior Beliefs	-0.056	0.035	1.081	0.127**	0.034	1.205	0.030**	0.006	1.044
No Exposure	-0.011	0.159	2.762	-0.211	0.113	2.680	0.070*	0.030	2.355
Constant	0.110	0.157		0.138	0.112		-0.078*	0.031	
R-Square	0.339			0.417			0.338		
N	757			802			825		

Note: *$p < 0.05$, **$p < 0.01$

Table 4.7a. Modified Social Influence Models for Forum 6

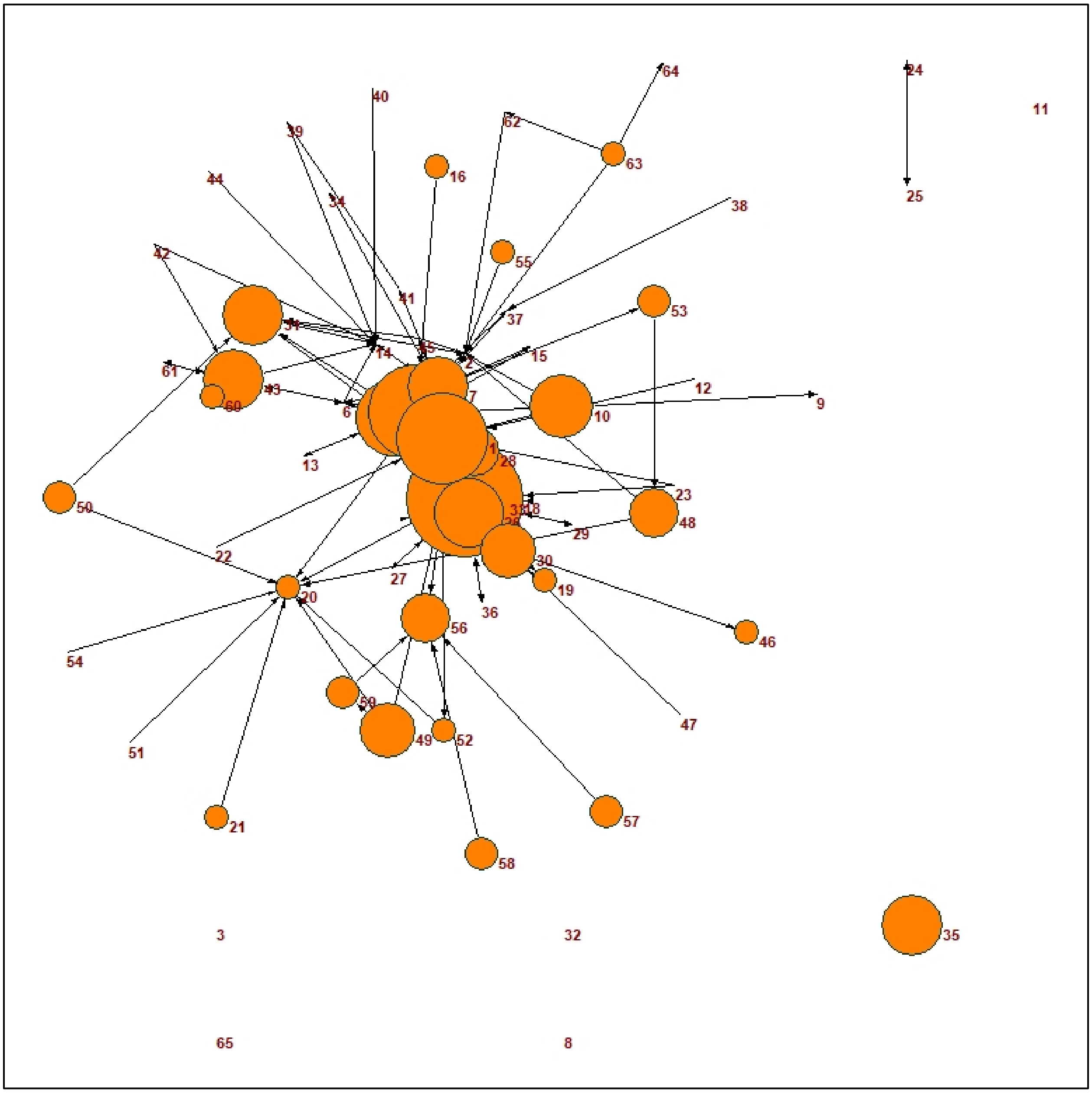
	Model T10a		
	Regression Coefficient	Std. Error	VIF
Social Learning			
Exposure	0.061	0.052	1.636
In-Degree	0.000	0.013	1.137
Movement Image	-0.368*	0.184	1.369
Movement Name	-0.363	0.550	1.051
Control			
Length	-0.004*	0.001	1.078
No. Thread Started			
Self-Claim	2.556**	0.470	1.024
Prior Beliefs	0.019	0.042	1.075
No Exposure	-0.398**	0.138	1.868
Constant	0.717**	0.143	
R-Square		0.313	
N		664	

Note: *$p < 0.05$, **$p < 0.01$

For control variables, the correlations of three variables were relatively consistent. First, users' length of participation was a significant predictor within this forum. Its negative correlation with users' changes in extreme ideological beliefs appeared to be consistent with current literature on users' behaviors in forums where users who had been on the forums for a longer period of time tended to answer questions and share knowledge and information (Bowman-Grieve, 2009). Second, users' prior beliefs were significant and positive in three models. In two of the three models, users' prior beliefs were significant alongside with differential association and differential reinforcement.

The remaining control variables showed mixed correlation. The number of threads started by users was significant in four models. The correlation was positive in the first two models and negative in the last two models. For users' lack of exposure, the findings were significant in three models. Users' lack of exposure was significant and negative in Models T9 and T10a and positive in the Model 14. This suggested that users who experienced no exposure to other users expressed less extreme ideological beliefs. The correlation for users' claims on being supporters of the movement was significant in two models, but the direction of correlation was different.

Figure 4.7. Social Interactions among Users in Forum 7 (2011 – 2015)



Forum 7. Forum 7 was the third forum with no relationship to real-world groups and with no sub-forums. This forum had the second smaller number of users (65) and the smallest number of threads (103). Figure 4.7 illustrates the social interactions of all users between 2011 and 2015. The mean of extreme ideological beliefs was 2.20, with a standard deviation of 4.192 and a maximum value of 23. This indicated a high level of dispersion in the data, while the highest overall mean demonstrated that the forum was more extreme compared to the others in the sample.

To determine if the extreme ideological beliefs differed between time points, RM-ANOVA was utilized. The results of the RM-ANOVA with a Greenhouse-Geisser correction determined that the mean of extreme ideological beliefs for Forum 7 differed statistically significantly between time points (p = 0.006). Post hoc tests using the Bonferroni correlation indicated that the mean of expressed far-right ideological beliefs were statistically significantly higher at T1 and T3 when compared to the mean at T5. These results indicated a trend of descend with the expression of far-right ideological beliefs across time.

For this forum, a total of four models were conducted, ranging from 2011 and 2015 (see Table 4.8). For all models, collinearity diagnostics were performed and there was one instance where the VIF value was higher than the threshold values of 10 (Myers, 1990). In Model T4, the VIF values for differential association and no-exposure were respectively 72.197 and 73.734. An explanation for the high correlation between these two variables was the relatively low number of interactions between users at T4. As a result, no-exposure was excluded from Model T4.

Table 4.8. Social Influence Models for Forum 7

	Model T1			Model T2		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	0.148	0.29	1.582	0.238	0.257	6.812
In-Degree	-0.155	0.155	2.232	-0.174	0.111	3.592
Movement Image	0.337	0.583	1.222	0.645	0.584	2.326
Movement Name	-0.3	0.67	1.535	0.115	0.505	1.365
Control						
Length	0.021	0.029	1.159	0.016	0.018	1.171
No. Thread Started	-0.017	0.229	2.008	0.923**	0.284	3.163
Self-Claim				-1.016	1.45	1.144
Prior Beliefs	0.182	0.217	1.722	0.119	0.134	1.094
No Exposure	1.262	0.7	2.221	-0.026	0.912	6.063
Constant	-0.321	0.78		-0.5	0.916	
R-Square		0.358			0.634	
N		52			62	

Note: **p* < 0.05, ***p* < 0.01

Table 4.8.

	Model T3			Model T4		
	Regression Coefficient	Std. Error	VIF	Regression Coefficient	Std. Error	VIF
Social Learning						
Exposure	0.368*	0.182	3.39	0.775**	0.073	72.197
In-Degree	0.223	0.205	9.736	0.116**	0.032	10.397
Movement Image	-0.363	0.473	2.802	-0.012	0.04	3.449
Movement Name	0.424	0.464	1.298	-0.069	0.062	3.02
Control						
Length	0.002	0.011	1.075	-0.001	0.001	1.438
No. Thread Started	-0.024	0.2	5.814	-0.04**	0.014	5.687
Self-Claim						
Prior Beliefs	-0.094	0.059	1.876	-0.026*	0.01	4.335
No Exposure	0.437	0.571	3.795	2.263**	0.241	73.734
Constant	-0.373	0.642		-2.216**	0.232	
R-Square		0.508			0.891	
N		64			65	

Note: **p* < 0.05, ***p* < 0.01

Table 4.8a. Modified Social Influence Models for Forum 7

	Model T4a		
	Regression Coefficient	Std. Error	VIF
Social Learning			
Exposure	0.097**	0.02	2.104
In-Degree	-0.066	0.042	6.709
Movement Image	0.1	0.061	3.147
Movement Name	-0.234*	0.094	2.777
Control			
Length	0.001	0.001	1.281
No. Thread Started	0.021	0.02	4.465
Self-Claim			
Prior Beliefs	-0.006	0.016	4.14
No Exposure			
Constant	-0.06	0.05	
R-Square	0.684		
N	65		

Note: *$p < 0.05$, **$p < 0.01$

Across all four models, differential association and users with movement-related usernames were the only social learning component that were significant. Different association was significant in Models T3 and T4a. This indicated that the effect of differential association was stronger as the forum grew and became more stable. Sensitivity analyses suggested the results from both models were unlikely due to biases. To invalidate the inference, 44% of the cases for Model T3 and 59% of the cases for Model T4a would have to be replaced with cases for which there is an effect of zero (Frank et al., 2013). This meant that users changed their attitudes based on whom they interacted with in the prior year. In Model 4a, users with movement-related usernames were found to have a negative correlation with extreme ideological beliefs in the following year. As for control variables, number of threads started was significant in model T2-T3. In other words, users who started more threads during T2 expressed more extreme ideological beliefs in T3.

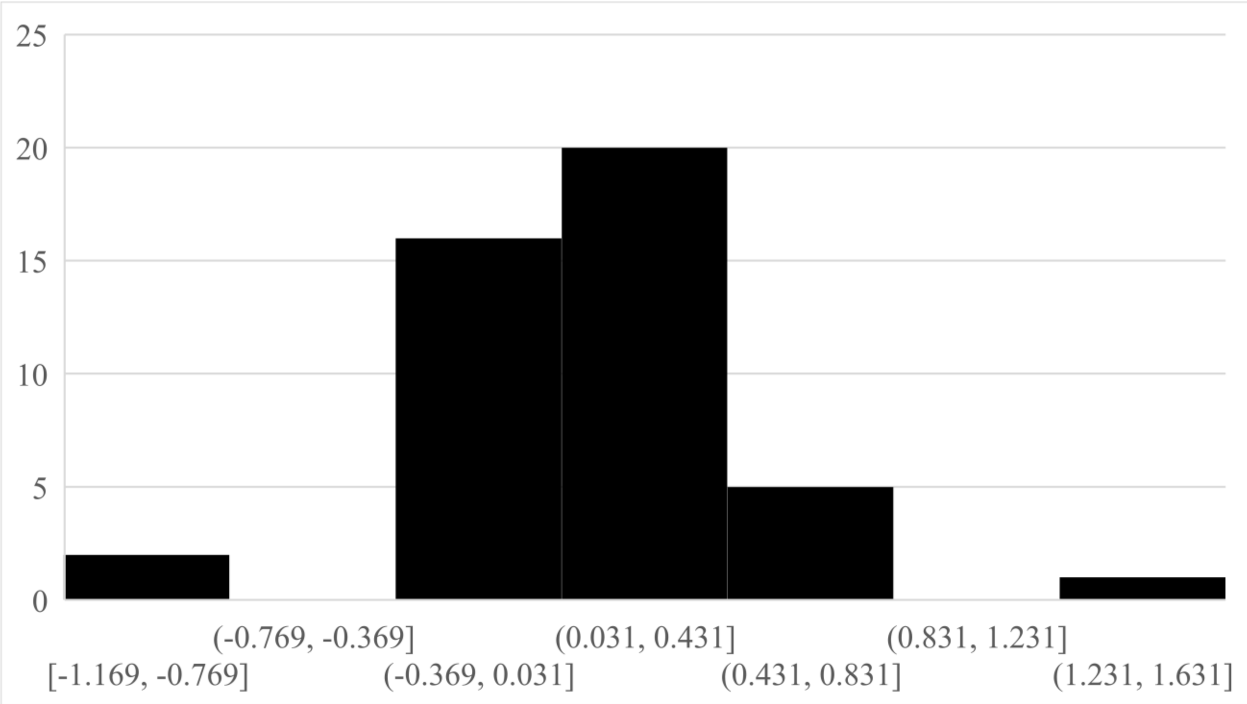
Summarizing Individual Forum Results

The results from all seven forums indicated a pattern that requires examination. The results from the within-forum analyses provided preliminary answers to the questions of whether online radicalization occurs and if so, through what mechanisms does it occur. Findings from the RM-ANOVA for all but one forum suggest that online radicalization occurred, but for most of the forums, the pattern appeared to be downward. As for the second question, the within-forum analyses are generally favorable towards the SLT. Each of the four theoretical concepts was significant in at least one model within each forum, except for Forum 1. Specifically, there seems to a temporal pattern with the results. When looking across models within each forum, it appeared that more variables were significant in the later models. This could simply be a result of the increase in sample sizes as the number of registered members in forums grew.

Among these significant findings, there is the issue of changes in correlations for the same variable across time within forums. A possible explanation for the changes in correlations is sampling distribution over time. Given the large number of models conducted for the within-forum analyses, negative correlations of a variable could be attributed to sampling distribution. To test this relationship, a histogram including coefficients of differential association from all models was created. Figure 4.8 shows that the coefficients were normally distributed, suggesting that the negative coefficients for differential association are byproducts of sampling distributions. Nonetheless, these issues point to the need to compare results across forums.

The effects of social learning components also varied across forums. In all forums, apart from Forum 1, there was at least one model where social learning components were significant. Differential association tended to be significant in later models for each forum. It is possible that the effect of social interactions became more evident as forums reached a threshold of perceived stability. Another possible explanation is the fluctuation in sample sizes. As a forum develops, the number of users tends to increase, resulting in larger sample size. For regression models, the larger the sample sizes, the less bias there is in the estimated coefficients.

Figure 4.8. Distributions of Coefficients for the Exposure Term



Full-Forum Models

To compare results across forums, all within-forum models were compiled to create the full-forum dataset. A few adjustments were made to the full-forum dataset. First, users' rank in forums was excluded from the exposure term due to dissimilarities in forums' hierarchical structures. Second, binary variables for the year and forum of specific models were added. For example, Model T1 from Forum 1 would be coded as "1" for Year2008 and Forum1. Please refer to Table 4.9 for the number of forums included at each time point.

Table 4.9. Forums at Time Points

Time Point	Year	Forums Included
T1	2001	1. Forum 6 (T1)
T2	2002	N/A
T3	2003	1. Forum 6 (T3)
T4	2004	1. Forum 6 (T4)
T5	2005	1. Forum 3 (T1) 2. Forum 6 (T5)
T6	2006	1. Forum 3 (T2) 2. Forum 6 (T6)
T7	2007	1. Forum 3 (T3) 2. Forum 6 (T7)
T8	2008	1. Forum 1 (T1) 2. Forum 2 (T1) 3. Forum 3 (T4) 4. Forum 6 (T8)
T9	2009	1. Forum 1 (T2) 2. Forum 2 (T2) 3. Forum 3 (T5) 4. Forum 6 (T9)
T10	2010	1. Forum 1 (T3) 2. Forum 2 (T3) 3. Forum 3 (T6) 4. Forum 5 (T1) 5. Forum 6 (T10)
T11	2011	1. Forum 1 (T4) 2. Forum 2 (T4) 3. Forum 3 (T7) 4. Forum 4 (T1) 5. Forum 5 (T2) 6. Forum 6 (T11) 7. Forum 7 (T1)
T12	2012	1. Forum 1 (T5) 2. Forum 2 (T5) 3. Forum 3 (T8) 4. Forum 4 (T2) 5. Forum 5 (T3) 6. Forum 6 (T12) 8. Forum 7 (T2)
T13	2013	1. Forum 1 (T6) 2. Forum 2 (T6) 3. Forum 3 (T9) 4. Forum 4 (T3) 5. Forum 5 (T4) 6. Forum 6 (T13) 9. Forum 7 (T3)

Table 4.9. (cont'd)

Time Point	Year	Forums Included
T14	2014	1. Forum 1 (T7) 2. Forum 2 (T7) 3. Forum 3 (T10) 4. Forum 4 (T4) 5. Forum 5 (T5) 6. Forum 6 (T14) 7. Forum 7 (T4)
T15	2015	1. Forum 1 (T8) 2. Forum 2 (T8) 3. Forum 3 (T11) 4. Forum 4 (T5) 5. Forum 5 (T6) 6. Forum 6 (T15) 7. Forum 7(T5)

Table 4.10 contains the descriptive statistics for the full-forum dataset. Most posts within this dataset were from Forum 2 and Forum 6 and made in 2008 and beyond. The dependent variable, extreme ideological beliefs, appeared to be skewed as most values clustered around the value of zero. Similarly, the exposure term remained skewed despite transforming the variable using the natural log function. The low mean also suggested that most users did not experience exposure or was exposed to non-ideological content while participating in these forums. In addition, a majority of users across these forums and time points did not start threads, used movement-related images and usernames, or claimed to a supporter of the movement. The number of cases for users' length of participation were reduced in comparison because users that have yet to join the forum at a specific time point where excluded from the specific within-forum model for that time point.

Table 4.10. Descriptive Statistics for Variables

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Ideological Beliefs	24308	0	134	0.29	2.49
Exposure	24308	0	8.46	0.28	0.98
In-Degree	24308	0	258	0.80	5.90
Movement Image	24308	0	1	0.08	0.28
Movement Name	24308	0	1	0.05	0.23
Length	16557	0	160	43.04	31.17
No. of Thread Started	24308	0	104	0.17	1.62
Self-Claim	24308	0	1	0.01	0.09
Prior	24308	0	134	0.28	2.45
No Exposure	24308	0	1	0.85	0.36
Real-Life	24308	0	1	0.98	0.13
Users' Ranking	24308	0	15	4.19	2.084
2003	24308	0	1	0.03	0.18
2004	24308	0	1	0.03	0.18
2005	24308	0	1	0.05	0.22
2006	24308	0	1	0.05	0.22
2007	24308	0	1	0.05	0.22
2008	24308	0	1	0.10	0.30
2009	24308	0	1	0.10	0.30
2010	24308	0	1	0.11	0.32
2011	24308	0	1	0.12	0.32
2012	24308	0	1	0.11	0.31
2013	24308	0	1	0.12	0.32
2014	24308	0	1	0.12	0.32
Forum1	24308	0	1	0.07	0.26
Forum2	24308	0	1	0.27	0.44
Forum3	24308	0	1	0.18	0.39
Forum4	24308	0	1	0.01	0.09
Forum5	24308	0	1	0.05	0.22
Forum6	24308	0	1	0.41	0.49
Forum7	24308	0	1	0.01	0.10

Using the full-forum dataset, a total of four models were conducted to understand the effects of the variables. Model 1 included the independent variable while Model 2 added control variables. Models 3 and 4 included forum and year binary variables to control for fixed forum and year effects.

Results from Model 1 showed that the SLT accounted for 26.4% of variance. The results indicated that users with higher exposure and received higher number of responses were more likely to hold extreme ideological beliefs in the following year. Specifically, differential reinforcement had the largest beta coefficient ($\beta = 0.176$), followed by differential association ($\beta = 0.144$). This result is unexpected because it contradicts Akers's (2009) proposition on differential association as the concept that provides social contexts for the remaining three components. Similarly, using movement-related images in posts was negatively correlated to extreme ideological beliefs. In contrast, the use of a movement-related username was not significant, but the correlation was positive. These results showed initial support for SLT as an appropriate framework for understanding online radicalization.

In Model 2, control variables were added with the exception of users' ranking. The sample size for Model 2 is reduced (n =16557) due to the inclusion of users' length of participation. The inclusion of control variables also led to a small increase in the standard errors of some variables, suggesting a potential issue with multicollinearity. The VIF values did not suggest an issue in Model 2. Consequently, it is safe to conclude that multicollinearity was not an issue for Model 2.

Model 2 accounted for 32.4% of variance. The social influence model indicated that across all forums, users who experienced more exposure, received a higher number of responses, used movement-related usernames, were newer members, started fewer threads, did not claim to

Table 4.11. Model 1 and Model 2 of Full-Forum Social Influence Models

	Model 1			Model 2		
	Regression Coefficient	Std. Error	Beta	Regression Coefficient	Std. Error	Beta
Social Learning						
Exposure	0.365**	0.020	0.144	0.422**	0.024	0.190
In-Degree	0.074**	0.003	0.176	0.089**	0.004	0.264
Movement Image	-0.246**	0.067	-0.028	0.051	0.075	0.006
Movement Name	0.097	0.078	0.009	0.183*	0.082	0.019
Control						
Length				-0.003**	0.001	-0.035
No. Thread Started				-0.070**	0.014	-0.053
Self-Claim				-0.980**	0.182	-0.041
Prior Beliefs				0.013	0.007	0.015
No Exposure				0.442**	0.068	0.071
Real Life				0.036	0.129	0.002
Constant	0.143**	0.016		-0.270	0.141	
R^2		0.264			0.324	
n		24308			16557	

Note: * $p < 0.05$, ** $p < 0.01$

Table 4.11a. Sensitivity Analyses for Model 1 and Model 2

	Model 1		Model 2	
	Percentage	No. of Cases	Percentage	No. of Cases
Social Learning				
Exposure	***89***	***21697***	***89***	***14711***
In-Degree	***92***	***22367***	***91***	***15098***
Movement Image	***47***	***11331***	65	
Movement Name	37		***12***	***2015***
Control				
Length			***35***	***5739***
No. Thread Started			***61***	***10066***
Self-Claim			***64***	***10530***
Prior Beliefs			5	
No Exposure			***70***	***11564***
Real Life			86	

Note. The non-italicized and non-bolded numbers refer to the percentage of cases that need to be replaced with cases at the threshold for inference in order to sustain an inference ($p < 0.05$)

be a supporter, and experienced no exposure were more likely to hold extreme ideological beliefs. Of these predictors, differential reinforcement had the strongest effect ($\beta = 0.246$), followed by differential association ($\beta = 0.190$) and the absence of exposure ($\beta = 0.071$).

All measures of SLT, apart from the use of movement-related image, reached statistical significance. Differential reinforcement was again the strongest predictor in Model 2, followed by differential association. This finding is similar to the results from Model 1 but again contradictory to the theoretical propositions of SLT. The support is less strong for imitation; the use of movement-related imagery in posts was insignificant while the effect of using movement-related usernames was the lowest among all significant variables. Overall, the results from Model 2 showed support again for the SLT.

All control variables, with the exceptions of users' prior beliefs and forums' association with real-life organizations, were statistically significant. Users' who participated longer in all forums experienced lesser change in expressed extreme ideological beliefs compared to users that were newer members of the forums. Also, users who did not claimed to be a supporter were more receptive towards extreme ideological beliefs. This suggests that the possibility of variations among users in terms of their stages of radicalization (Borum, 2011; Holt, Freilich, Chermak, & McCauley, 2015; Koehler, 2014; McCauley & Moskalenko, 2008).

The positive correlation between users with no exposure and extreme ideological beliefs was surprising. Users who did not actively respond to other users' posts, or potential lurkers of forums, were radicalized as well. This may point to the possibility of a different subset of users within these forums. This specific findings coincide with McCauley and Moskalenko's (2008) mechanism of slippery slope that describes users who gradually become more radicalized through self-persuasion and justification. For this subset of users, it is likely that their motivation for joining online forums was driven by information seeking rather than by the search for social supports from the virtual community that emphasizes social interactions (Bowman-Grieve, 2009; De Koster & Houtman, 2008).

Sensitivity analyses for Model 2 further supported the suitability of SLT as a theoretical framework for understanding online radicalization. To invalidate the significant inferences of differential association and differential reinforcement, 89% and 92% of cases respectively need to be replaced with null cases (Frank et al., 2013). Sensitivity analysis confirmed the weaker effect found for the use of movement-related usernames. To invalidate the inference, only a replacement of 12% of cases was required. On the other hand, for users' inclusion of movement-related image to reach significance, it required a replacement of 65% of null cases with cases that meet the threshold of inference in order to sustain an inference, which further proved its lack of unique contribution in predicting extreme ideological beliefs. These findings demonstrate the effects for differential association and reinforcement were unlikely to be a result of biases.

As for control variables, the number of threads started, users' claim as supporter, and users' lack of exposure all required replacement of more than 64% of cases to invalidate the inference. Users' length of participation had the weakest inference. Only 35% of cases need to be replaced with null cases to invalidate the inference (Frank et al., 2013).

The inclusion of years in Model 3 yielded similar results to Model 2. The findings from Model 3 showed that three of the four SLT variables reached statistical significance. Differential reinforcement and differential association continued to be the two strongest predictors in the model. The use of movement-related username continued to be significant but with weak effect, while the use of movement-related imagery failed to reach significance again. As for control variables, similar results for the number of threads started, users' claims to be supporters, and users' lack of exposure were seen in this model.

Table 4.12. Model 3 of Full-Forum Social Influence Models

	Model 3		
	Regression Coefficient	Std. Error	Beta
Social Learning			
Exposure	0.424**	0.024	0.191
In-Degree	0.089**	0.004	0.245
Movement Image	0.069	0.075	0.009
Movement Name	0.192*	0.082	0.020
Control			
Length	-0.001	0.001	-0.017
No. Thread Started	-0.069**	0.014	-0.052
Self-Claim	-0.965**	0.182	-0.041
Prior Beliefs	0.014*	0.007	0.016
No Exposure	0.463**	0.069	0.075
Real Life	-0.084	0.131	-0.005
Year			
2003	0.206	0.318	0.005
2004	0.247	0.182	0.011
2005	-0.260	0.144	-0.015
2006	-0.164	0.113	-0.013
2007	-0.151	0.108	-0.012
2008	0.107	0.096	0.011
2010	-0.067	0.085	-0.008
2011	-0.252**	0.083	-0.033
2012	-0.292**	0.083	-0.038
2013	-0.230**	0.081	-0.033
2014	-0.296**	0.082	-0.043
Constant	-0.063	0.156	
R^2	0.328		
n	16557		

Note: * $p < 0.05$, ** $p < 0.01$

There were two minor differences between the results of Model 2 and Model 3. First, users' length of participation went from significant in Model 2 to insignificant in Model 3. This is unsurprising given its weak effect in Model 2 and low percentage of case replacement to invalidate the inference as shown in the sensitivity analysis. Similarly, sensitivity analyses for Model 3 showed that to sustain the inference for users' length of participation, 49% of cases need to be replaced with cases that meet the threshold for inference (Frank et al., 2013). This means that the lack of significant correlation for users' length of participation is a strong finding since it would require a replacement of almost half of the null cases for the variable to reach significance.

Table 4.12a. Sensitivity Analysis for Model 3

	Percentage	No. of Cases
Social Learning		
Exposure	***89***	***14720***
In-Degree	***91***	***15098***
Movement Image	53	
Movement Name	***16***	***2697***
Control		
Length	49	
No. Thread Started	***60***	***9972***
Self-Claim	***63***	***10436***
Prior Beliefs	***2***	***330***
No Exposure	***71***	***11721***
Real Life	67	
Year		
Year2003	67	
Year2004	31	
Year2005	8	
Year2006	26	
Year2007	29	
Year2008	43	
Year2010	60	
Year2011	***35***	***5868***
Year2012	***44***	***7332***
Year2013	***31***	***5128***
Year2014	***46***	***7567***

Note. The non-italicized and non-bolded numbers refer to the percentage of cases that need to be replaced with cases at the threshold for inference in order to sustain an inference ($p < 0.05$)

Second, users' prior beliefs were significant in Model 3. Users with higher prior beliefs were more likely to expressed higher levels of extreme ideological beliefs. The findings point to the possibility of self-radicalization (McCauley & Moskalenko, Mechanisms of Political Radicalization: Pathways Toward Terrorism, 2008). However, the effect of users' prior beliefs was the lowest among all significant variables. Sensitivity analysis also showed that to invalidate the inference, a mere 2% of cases need to be replaced with null cases (Frank et al., 2013). Aside from the two relatively weak differences, the results from Model 3 reaffirmed the results from Model 2. This again demonstrates that the SLT is a suitable framework for online radicalization but there are other mechanisms at play.

In Model 4, users' ranks in forums and binary variables for forums were included and Table 4.13 reports the results of the social influence model. Interaction terms between users' ranks and binary variables for forums were created to account for differences in hierarchical structures across the seven forums. Multicollinearity was an issue in this model where the VIF values for users' ranks and all interaction terms were higher than ten. The standard errors of some variables also increased compared to Model 3.

The Model 4 output concurs with the findings of Model 3 but there are two exceptions worth highlighting. First, differential association ($\beta = 0.166$) was not the second strongest predictor. The effect of users' ranks in Forum 2 showed stronger effect ($\beta = 0.2$) while neither of the respective variables reached significance. The significant correlation of users' rank and Forum 2 meant that the effect of users' rank in Forum 2 is distinct from the effect of users' rank in Forum 5. Second, the use of movement-related username and users' prior beliefs failed to reach significance in Model 4. This is unsurprising given the low number of cases that needed to be replaced to invalidate both inferences in Model 3.

Table 4.13. Model 4 of Full-Forum Social Influence Models

	Model 4		
	Regression Coefficient	Std. Error	Beta
Social Learning			
Exposure	0.369**	0.025	0.166
In-Degree	0.093**	0.004	0.256
Movement Image	0.011	0.077	0.001
Movement Name	0.135	0.083	0.014
Control			
Length	-0.001	0.001	-0.008
No. Thread Started	-0.072**	0.014	-0.055
Self-Claim	-0.796**	0.183	-0.033
Prior Beliefs	0.007	0.007	0.008
No Exposure	0.394**	0.069	0.063
Year			
2003	0.193	0.320	0.005
2004	0.247	0.185	0.011
2005	-0.239	0.148	-0.013
2006	-0.155	0.115	-0.012
2007	-0.142	0.110	-0.012
2008	0.117	0.096	0.012
2010	-0.074	0.085	-0.009
2011	-0.289**	0.084	-0.038
2012	-0.362**	0.087	-0.048
2013	-0.299**	0.087	-0.043
2014	-0.375**	0.090	-0.055
Users' Ranking	-0.091	0.088	-0.076
Forum			
Forum 1	-0.103	0.331	-0.012
Forum 2	-0.407	0.321	-0.067
Forum 3	-0.106	0.329	-0.017
Forum 4	-0.148	0.736	-0.005
Forum 6	-0.028	0.318	-0.005
Forum 7	-0.335	0.542	-0.016
Interaction			
Rank X Forum 1	0.094	0.091	0.063
Rank X Forum 2	0.246**	0.090	0.200
Rank X Forum 3	0.112	0.092	0.073
Rank X Forum 4	0.128	0.204	0.016
Rank X Forum 6	0.104	0.089	0.101
Rank X Forum 7	0.337	0.186	0.043
Constant	-0.103	0.317	
R^2	0.337		
n	16557		

Note: * $p < 0.05$, ** $p < 0.01$

Table 4.13a. Sensitivity Analysis for Model 4

	Percentage	No. of Cases
Social Learning		
Exposure	***87***	***14358***
In-Degree	***92***	***15161***
Movement Image	93	
Movement Name	17	
Control		
Length	49	
No. Thread Started	***62***	***10247***
Self-Claim	***55***	***9096***
Prior Beliefs	49	
No Exposure	***66***	***10874***
Year		
2003	69	
2004	32	
2005	18	
2006	31	
2007	34	
2008	38	
2010	56	
2011	***43***	***7124***
2012	***53***	***8757***
2013	***43***	***7114***
2014	***53***	***8768***
Users' Ranking	47	
Forum		
Forum 1	84	
Forum 2	35	
Forum 3	84	
Forum 4	90	
Forum 6	96	
Forum 7	68	
Interaction		
Rank X Forum 1	47	
Rank X Forum 2	***28***	***4684***
Rank X Forum 3	38	
Rank X Forum 4	68	
Rank X Forum 6	40	
Rank X Forum 7	8	

Note. The non-italicized and non-bolded numbers refer to the percentage of cases that need to be replaced with cases at the threshold for inference in order to sustain an inference ($p < 0.05$)

Table 4.13b. Model 4a of Full-Forum Social Influence Models

	Model 4a		
	Regression Coefficient	Std. Error	Beta
Social Learning			
Exposure	0.383**	0.025	0.172
In-Degree	0.093**	0.004	0.255
Movement Image	0.118	0.076	0.015
Movement Name	0.150	0.083	0.016
Control			
Length	-0.001	0.001	-0.007
No. Thread Started	-0.073**	0.014	-0.055
Self-Claim	-0.835**	0.183	-0.035
Prior Beliefs	0.010	0.007	0.011
No Exposure	0.412**	0.069	0.066
Year			
2003	0.209	0.320	0.005
2004	0.248	0.185	0.011
2005	-0.242	0.148	-0.014
2006	-0.157	0.115	-0.012
2007	-0.142	0.110	-0.012
2008	0.122	0.096	0.012
2010	-0.074	0.085	-0.009
2011	-0.282**	0.084	-0.037
2012	-0.349**	0.087	-0.046
2013	-0.281**	0.087	-0.040
2014	-0.353**	0.090	-0.051
Forum			
Forum 1	0.245**	0.113	0.028
Forum 2	0.580**	0.100	0.095
Forum 3	0.305**	0.107	0.048
Forum 4	0.283	0.234	0.010
Forum 6	0.364**	0.107	0.069
Forum 7	0.604**	0.180	0.028
Constant	-0.476**	0.126	
R^2	0.332		
n	16557		

Note: * $p < 0.05$, ** $p < 0.01$

Given the issues of multicollinearity with Model 4, the results need to be interpreted with care as there is an increased chance of bias. To do so, a modified model (Model 4a) without users' ranking and interaction terms with forums was ran. By comparing the results between

Model 4 and Model 4a, it is possible to determine if the inclusion of users' ranking added more to the findings.

When contrasted against the original model, Model 4a painted a picture of the dataset and online radicalization much like Model 4 but highlighted two minor differences. First, the coefficients for these forums suggest three levels in far-right ideological beliefs. The highest level consisted of Forum 2 ($\beta = 0.095$) and Forum 6 ($\beta = 0.069$), followed by the second level with Forum 1 ($\beta = 0.028$), Forum 3 ($\beta = 0.048$), and Forum 7 ($\beta = 0.028$). Forum 4 had the lowest effect across all forums ($\beta = 0.01$).

Second, results from the modified model found that all forums, apart from Forum 4, had significantly higher level of expressed extreme ideological beliefs compared to the reference forum. This is surprising since the reference forum, Forum 5, has ties to a well-known offline far-right organization. This contrast suggests that forums' hierarchical structures may be one factor contributing to between-forums differences in level of expressed extreme ideological beliefs.

Across all models, the inclusion of binary variables for year revealed a temporal pattern across these forums. Compared to the year of reference, 2009, posts between 2003 and 2007 were not significantly different in extreme ideological beliefs but posts from 2011 and onward were significantly less radical. This comparison indicated a spike in expressed extreme ideological beliefs across all seven forums, which may reflect the political climate between 2008 and 2009 in the United States. In 2008, Barack Obama was elected and was the first black president (History.com, 2012). Given President Obama's race, it is highly possible that his election contributed to the spike in discussions on far-right ideological beliefs during 2009.

Table 4.14. Social Influence Model with Interaction Term

	Regression Coefficient	Std. Error	Beta
Exposure*Post2009	0.194**	0.047	0.082
Independent Variable			
Exposure	0.229**	0.047	0.103
In-Degree	0.093**	0.004	0.256
Movement Image	0.103	0.076	0.013
Movement Name	0.138	0.083	0.014
Control			
Length	-0.002**	0.001	-0.026
No. Thread Started	-0.076**	0.014	-0.058
Self-Claim	-0.796**	0.183	-0.033
Prior Beliefs	0.008	0.007	0.010
No Exposure	0.390**	0.070	0.063
Year			
Post2009	-0.209**	0.063	-0.032
Forum			
Forum1	0.409**	0.110	0.047
Forum2	0.598**	0.099	0.098
Forum3	0.439**	0.103	0.069
Forum4	0.217	0.234	0.007
Forum6	0.497**	0.102	0.094
Forum7	0.595**	0.180	0.028
Constant	-0.523**	0.117	
R-Square		0.330	
N		16557	

Note: * $p < 0.05$, ** $p < 0.01$

This temporal pattern was further confirmed in Table 4.14 that reports the results of social influence model with the inclusion of a new binary variable. Posts made after 2009 were coded as “1” for this new variable. The results from this model found that posts after 2009 contained significantly less extreme ideological beliefs than posts prior to 2009. To determine if the effect of differential association differs before and after the year 2009, a fifth model was conducted and included an interaction term between posts made after 2009 and the exposure term. The interaction term was significant and therefore indicated a difference in the effect of differential association before and after 2009. Posts made after 2009 also included significantly less extreme ideological beliefs.

CHAPTER 5: DISCUSSION AND IMPLICATION

Information and technology afford governments, businesses, and individual users with convenience and opportunities (Holt, 2013; Newman & Clarke, 2003; Taylor et al., 2011; Wellman, et al., 1996). As society continues to integrate the Internet into all facets of life, it increases the probability of individuals becoming both victims and perpetrators of cybercrime. One factor contributing to this problem is the growing popularity of the Internet across subcultural groups due to the anonymous and far-reaching nature of the Internet (Holt, 2010; Newman & Clark, 2003). To many subcultural groups, the Internet serves the functions of recruitment, networking, and information sharing (Holt, 2007; Holt et al., 2014; Jordan & Taylor, 1998; Kinkade et al., 2013; Maratea, 2011; Milrod & Weitzer, 2012; Thomas, 2002).

Much like other subcultural groups, online extremist groups use the Internet for similar functions but also as a tool to radicalize potential individuals (Borum, 2011; King & Taylor, 2011; Mandel, 2009). Radicalization refers to the process through which an individual develops and/or accepts extreme ideologies and beliefs, and it is acknowledged as a specific stage in one's transition from extremism to terrorism (Borum, 2011; Conway, 2017; Holt, Freilich, & Chermak, 2017; Mandel, 2009; McCauley & Moskalenko, 2008). Several theories and mechanisms, such as social movement theory (Borum, 2011) and personal grievances (McCauley & Moskalenko, 2008), were proposed by scholars to understand radicalization. These theories and mechanisms are supported by current literature on far-right movement in the United States (Bowman-Grieve, 2009; Warner, 2010)

Within current literature, however, there are still debates on the role of the Internet in the radicalization process as there is no single agreed upon theory of radicalization. One possible role of the Internet is that of an echo chamber, which creates an environment that allows for polarization (Sunstein, 2007). An echo chamber refers to an environment where individuals surround themselves with information that confirm their own beliefs, opinions, and views (Sunstein, 2007). The filtering and personalization of information and online interactions afforded by the Internet restricted individuals' exposure to like-minded information and materials, resulting in the creation of echo chamber (Sunstein, 2007). Online environments like Facebook and forums enable groups of like-minded individuals to talk and listen to one another in ways that enable echo chamber formation (Sunstein, 2007). These homogeneous interactions are then likely to increase one's level of extremism due to group polarization where opinions tend to become more extreme in the original direction that group member favored after they participate in group discussions. The impacts of group polarization are more likely to occur and at an extreme degree if the members perceive themselves as "part of a group having a shared identity and a degree of solidarity" (Sunstein, 2007, p. 67).

The existence of echo chambers coincides with other mechanisms of radicalization discussed in the context of extremism and terrorism (O'Hara & Stevens, 2015). For example, McCauley and Moskalenko (2008) listed group polarization as one of the 12 radicalization processes. Costello and colleagues (2016) also found that 31.8% of their sample of 1034 Internet users sought out extremist materials online and 14% of the sample encountered such material via the referral of a friend or acquaintance. In this sense, the danger of echo chamber and polarization is more prominent in online far-right groups given that the Internet creates echo chamber and polarization and therefore merits scholarly attention. This concern is reflected in a current review of key questions related to violent radicalization (Bouchard & Nash, 2015; Conway, 2017; Ducol, Bouchard, Davies, Ouellet, & Neudecker, 2016). Specifically, Conway (2017) encouraged future studies on violent radicalization to focus on two questions: 1) does radicalization occur in online contexts, and 2) what are the specific mechanisms and differences of violent online radicalization (p. 82).

Social Learning Theory (SLT) is a suitable framework to examine these two questions as it is applicable to online group membership, group dynamics, and social relations. Additionally, SLT has been utilized to understand the relationship between exposure to extremist content in social media and self-reported violence (Pauwels & Schils, 2016). Social learning is compatible with the views that the Internet is an echo chamber since it accounts for such autonomy and agency by recognizing that one's choice of association dictate one's exposure to definitions, reinforcement, and models for imitation.

This dissertation assessed the role of Internet in the radicalization process by analyzing 27,407 posts collected from seven online far-right extremist web forums. This study addressed Conway's (2017) key research questions through the use of repeated-measure analysis of variance (RM-ANOVA) and influence model of social network analysis. RM-ANOVA was suitable for comparing multiple measures across time. Social influence models are appropriate for this study because it allows for a statistical model to identify changes in individuals' attitudes or behaviors as an outcome of social interactions among other possible predictive factors (Frank & Fahrbach, 1999).

Did Online Radicalization Occur?

For the first question on the occurrence of online radicalization, the RM-ANOVA provided preliminary answers. For six of the seven forums, the results of the RM-ANOVA, with a Greenhouse-Geisser correction due to violation of sphericity assumption, determined that the mean of extreme ideological beliefs differed statistically significantly between time points. In other words, six of the seven forums experienced online radicalization at the group level. Post hoc tests of each forum revealed different trends and peaks overtime, but all six forums ended with a lower level of expressed extreme ideological beliefs compared to the beginning. This trend was also evident in the full-forum model where extreme ideological beliefs were significantly lower after the year of 2009.

One possible explanation for forums and users expressing lower levels of extremist ideologies is the recent changes in far-right movements in the United States. In this context, the historical election of the first African American president in 2008 may have been be a possible catalyst for the spike in expressed far-right extremism in online forums in 2009. Individuals may have turned to online forums for social support and information during that time period, especially if individuals experienced social rejection or discrimination in offline settings (Bowman-Grieve, 2009; De Koster & Houtman, 2008; Hale, 2012). Given that online forums offered users the freedom to speak freely about their beliefs (De Koster & Houtman, 2008), individuals may be more drawn towards online forums to cope with overall political climate during that time period.

Additionally, the decrease in expressed extreme far-right ideologies after 2009 is possibly the byproduct of the movement becoming more mainstream. About two decades ago, scholars suggested that the far-right movement incorporated the broader ideologies of “white as victim” and “angry white male” as an attempt to become more mainstream and increase recruitment (Berbrier, 2000; Perry, 2000). The integration of the broader ideologies results in a shift in discourse. A recent case study on far-right propaganda suggested that far-right extremists in the United States, rather than highlighting stereotypes and the inferiority of other minority groups, are framing the movements as a fight against the suppression of the White race (Castle, Kristiansen, & Shifflett, 2018). Such shifts in discourse may explain the observed decrease in expressed extreme far-right ideological beliefs given the measures of extreme ideologies for this study.

Besides the peak at 2009, the variations in far-right extremism in six of the seven forums across time provide empirical support on the current notion that radicalization is a gradual and dynamic process (Ducol et al., 2016; Holt et al., 2015). This is evident in the findings of this analysis even though it focused solely on online data. Additionally, the variations observed across six forums concurred with current understandings on cyclical patterns of posting behaviors in online forums in two manners. The results provide partial support for that of Scrivens and colleagues (2018) who found that users in online radical right-wing forums initially expressed less extreme ideological beliefs but experienced gradual and steady increases over time. They also found that users tended to decrease their posting behaviors within the first two years of participation (Scrivens, Davies, & Frank, 2018). These findings mean that theories and mechanisms explaining radicalization process in general may need to take time and the online environment into account.

The findings from this study also highlight the need for greater data collection from forums. The longitudinal nature of the datasets used in this dissertation allowed for the examination of temporal patterns within forums. Since the datasets were convenience samples that contained public forum posts over time, the results have limited generalizability. To address this issue, future studies should consider the use of big data in this field where the "collection and analysis also needs to be ongoing" (Conway, 2017, p. 87), which would allow scholars to derive a more comprehensive understanding on radicalization process in online contexts.

These big datasets should focus on two aspects. First, datasets derived from online forums should aim for comprehensiveness. Beyond length of time, these datasets should consider collecting information beyond public posts. Second, these datasets should be collected from a variety of forums and social media platforms. This variation in data sources would allow scholars to compare and explore if far-right extremist groups differ in operations or dynamics across social media platforms.

This study also noted differences in level of extremism observed across seven forums, but high level of similarities in online radicalization and relevant mechanisms. The similarities in online radicalization mechanisms may be attributed to the similar affordances of online forums (Holt, 2007; Mann & Sutton, 1998). Other social media platforms such as Twitter and YouTube differ in features and affordances and can potentially have different effects on participants' political extremism and behaviors (Conway, 2017; Pauwels & Schils, 2016; Warner, 2010). Also, there are differences in the age of users across social media platforms. For example, individuals between 18 and 49 all ranked Facebook and YouTube as the top two most-visited social media pages. However, the third most-visited social media pages varied by age with younger adults preferring Snapchat whereas adults between the ages of 30 and 49 chose Instagram (Pew Research Center, 2018). Expanding on the depth of datasets would advance current knowledge on far-right extremist groups' purposes and motivations for using social media platforms.

Together, the results from the current study indicated that radicalization occurs in online forums. Specifically, this study shed light on the relationship between participation in online forums and the radicalization of opinions. For policymakers, this points to the need for continuous data collection and analysis to better understand the evolution of the far-right movements rather than disrupting or shutting down these forums. The reasoning is twofold. First, very little known is about the effectiveness of disrupting online platforms such as online stolen data markets (Hutchings & Holt, 2017; Neumann, 2013). Second, taking down an online platform does not address the root cause of online radicalization because there will always be other platforms. For example, in the United States, there is an shift to using social media sites such as Gab and Telegram after sites such as Twitter and Facebook began to manage content and ban users (Livni, 2019).

With a more concrete understanding of the platforms where radicalization occurs, it would provide insight into several areas of interest, including possible connections between radicalization of opinions and radicalization of actions. Within this current study, most users did not publicly claim to be supporters of the movement. This lack of claims can potentially be a result of administrators' and moderators' motivation to protect the communities by keeping attention away from the forums. Forums generally discouraged users from initiating or engaging in discussions about violence on forums to prevent shutdown and unwanted attention (Bowman-Grieve, 2009) or to establish non-violent public images (Hale, 2012). Until more empirical evidence is discovered on the relationship between the radicalization of opinions and radicalization of actions, the best course of action is to engage in continuous data collection and analysis.

How Did Online Radicalization Occur?

Comprehensive longitudinal datasets would also be highly beneficial to examine the mechanisms of online radicalization. The results from this analysis are consistent with current knowledge on SLT where differential association and definition had the strongest effects compared to the other theoretical concepts of SLT (Akers, 2009; Pratt, et al., 2010). More importantly, the findings indicated that the SLT is a plausible theoretical framework for understanding the online radicalization. Differential association and reinforcement were the two strongest predictors in the full-forum model while holding all other variables constant. Users who interacted with more radicalized users and received more responses from other users were more likely to experience radicalization. This finding provides empirical support for the current literature on the role of social interactions in online communities as a pull factor towards radicalization and extremism (Bowman-Grieve, 2009; De Koster & Houtman, 2008; Hale, 2012; McCauley & Moskalenko, 2008; Neumann, 2013).

Despite the strong effect, the findings from this study also suggest that other mechanisms were at play across these forums. The inclusion of control variables increased the accounted variance compared to the model with only SLT variables. The significant, unique contributions of some control variables also point to the possibility of multiple mechanisms. For example, across the seven forums, users with no exposure to others expressed more extreme ideological beliefs and was the predictor with the third highest effect in three of the four models. For these users who did not engaged socially in these online communities, radicalization still occurred. This points to the possibility of a different subset of users across the seven forums. For this subset of users, it is likely that their motivation for joining online forums was driven by information seeking rather than by the search for social supports from the virtual community that emphasizes social interactions (Bowman-Grieve, 2009; De Koster & Houtman, 2008).

Another variable of interest is users' prior beliefs because it points to the possibility of alternative mechanisms towards radicalization. The findings showed that users with higher beliefs in the previous year were more likely to experience radicalization of opinions. Specifically, the variable was significant in two of the five full-forum models, albeit smaller effects. Alongside with the effects of users' lack of exposure, this finding points to the presence of slippery slope as an alternative mechanism towards radicalization. McCauley and Moskalenko

(2008) described the slippery slope mechanism as individuals who gradually become more radicalized through self-persuasion and justification. Findings from the study suggest that users with some level of acceptance in far-right extreme ideological beliefs were more likely to continue to accept more extreme ideological beliefs.

This does not negate the effects of participation in online forums. Holt and colleagues (2019) argued that individuals who had been self-radicalized could be further radicalized through participations in online forums, as evident in cases like Dylann Roof. Also, online far-right forums can be seen as a "criminogenic environment" where individuals learned to normalized extreme ideological beliefs and were positively rewarded on these forums (Neumann, 2013). The current findings suggested that similar mechanisms were present across the seven forums since differential association and differential reinforcement were also significant predictors in the models. Thus, in addition to being radicalized through interacting with others, online radicalization occurred also occurred through passive participation in these forums and communities.

There also appeared to be divisions in users' roles across these forums. Specifically, users who participated in the forums for longer periods of time, users who claimed to be supporters, and users who started more threads expressed less extreme ideological beliefs. As a whole, it may be that more engaged users were less likely to experience radicalization online. Another possible explanation is that users who were experienced members in the forums had different responsibilities; they were expected to be knowledge and information providers (Bowman-Grieve, 2009). In this case, users who were involved in the forums for longer periods of time are hypothetically at later stages of radicalization and therefore less likely to accept more extreme ideological beliefs. Another reason could be that more engaged users viewed online forums as platforms for non-political social activities (Koehler, 2014) and were therefore less likely to experience radicalization on these forums.

All in all, the presence of multiple mechanisms towards radicalization in this study is in agreement with current literature on online radicalization (Borum, 2011; McCauley & Moskalenko, 2008). McCauley and Moskalenko (2008) recognized the challenges of having one theory that encapsulates all twelve mechanisms and that multiple mechanisms can be identified in known trajectories to terrorism. Borum (2011) also suggested the integration of theories to better understand radicalization and extremism and stated that "no single theory is likely to explain all violent radicalization." (p. 31). These scholars reinforce that the complexities of online radicalization merit a multi-theoretical approach to examine the issue.

To address such complexities, future studies should focus on three aspects. The first is to test the SLT alongside with other mechanisms and theories. The mechanism and theories can be from the extremism and terrorism literature, which include the slippery slope mechanism (McCauley & Moskalenko, 2008) and social movement theory (Borum, 2011). Mechanisms and theories from criminology can also be suitable, as the findings from this study illustrated. Some appropriate examples are strain theories and social control theories since concepts from these theories were found to be significant predictors towards violent political extremism (LaFree, Jensen, James, & Safer-Lichtenstein, 2018; Pauwels & Schils, 2016). LaFree and colleagues (2018) found that the lack of stable employment and criminal records were significant predictors of violent acts by extremists.

Another suitable criminological theory is techniques of neutralization (Borum, 2011). This theory shows promises given the recent shifts in the discourse of far-right movements in the United States (Berbrier, 2000; Perry, 2000). The inclusion of the "White as victims" ideology potentially provides grounds for rationalization to individuals who resolve to violence (Sykes & Matza, 1957). The notion of seeing Whites as victims allows individuals to justify their violent acts by framing their behaviors as understandable measures for ensuring the survival of the race (Berbrier, 2000). Thus, techniques of neutralizations are applicable to understand the acceptance of extreme ideological beliefs as well as the relationship between radicalization of opinions and actions.

The second approach is the inclusion of online peer association. The current study showed that social interactions and participation in online forums were positively associated with radicalization, which suggests that the role of online forums as secondary and reference groups for individuals. Relatively few studies include both online and offline peer groups in their studies on radicalization (Wojcieszak, 2010). Studies on physical violence are beginning to examine the effects of online and offline peer groups, but it is inconsistent and mainly based on qualitative case studies. There is therefore a need to understand the interaction between the dynamics of primary groups and online secondary groups contribute to both the radicalization of opinions and radicalization of actions.

Lastly, it is necessary to understand if findings from this study can be replicated in other contexts. Conway (2017) pointed to the need to examine the effectiveness of the Internet in various groups such as *jihadists* and extreme left. The current study provided a possible theoretical framework and highlights the need for longitudinal studies in future comparison studies. However, since the current study focused on far-right movement in the United States, it may not be generalizable to far-right movement outside of the United States or other extremist movements in general.

The present study has other limitations due to the nature of the dataset. First, the dataset captures public interactions on the forums via threads and posts. It does not account for other forms of interactions and are therefore limited in addressing offline dynamics. This dataset, however, captures public display of attitudes and allows for the examination of the radicalization process in forums. Second, the dataset does not examine social networks and dynamics from the users' perspective. It is possible that discrepancies exist between users' identifications of friends and the frequency of interactions in general versus the public interactions captured in the dataset. Future studies should aim to include private messaging and interactions between participants, which may more accurately reflect engagement.

Despite these limitations, the present study offer material for further studies on online radicalization. First, this study found evidence of online radicalization across seven forums between 2003 and 2015. In particular, the findings showed variations in the patterns of change and peaks in mean extreme ideological beliefs across these forums, which lent support to the notion that online radicalization is a gradual and dynamic process. It appears that historical events may be a contributing factor. This indicates that an important task for future research lies in the continuous collection and analyses of online far-right extremist groups and other extremist groups, allowing for more in-depth understanding on the life cycles and susceptibility of these groups to real-life events.

The present study, through a social influence model, showed that the SLT provides some theoretical explanation for online radicalization. Differential association and differential reinforcement emerged as the two strongest predictors. The findings also revealed the possibility of multiple mechanisms at play; some of the control variables accounted for McCauley and Moskalenko's (2008) slippery slope mechanism. The findings from the present study also indicate the need for the collection and analysis of comprehensive studies and for future studies to develop and test an integrated theoretical model accounting for the types of social media platforms, multiple theoretical explanations, and various extreme political movement and groups.

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