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IMPACT OF PERCEIVED PEER ATTITUDES AND SOCIAL NETWORK DIVERSITY ON
VIOLENT EXTREMIST INTENTIONS

by

WOJCIECH KACZKOWSKI

Under the Direction of Kevin Swartout, PhD

ABSTRACT

Perceived peer attitudes often influence young adult men's violent attitudes and intentions, whereas the structure of peer networks can moderate this relationship. For example, people with more diverse social networks are less likely to adopt their close peers' violent attitudes and behaviors. Despite that, there is currently limited research examining the role of structural features of peer networks in the relationship between perceived peer attitudes and violent extremist attitudes or intentions. Consequently, the current study sought to address this gap in research and answer the following questions: (1) To what extent are perceived peer attitudes, personal attitudes, and violent extremist intentions related to each other? (2) To what extent does the relationship between perceived peer attitudes and violent extremist intentions

differ at different levels of social network diversity? The study sample consisted of 340 young adult men (i.e., 18-29 years old). Data collection took place via Amazon Mturk, an online-based crowdsourcing platform. Participants first indicated a social group with which they most strongly identify and listed their five closest male peers from the same group. Next, participants reported their violent extremist attitudes, intentions, and their perceptions of their peers' opinions. Overall, perceived peer attitudes were positively and significantly associated with violent extremist intentions through their relationship with personal attitudes. The mediating effect, however, was partial: personal attitudes did not fully account for the total association. Furthermore, social network diversity moderated the relationship between personal and perceived peer attitudes: participants with more diverse social networks were less likely to hold beliefs similar to their perceived peer attitudes. In general, study findings were in line with past research on the impact of perceived peer attitudes and social network structure on violent outcomes. Thus, future studies should explore the potential role of other aspects of peer networks in the development of violent extremist attitudes and intentions. Regarding its policy implications, the study highlights the need for social-ecological approaches to counter violent extremism, offering young adult men opportunities for community involvement and growth of social ties.

INDEX WORDS: Violent extremism, Peer influence, Social networks, Social network diversity, Perceived norms, Perceived peer attitudes

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VIOLENT EXTREMIST INTENTIONS

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WOJCIECH KACZKOWSKI

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

in the College of Arts and Sciences

Georgia State University

2020

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Wojciech Kaczkowski
2020

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VIOLENT EXTREMIST INTENTIONS

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May 2020

DEDICATION

Chciałbym zadedykować tę pracę doktorską mojemu dziadkowi, Stanisławowi Cieśli, który nasze ostatnie wakacje spędził pomagając mi zebrać się do pracy, gdy brakowało mi motywacji.

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1 INTRODUCTION

Violent extremism, or the use of or support for ideologically motivated violence to further political objectives (United States Agency for International Development, 2011), is one of the critical national security issues of our times. The number of violent extremist attacks in the United States has been steadily increasing in the past decade, mostly due to the rise in far-right extremism (Jones, 2018). Since 2001, approximately 496 violent extremist attacks have occurred in the United States, resulting in the deaths of at least 237 people (Bergen et al., 2019). Although extremism comprises only a small fraction of violent crimes, it often has an immense impact on public opinion and policymaking. For example, the recent wave of anti-Semitic attacks or the mass shooting in El Paso, Texas, has received considerable international attention and sparked a nationwide debate (Jacobs, 2019; King, 2019). As a result, nearly 80% of American adults are now concerned that politically motivated violence is likely to increase in the near future (Montanaro, 2018).

Social scientists need to identify the potential risk factors for violent extremism to design and implement successful policies to counter politically motivated violence. For example, perceived peer attitudes can indirectly influence violent extremist intentions through their impact on one's personal attitudes (Dahl & Van Zalk, 2014; Kuhn, 2004). In other words, people who believe that their peers would approve of violent political actions are more likely to hold such attitudes themselves and, consequently, express readiness to engage in violent extremism. This relationship is most pronounced for young adult men (i.e., between 18 and 29 years old), as this population is both particularly vulnerable to peer influence (McCoy et al., 2019; Steinberg & Monahan, 2007) and at a heightened risk for engaging in violent extremism (Kimmel, 2018).

In addition to the attitudinal composition of peer networks, their structural features may also play a significant role in shaping one's violent attitudes and behaviors (Jose et al., 2016). For instance, social network diversity, or the number of social domains in which people interact with their peers (S. Cohen et al., 1997), is associated with a lower likelihood of endorsing prejudiced beliefs (Walter et al., 2017) or perpetrating sexual violence (Kaczkowski et al., 2017). However, research has not yet fully explored the role of social network diversity in the relationship between perceived peer attitudes, personal attitudes, and violent extremist intentions.

The current study seeks to address this gap in research. First, the study examines the relationship between perceived peer attitudes, personal attitudes, and violent extremist intentions. Second, the study assesses whether the strength of the relationship between perceived peer attitudes and personal attitudes differs depending on the extent of social network diversity. Based on past research (e.g., Dahl & Van Zalk, 2014; Kuhn, 2004), I hypothesize that perceived peer attitudes are significantly and indirectly associated with violent extremist intentions through their relationship with personal attitudes. In other words, people who view their peers as supportive of violent extremism are more likely to hold similar attitudes and express willingness to engage in such behaviors themselves. Furthermore, I hypothesize that social network diversity moderates the association between perceived peer attitudes and personal attitudes: the strength of this relationship is reduced for people with high social network diversity. Namely, people with more diverse networks are less likely to hold violent extremist attitudes, even when they think their close peers would support such beliefs.

1.1 Violent Extremism

The United States Agency for International Development (2011) defines violent extremism as “advocating, engaging in, preparing or otherwise supporting ideologically

motivated or justified violence to further social, economic, or political objectives” (p. 8). Based on this definition, violent extremism encompasses both attitudinal (“supporting”) and behavioral (“advocating, engaging in, preparing”) outcomes, including terrorism and other forms of politically motivated violence. Furthermore, it comprises both violent/illegal (“engaging in”) and non-violent/legal actions (“advocating”).

Men are more likely than women to endorse violent extremist attitudes and behaviors, particularly in their early adulthood (Kimmel, 2018). For instance, Gallup Poll (2011) found that 47% of respondents in Canada and the United States considered it sometimes or always justifiable for the military to target and kill civilians, with young adult men most likely to agree with this statement. Similarly, Pew Research Center (2007) reported that 25% of American Muslim men under the age of 30 years old considered suicide bombings to be justified at least in some circumstances, compared to only 9% of older Muslim Americans.

Research on the perpetrators of violent extremist attacks reveals a similar association of age and gender with the likelihood of engaging in politically motivated violence. The demographic analyses of violent extremist organizations found that the proportion of young adult men (i.e., between 18 and 29 years old) within their ranks has ranged from 93% in radical Islamic and 91% in far-right to 54% in far-left groups (Handler, 1990; Sageman, 2004). Furthermore, the examination of politically motivated violent incidents in the United States from 2001 to 2016 revealed that young men made up the overwhelming majority (93%) of perpetrators; their median age was 26, and 83% of them were less than 35 years old (United States Government Accountability Office, 2017).

The overrepresentation of young men among violent extremists is in line with their overall tendency to engage in risky and aggressive behaviors (Steffensmeier & Allan, 1995). For

example, men made up nearly 90% of perpetrators of homicides in the United States from 1980 through 2008 (Cooper & Smith, 2011). The National Crime Victimization Survey also found a long-term trend towards younger age-crime distributions, with the peak age of criminal involvement at less than 25 years of age (Ulmer & Steffensmeier, 2014). Regarding biological factors contributing to this effect, there are considerable age and gender differences for physical traits that affect one's ability to perpetrate interpersonal violence, such as strength or physical stamina, with peak functioning typically reached for men before the age of 30 years old (Isen et al., 2015). Men may be biologically and evolutionarily predisposed towards interpersonal aggression, as they often need to resort to violence to procure resources that would make them more attractive to potential mates (McDonald et al., 2012). On the other hand, several social and cognitive factors may also contribute to the observed age and gender differences in aggressive behavior, including social norms, patterns of illegitimate opportunities, and personality traits, such as egocentrism, hedonism, and a sense of invincibility (Steffensmeier & Allan, 1995).

The effect of age and gender on violent extremism may also be due to the normative age- and gender-graded influences in political participation (Bennett & Bennett, 1989; Quintelier, 2007). Young adults, in general, infrequently engage in conventional political activities, such as voting or membership in political parties (O'Toole et al., 2003; Quintelier, 2007). In particular, young adult men are more likely to feel disillusioned with the perceived injustices of the political system and believe in the need for radical change. Consequently, they tend to approve of more unconventional political tactics, such as public demonstrations or even violent extremist actions (Watts, 1999). Interest in politics is still relatively low in adolescence but increases in early adulthood as men find politics to be more pertinent to their everyday lives. Support for unconventional political participation peaks in early adulthood and then gradually shifts to more

conventional actions, as changes in men's personal circumstances (e.g., family, career, stable residence) alter their political needs and outlook (Watts, 1999).

1.2 Perceived Peer Attitudes

One of the most notable risk factors for engagement in interpersonal violence, particularly for young men, is the belief that one's close peers would approve of such actions (Ali et al., 2011; Mesch et al., 2003). Perceived peer attitudes are closely related, yet distinct, from collective or perceived social norms. Collective norms refer to the prevailing codes of conduct that guide the appropriate behaviors for group members, while perceived social norms refer to one's understanding and interpretations of those norms (Lapinski & Rimal, 2005). Collective norms exist at the level of the social system (i.e., a larger social network or the entire society), while perceived social norms exist at the individual, psychological level. Concurrently, peer norms refer to the standards of behavior within one's network of close friends of the same age group, while perceived peer norms refer to one's understanding of those norms (Martens et al., 2006). Peer norms can be compatible with collective norms, as members of peer networks tend to be part of the larger social network. However, peer norms may also conflict with other social norms, particularly for adolescent and young adult men, who often challenge broader social norms as a means to exert their autonomy and explore possible identity alternatives (Mercer et al., 2017).

Age, gender, and perceived peer attitudes. Regarding age and gender differences in the association between perceived peer attitudes and violent outcomes, young adult men tend to be more susceptible to peer influences that encourage aggressive and risk-taking behaviors, compared to both older adults and women in the same age group (McCoy et al., 2019). According to the gender role socialization theory, masculine gender norms emphasize the need

for status and dominance, with violence often justified as a means for achieving such goals. Consequently, men are more likely to be excused or even encouraged to engage in violence as a way to conform to such masculine gender norms (Baugher & Gazmararian, 2015).

The impact of peer networks increases in adolescence and peaks in early adulthood, at which point people begin to more strongly exhibit the capacity to resist it (Monahan et al., 2009; Steinberg & Monahan, 2007). As adolescents become more socially and emotionally autonomous from their parents, they often turn to peers for guidance in evaluating and responding to social situations (Steinberg & Monahan, 2007). In later adulthood, men gain a better understanding of their social surroundings and, consequently, exert a greater degree of autonomy over their decision making (Monahan et al., 2009). Neurobiological studies offer further evidence in support of this hypothesis. For instance, brain processes relevant to the analysis of social information do not fully develop until the mid to late twenties, which means that young men need to rely on external sources, such as their peers, for evaluating such information (Nelson et al., 2005).

Perceived peer attitudes and personal attitudes. Perceived peer attitudes impact personal attitudes through the conceptually distinct, but not mutually exclusive processes of peer influence and peer selection. In the process of peer influence, the social need to maintain peer relationships drives people to adopt their peer's beliefs as their own (Baumeister & Leary, 1995). Peer networks also indicate which attitudes are socially acceptable: people are socially rewarded for expressing beliefs that reinforce the majority opinion. At the same time, they are reprimanded for attitudes that are not in line with those of their peers. Thus, peer networks with congruent norms may shape personal attitudes through the interpersonal costs of social deviation (Schachter, 1951). People assess the validity of their opinions by comparing them to those of

their peers, even when other information is readily available to them (Festinger, 1950, 1954). As a result, attitudes within peer networks are gradually consolidated. Repeated public expressions of one's views render them stronger (Hovland et al., 1957) and more extreme (Downing et al., 1992). Additionally, this process increases their accessibility (Fazio et al., 1982), or the strength of the association between an idea or object and one's attitudes towards it.

In contrast, the process of peer selection refers to people seeking out and interacting with peers who are similar to them in values and attitudes (McPherson et al., 2001). The reinforcement-affect hypothesis states that people select their peer networks based on the similarity of their attitudes, which in turn reinforces their own values and elicits a positive affective response (Byrne & Clore, 1970). For violence-related outcomes, peer selection often occurs through the mediating role of another construct that is closely related but more socially appropriate and readily observable. For example, eco-terrorist groups frequently recruit new members from non-violent environmental protection movements, identifying activists who are firmly devoted to the cause but disillusioned with non-violent political actions (Joesse, 2007).

The processes of peer selection and peer influence are not mutually exclusive. Instead, the impact of peer attitudes on personal attitudes is a result of multiple processes occurring simultaneously (Jose et al., 2016; Monahan et al., 2009). In fact, the interactional theory argues that both processes may act simultaneously and are embedded in a reciprocal causal relationship (Seddig, 2014). Further research suggests that peer influence may exert a stronger influence on one's attitudes and behavior in adolescence and early adulthood, when people experience a greater need to establish social ties and continue to form their social identity (Seddig, 2014; Monahan et al., 2009). Once people have more well-established social networks, they begin to

engage in peer selection more frequently as a way to reaffirm their attitudes and strengthen the social ties within their peer networks.

Notably, perceived peer attitudes do not always reflect the peers' actual attitudes but can still have a significant impact on personal beliefs (Martens et al., 2006). As a result, people may change their attitudes to conform to their inaccurate perceptions of peer attitudes. They may also use their perceptions of peer attitudes to rationalize their own actions and beliefs. For example, Martens et al. (2006) found that college students tend to overestimate alcohol use, drug use, and risky sexual behavior among their peers. They also found a significant positive relationship between actual behavior and perceived peer attitudes: participants who overestimated the prevalence of substance use and risky sexual behaviors among their peers were more likely to engage in such behaviors themselves.

Perceived peer attitudes and behavioral intentions. According to the theory of planned behavior (Ajzen, 1991), behavioral intentions serve as an indication of one's readiness to engage in a given behavior. They are based on one's attitudes towards the behavior, subjective norms, and perceived behavioral control, with each predictor weighted for its importance in relation to the behavior and its possible outcomes. Personal attitudes refer to one's overall evaluation of the behavior, while subjective norms consist of one's belief about whether others think that one should engage in that behavior. Perceived behavioral control refers to one's perception of how difficult it would be to perform the behavior in question. More favorable personal attitudes and subjective norms towards the behavior, along with greater perceived behavioral control, are likely to result in stronger intention to perform that behavior (Ajzen, 1991). Although intent is not necessarily a prerequisite for engaging in any behavior, it can serve as a strong predictor for subsequent actions (Godin & Kok, 2016). Thus, researchers often use it as a proxy for assessing

antisocial and health-related behaviors (for review, see Godin & Kok, 2016), including violent extremism (e.g., Corning & Myers, 2002; Doosje et al., 2013; Moskalenko & McCauley, 2009).

Personal attitudes not only work as a strong antecedent to behavioral intentions but also mediate the effect of other factors, including perceived peer attitudes, on intentions (Kim & Hunter, 1993). For example, Seddig (2014) examined the associations between attitudes in support of violence and engagement in violent behavior in a longitudinal study of German high school students. Overall, peer attitudes supporting violence significantly increased the odds of subsequent personal support for violence, willingness to engage in violent behavior, and, lastly, violence perpetration. Importantly, Seddig (2014) observed the peer influence effect on violent attitudes and behaviors among adolescent boys, but not girls. Additional studies observed a similar mediating effect for other violent outcomes, such as bullying (Salmivalli & Voeten, 2004) or delinquency (Megens & Weerman, 2010).

Perceived peer attitudes and violent extremism. Perceived peer attitudes also have a significant effect on the development of violent extremist attitudes and intentions. For instance, Kuhn (2004) found that peer voting preferences served as the strongest predictor for expressing readiness to use violence in political actions and voting for a right-wing extremist party among East German young adults (i.e., 18-19 years old). Notably, the effect was most pronounced for peer groups that frequently discussed political and social issues. In a similar study, Dahl and Van Zalk (2014) examined the impact of peer networks in the development of illegal political behavior among adolescent men (i.e., 16-18 years old) in Swedish secondary schools. Overall, the peers' support for and involvement in illegal political behavior predicted the adolescents' later engagement in similar behaviors. The process of peer influence played a more significant role in this relationship than peer selection: participants did not seek out peers with similar

violent extremist attitudes but rather shifted their attitudes in line with those of their current peers (Dahl & Van Zalk, 2014).

Research on terrorist recruitment provides further evidence for the importance of perceived peer attitudes in the development of violent extremist attitudes and intentions. For example, Reynolds and Hafez (2019) found in their analysis of recruitment patterns of German foreign fighters in Syria and Iraq that peer networks and a close relationship with a person with an already established contact with the group served as the most significant predictors for engagement in violent extremism. Such findings are not just limited to the Islamic State's foreign fighters. Close peer networks also played a central role in the recruitment of new members among domestic extremists in the United States (Jasko et al., 2017) or Italian left-wing terrorist organizations active during the Cold War (Della Porta, 1988).

While peer attitudes supportive of politically motivated violence facilitate the development of violent extremist attitudes and intentions, peer attitudes opposing violent extremism (i.e., condemning politically motivated violence or encouraging non-violent and legal forms of political engagement) may serve as a protective factor against them (Dahl, 2017). Niemi and Sobieszek (1997) first identified peer influence as a crucial factor contributing to the development of one's political identity, with subsequent studies suggesting that peer networks have a stronger impact on the process of political socialization than parents or schools (Quintelier, 2015). For instance, politically engaged peer networks with a sense of collective identity and a non-violent stance promote subsequent participation in civic actions (Lee & Chan, 2010; Šerek & Machackova, 2015) and foster a sense of trust towards political institutions (Putnam, 2001). Regarding violent extremism, peer networks with moderate or mixed attitudes towards political violence inhibit the adverse effects of risk factors for violent extremism by

exposing people to a broader range of political beliefs and providing other opportunities for civic activism and self-expression (Dahl, 2017; Walter et al., 2017).

In addition to influencing one's decision to endorse or perpetrate politically motivated violence, close peers are often best positioned to identify early signs of violent extremism (Williams et al., 2016). For example, studies on lone-wolf terrorists in the United States found that some of their close friends or family members were aware of their violent intentions in nearly two-thirds (63.9%) of the examined cases. In 79.0% of the examined cases, their peers also knew of the perpetrator's commitment to a specific extremist ideology before the attack (Gill et al., 2014). In most cases, peers aware of the individual's intentions did not report this information to law enforcement or other authorities. Such findings suggest that peers can play an essential role in violent extremism prevention efforts but require more information about the indicators of radicalization and the appropriate outlets for reporting.

1.3 Social Network Diversity

Social network structure refers to the pattern of social ties between individuals, usually measured through their size and frequency. The structural features of peer networks (e.g., their size, density, or diversity) have a significant effect on the relationship between perceived peer attitudes, personal attitudes, and behavioral intentions for several violent outcomes, including bullying (Sentse et al., 2014), delinquency (Jose et al., 2016), and violence against women (Swartout, 2013). One of the most commonly cited structural dimensions in this literature includes social network diversity, which refers to the number of social domains in which people interact with their peers (S. Cohen et al., 1997). High social network diversity serves as a protective factor against several health risk behaviors, such as alcohol and substance use (S. Cohen & Lemay, 2007). Furthermore, social network diversity indirectly reduces the likelihood

of violence perpetration through its effect on personal attitudes. For example, men with more diverse networks tend to hold fewer hostile attitudes towards women, which makes them less likely to engage in sexual violence (Kaczkowski et al., 2017). These results suggest that diverse peer networks can be protective against the influence of peer attitudes supportive of violence.

Social network diversity also moderates the influence of perceived peer attitudes on political attitudes and intentions. People with more politically diverse social networks are more likely to form their own political beliefs, rather than adopt the beliefs of their peers (Quintelier et al., 2012; Scheufele et al., 2004). Greater network diversity exposes people to a broader range of norms and attitudes; thus, they experience less pressure to adopt uniform group beliefs, while their sense of personal identity and self-worth is not associated with membership in any specific group (Putnam, 2001). In other words, diverse social networks allow people to “constantly rethink and refine their issue stances as a result of potentially being challenged in their opinions by non-likeminded others” (Scheufele et al., 2004, p. 316). This process fosters a heightened awareness of one’s social, cultural, and political identities, which, in turn, spurs engagement in conventional political activism (Eveland & Hively, 2009). Consequently, young men with more diverse social networks are more likely to participate in non-violent forms of civic engagement (Quintelier et al., 2012).

Group polarization, or the tendency for members of a social group to endorse beliefs or make decisions that are more extreme than their initial inclinations (Myers & Lamm, 1975), may further explain the impact of social network diversity and perceived peer attitudes on personal attitudes and intentions. According to the social comparison theory, group polarization is a result of people’s desire to gain social acceptance from their peers (Festinger, 1954; Swol, 2009). In a group setting, people first compare their own ideas to those of other group members and

subsequently form a position that is similar to those of their peers but slightly more extreme. Thus, they can support the group's beliefs but still present themselves as distinct from others and potentially leading the group (Swol, 2009). Greater social network diversity can effectively inhibit this process: when people interact with more social groups and are exposed to a broader range of beliefs, they feel less pressure to conform to and endorse beliefs of one particular group (Putnam, 2001; Scheufele et al., 2004).

Social network diversity and violent extremism. The possible role of social network diversity as a protective factor against violent extremism has not yet been fully examined. Further research, however, highlights the impact of social marginalization, or the loss of social networks, on the process of engagement in violent extremism (e.g., Doosje et al., 2013; Lyons-Padilla et al., 2015). Socially marginalized people seek social acceptance and are more willing to join any social group. As a result, they are more likely to join violent extremist groups, and their sense of self-worth and personal identity is more closely associated with their membership in such groups (Lyons-Padilla et al., 2015). Due to the loss of other social ties, they are not exposed to different beliefs that could potentially contrast with extremist ideologies. For example, Wasmund (1986) found that recruits for far-left terrorist organizations in West Germany underwent a process of social isolation before joining the group, which effectively reduced the structural diversity of their existing social networks. Notably, the recruits did not endorse violent extremist attitudes before joining the group. Instead, their social marginalization and loss of ties to other social groups facilitated their gradual engagement in violent extremism.

The idea that the lack of diverse social networks may serve as a risk factor for engagement in violent extremism is related to Sageman's (2008) "bunch of guys" theory. According to this theory, social marginalization can play a more significant role in the

development of violent extremist attitudes and behaviors than economic despair or religious indoctrination. In his analysis of open-source materials on 172 al-Qaeda members, Sageman (2004) found that 78% of them have experienced social marginalization and cultural disorientation, mostly as a result of immigration, prior to their involvement in terrorism. They sought companionship with other, similarly alienated Muslim immigrants, often in local mosques. In these isolated social networks, they developed a common religious collective identity and facilitated each other's further radicalization. In other words, Sageman (2004; 2008) suggests that social marginalization and low diversity of peer networks may drive group polarization and engagement in violent extremism.

In *Turning to Political Violence*, Sageman (2017) expands on his theories by delineating the progression of violent extremists from having a healthy social identity to endorsing a violent political identity. According to Sageman (2017), the turn to violent extremism often results from an escalation in the conflict between political protest groups and their salient out-groups, usually the state government. The out-group threat solidifies the members' in-group identity and drives them towards more radical and violent actions in an effort to defend the in-group from the perceived threat. Their concept of the out-group gradually expands to incorporate the entire population. As a result, the group becomes socially marginalized, which narrows their exposure to other ideas and perspectives. In turn, their isolation and exclusive interaction with other extremists within their in-group leads to mutual approval and reinforcement of their views, validating and strengthening their attitudes about the necessity of violence. In other words, the in-group/out-group identification and the resultant social marginalization, or loss of diverse social networks, results in a higher propensity for violent extremism.

1.4 Current Study

Overall, perceived peer attitudes serve as an essential factor contributing to the development of violent attitudes and intentions among young adult men (Ali et al., 2011; Mesch et al., 2003), although structural features of peer networks, such as their diversity, can influence the strength and direction of this association (Jose et al., 2016). However, research has not yet fully examined the role of social network diversity in the relationship between perceived peer attitudes and violent extremist intentions. Consequently, this study addresses the following research questions:

Research question 1: To what extent are perceived peer attitudes, personal attitudes, and violent extremist intentions related to each other?

Hypothesized model 1: Perceived peer attitudes are positively and indirectly associated with violent extremist intentions through their relationship with personal attitudes. People who consider their peers to be supportive of violent extremism are more likely to hold similar attitudes and report greater willingness to engage in such behaviors themselves (see Figure 1).

Research question 2: To what extent does the relationship between perceived peer attitudes and violent extremist intentions differ across levels of social network diversity?

Hypothesized model 2: In addition to the relations hypothesized in Model 1, social network diversity moderates the relationship between perceived peer attitudes and personal attitudes and, consequently, violent extremist intentions, with higher social network diversity associated with reduced strength of this relationship (see Figures 2-3).

Figure 1. Model 1 with the mediation effect

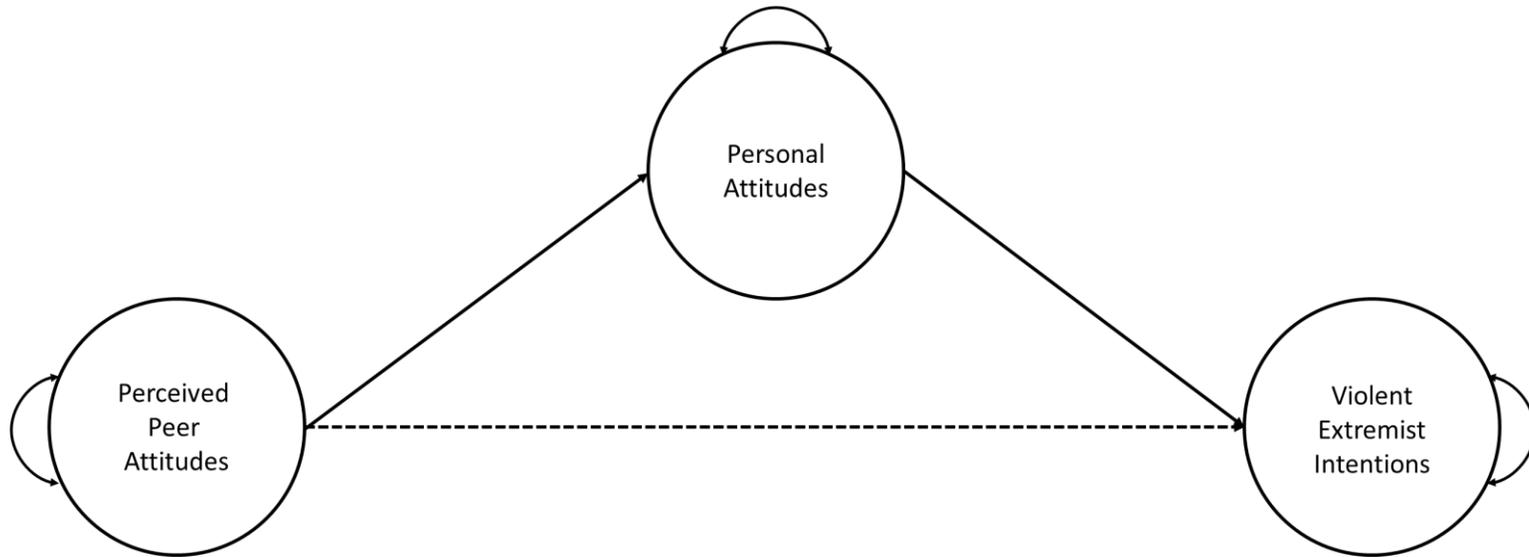


Figure 2. Model 2 with social network diversity

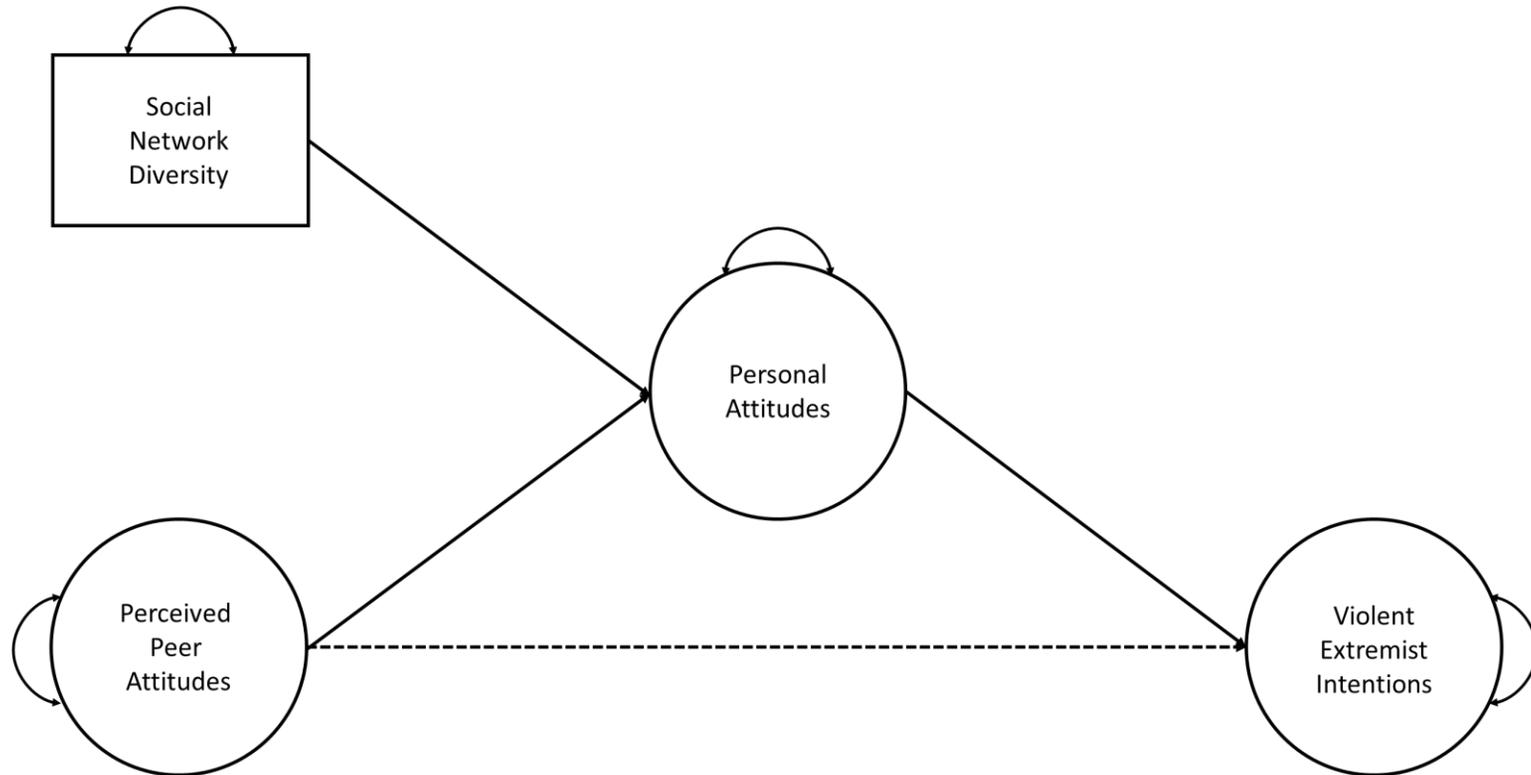
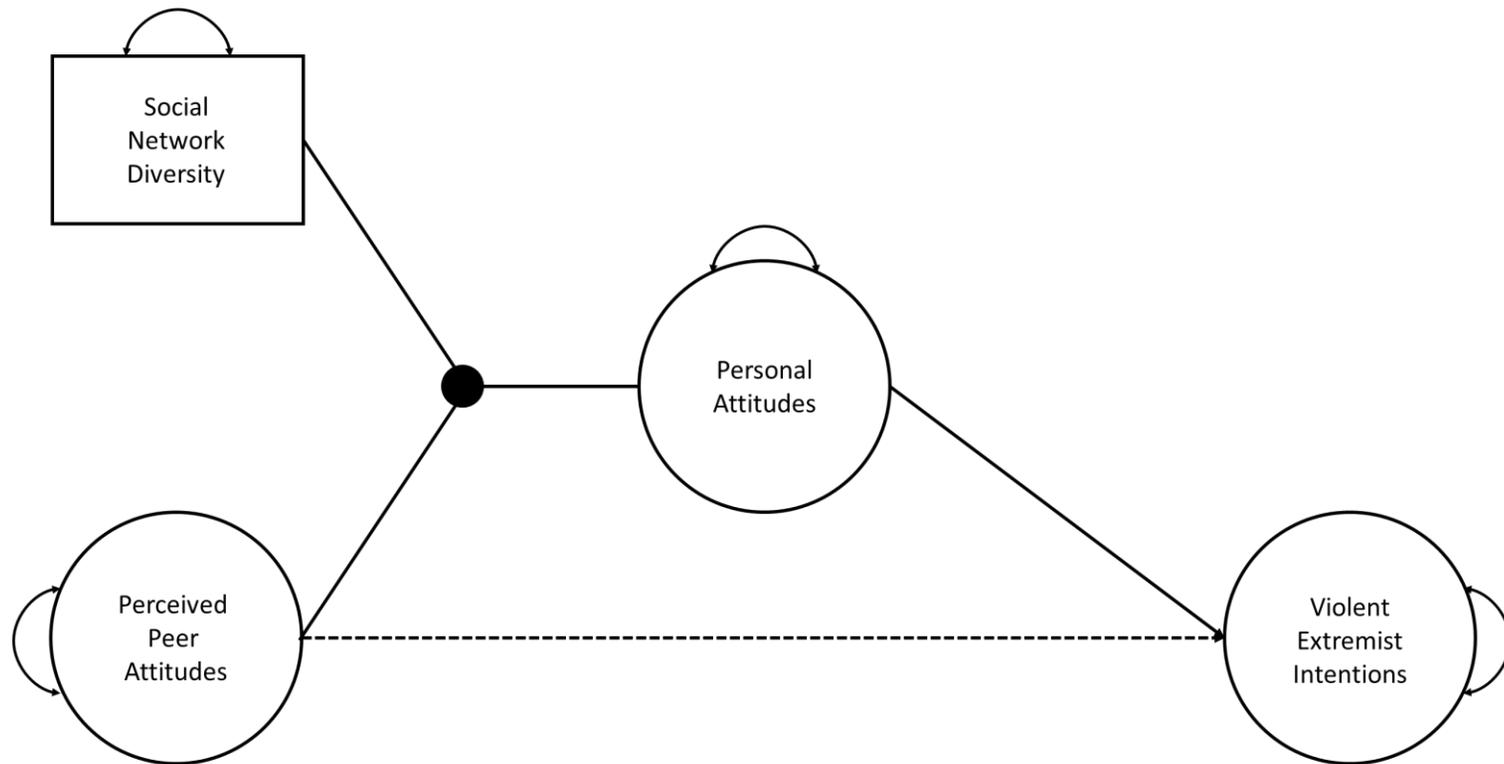


Figure 3. Model 3 with the latent interaction term



Note: Black dot indicates interaction term

2 METHODS

2.1 Sample Size and Power Analysis

Using Mplus Version 8.1, I conducted a series of Monte Carlo simulations (L. K. Muthén & Muthén, 2002) to estimate the sample size required for the statistical power of ≥ 0.80 to detect significant associations of perceived peer attitudes, personal attitudes, and social network diversity with violent extremist intentions. I based the model on a single group with 10,000 replications estimated from the simulated data. Past research findings denote small to moderate effect sizes for the associations between the variables in the hypothesized model (Dahl & Van Zalk, 2014; Steinmetz et al., 2016). Cohen (1988) suggests the effect size values of 0.10, 0.20-0.25, and 0.35-0.39 as frames of reference indicating small, medium, and large effects, respectively, although he also recommends basing the exact values on theory or past research findings (pp. 184-185). Consequently, I varied the examined effect sizes for the associations between perceived peer attitudes, personal attitudes, and violent extremist intentions to include 0.14, 0.26, and 0.39. For the direct association between perceived peer attitudes and violent extremist intentions, I used the value of 0.05.

This power analysis indicated that a sample size of at least 284 would be required to estimate an accurate model with adequate power. This sample would provide 80% power to detect small effect sizes (0.14) for the associations between perceived peer attitudes, personal attitudes, social network diversity, and violent extremist intentions, as well as a 0.05 effect size for the direct association between perceived peer attitudes and violent extremist intentions while accounting for personal attitudes. The analysis of expected and observed values for the chi-square (χ^2), the root mean square of approximation (RMSEA), and the standardized root mean squared residual (SRMR) also suggests that this sample size would be adequate to assess fit of

the model to data, with estimates closely matching their expected values. Based on past research, I expect that the data cleaning process would likely result in the exclusion of approximately 20% of responses because of participants withdrawing from the study or providing random responses (McCambridge et al., 2011). Therefore, I collected 340 participant responses for the study.

2.2 Participants

Participant recruitment took place via Amazon's Mechanical Turk (MTurk), an online-based crowdsourcing platform consisting of over 10,000 users. To be eligible for the study, participants had to be (1) male, (2) between the ages of 18 and 29 years old, and (3) residents of the United States. The study also required a "HITs submitted" qualification rate of 500, indicating the number of prior tasks completed by the participant on MTurk, and "HITs approved" qualification rate of 97%, meaning the percent of those tasks that were subsequently approved as high quality. Based on the past analysis of MTurk data quality, such requirements ensure increased reliability and validity of the collected data (Berinsky et al., 2012).

Overall, 376 people took part in the study. The data cleaning process, however, resulted in the removal of 36 responses. Thus, the final dataset consisted of 340 participant responses. The mean age of participants was 24.32 years, with a standard deviation of 1.90 years. Regarding the race/ethnicity makeup of the sample, 83.2% of participants identified as White, 7.4% as Asian, 6.2% as Black or African American, 1.8% as more than one race, 1.2% as American Indian or Native American, and 0.3% as Native Hawaiian or other Pacific Islander. Furthermore, 9.4% of participants reported their ethnicity as Hispanic or Latino. Table 1 provides detailed information about the participant demographics, also including education, religious affiliation, sexual identity, and income.

Table 1. Demographics of Study Sample

Demographics	Count	Percent
Race		
White	283	83.2
Asian	25	7.4
Black or African American	21	6.2
More than one race	6	1.8
American Indian or Alaska Native	4	1.2
Native Hawaiian or other Pacific Islander	1	0.3
Ethnicity		
Non-Hispanic or non-Latino	306	90.0
Hispanic or Latino	32	9.4
Education		
Some high school	2	0.6
High school	46	13.5
Some college	80	23.5
Associate or Bachelor's Degree	183	53.8
Master's or Doctoral Degree	29	8.5
Religion		
Atheist/Agnostic	181	53.2
Protestant	56	16.5
Roman Catholic	51	15.0
Spiritual, not religious	30	8.8
Other, not listed	17	5.0
Jewish	3	0.9
Hindu	1	0.3
Sexual orientation		
Heterosexual	308	90.6
Bisexual	17	5.0
Homosexual	13	3.8
Other, not listed	2	0.6
Income		
\$0-\$25,000	66	19.4
\$26,000-\$50,000	117	34.4
\$51,000-\$75,000	92	27.1
\$76,000-\$100,000	32	9.4
\$101,000 or higher	33	9.7
<i>Note. N=340</i>		

2.3 Procedure

Data collection occurred in waves to ensure generalizability and greater representativeness of the sample. After collecting approximately 60 participant responses, I removed the posting until the next wave. Overall, six waves of data collection took place within a span of 12 weeks. I randomly varied the time and weekday of each posting to ensure greater diversity within the sample (Berinsky et al., 2012).

Once eligible MTurk users chose to participate in the study, they were redirected to an external Qualtrics webpage. A unique identifier code was assigned to all incoming participants. After completing the survey, participants received their identifier codes and submitted them on MTurk for compensation. Thus, the use of unique identifier codes ensured higher completion rates and greater anonymity, as Qualtrics-assigned codes were not associated with MTurk worker IDs or any other identifiable information.

The informed consent form, presented as the first screen of the online survey, did not mention violent extremism so as not to create any false beliefs about the study or evoke social inhibition. To reduce the participants' concerns about disclosing potentially sensitive information, the consent form informed them that their responses would be anonymous and submitted directly to a secure database, with no potentially identifiable information. Participants had an option to decline any questions or discontinue their participation at any time without penalty or negative consequences. The survey did not include any items assessing specific illegal behaviors. Making this information explicit minimized the likelihood that participants would fear repercussions related to reporting violent extremist attitudes or intentions.

Each measure was presented on a separate page and contained specific instructions for interpreting and responding to survey items. I counterbalanced questions on attitudes and

intentions to assess ordering effects and included instructional manipulation check (IMC) items to ensure that participants followed instructions and did not answer randomly. The last page of the survey included the debriefing form, which required participants to answer a final question allowing the use of their data after informing them about the full purpose of the study. After reading the debriefing form, participants received their unique identifier codes with instructions to enter this code into MTurk. At the end of each wave of data collection, I compared the Qualtrics-assigned codes to the list of participant-entered codes on MTurk. For each verified code, I approved and deposited a payment to the participant's MTurk user account. Each participant received \$3.50 for the completion of an approximately 30-minute long task.

2.4 Measures

At the beginning of the survey, participants received the following instructions: "People care about many different kinds of groups, including the following: *Religious* (e.g., Christians, Muslims); *Political* (e.g., Republican, Democratic); *Ethnic/Racial* (e.g., African-American, Native American); *National* (e.g., American, Mexican); and *Single-Issue* (e.g., environmental, abortion)." Each participant then wrote down the name of the particular group most important to them and read instructions that the following questions refer to the group they just named. Past studies on violent extremist attitudes and intentions used similar instructions to ensure that participants would list social groups relevant to subsequent questions rather than referring to family, community, or other non-pertinent groups (Moskalenko & McCauley, 2009).

When asked about the social group with which they most strongly identify, 12 participants provided responses that did not match any of the categories listed in the instructions and that were not relevant to subsequent questions, such as family or friends. Thus, I removed responses from these participants during the data cleaning process and did not include them in

any of the subsequent analyses. Among the remaining participants, 125 (37.76%) identified single-issue groups (e.g., environmental, gun control, pro-choice); 105 (30.88%) political (e.g., libertarian, progressive, democratic socialist); 61 (17.94%) religious (e.g., atheist, agnostic, Christian); 42 (12.35%) ethnic/racial (e.g., Caucasian, African American, Asian American); and 7 (2.06%) national, with American as the only disclosed national group.

Participants also named their five closest peers by responding to the following statement: “Please list the five (5) male peers with whom you most often interact, either face-to-face, over the phone, or through electronic means such as text messages, email, and social networking sites. Please make sure that the listed peers belong to the same social group that you listed in the previous question, specifically [name of the social group each participant identified in the previous question]” (S. Cohen et al., 1997). One participant did not list anyone when asked about his close peers; thus, I excluded his responses from subsequent analyses. Among the remaining participants, only four listed less than five peers.

Perceived peer attitudes. The Activism and Radicalism Intention Scale – Radicalism Subscale (ARIS; Moskalenko & McCauley, 2009) measured perceived peer attitudes towards violent extremism. I modified scale instructions to ask about peer attitudes rather than personal ones: “For the following activities, PLEASE ANSWER ACCORDING TO WHAT YOUR FRIENDS THINK, specifically [names of the five friends that each participant listed at the beginning of the study]. If these friends were hanging out, honestly discussing each activity without you there, how likely is it that they would agree or disagree with each statement?” The scale included four items assessing violent extremist attitudes, such as “You can continue to support an organization that fights for your group’s political and legal rights even if the organization sometimes resorts to violence.” These items served as individual indicators for the

latent construct of perceived peer attitudes. Respondents rated all items on a scale ranging from 1 (*disagree completely*) to 7 (*agree completely*), with higher scores indicating greater attitudinal support for violent extremism.

In past studies assessing personal violent extremist attitudes among American college students (Moskalenko & McCauley, 2009), the mean scores for the individual items varied from 1.70 to 2.91 (SD=0.68-1.49), while the internal reliability scores for the overall scale denoted strong reliability ($\alpha=0.70-0.84$). In the current study, Cronbach's alpha ($\alpha=0.85$) indicated good reliability for the ARIS items. Past studies also established support for the scale validity through its significant relationship with other measures of violent extremist attitudes and lack of significant relationship with factors unrelated to such attitudes. The scale's correlations with measures of national and ethnic importance differed significantly from the correlations of the same measures with scales assessing conventional political activism, indicating discriminant validity (Moskalenko & McCauley, 2009).

Violent extremist intentions. The Activism Orientation Scale – High-Risk Activism Subscale (AOS; Corning & Myers, 2002) assessed violent extremist intentions. Participants disclosed how likely they would be to engage in each of the listed activities in the future, with responses ranging from 0 (*extremely unlikely*) to 3 (*extremely likely*) and higher scores indicating greater willingness to engage in violent extremism. The scale consisted of seven items, such as “Engage in a political activity in which you suspect there would be a confrontation with the police or possible arrest.” These items served as individual indicators for the latent construct of violent extremist intentions.

In past studies with American college students (Corning & Myers, 2002), the mean scores for the individual items ranged from 0.42 to 1.24 (SD=0.50-2.45). The internal reliability

score for the overall scale was $\alpha=0.93$, and test-retest reliability at 4- and 6-week intervals was above 0.70. In the current study, the AOS items had excellent reliability, $\alpha=0.93$. Past studies established support for the validity of the scale through its significant relationship with factors hypothesized to be related to violent extremism, its lack of relationship with factors hypothesized to be unrelated to such outcomes, and its ability to differentiate among groups believed to vary in their levels of willingness to engage in violent extremism (Corning & Myers, 2002).

Personal attitudes. Three items adopted from Pedahzur et al. (PA; 2000) served as individual indicators for the latent construct of personal attitudes towards violent extremism. The items pertained, respectively, to sending threatening messages, using weapons, and physically injuring politicians in pursuit of political ends (e.g., “In certain situations, there are no other options but to use arms in order to prevent the government from carrying out its policy”). Participants ranked their support for such actions on a scale of 1 (*strongly disapprove*) to 5 (*strongly approve*), with higher scores indicating greater attitudinal support for violent extremism.

In past studies assessing violent extremist attitudes among male Israeli and Palestinian college students (Pedahzur et al., 2000), the mean scores for the individual items ranged from 1.60 to 3.21 ($SD=1.33-2.53$), and the internal reliability scores for the overall scale were $\alpha=0.60-0.69$. In the current study, Cronbach’s alpha ($\alpha=0.81$) denoted good scale reliability. Previous research established support for the scale validity through its significant relationship with related measures of support for violent extremism, its lack of significant relationship with factors unrelated to such attitudes, and its ability to differentiate among social groups believed to vary in their levels of support for violent extremism (Pedahzur et al., 2000).

Social network diversity. The Social Network Index (SNI; S. Cohen et al., 1997) measured the observed variable of social network diversity and assessed participation in 12 social relationships, including relationships with a spouse, parents, parents-in-law, children, classmates, etc. The index operationalizes network diversity as the number of different types of high-contact social roles in which the person participates, with high-contact roles defined as those in which the person reports engaging at least once every two weeks. For example, the question “Do you belong to a church, temple, or other religious group?” assesses the participant’s involvement in any religious organization. When participants respond “yes”, they are asked a follow-up question: “How many members of your church or religious group do you talk to at least once every two weeks?”, with response options ranging from “0” to “7 or more.” For the religious group to count as the respondent’s high-contact social role, the participant has to endorse “1” or higher for the follow-up question. Simply reporting membership in a church, temple, or another religious group (i.e., responding “yes” to the initial question) is necessary but not sufficient to count the religious group as a high-contact social role. At the end of the index, participants name other groups they belong to and the total number of members of that group that they interact with on a regular basis, or at least once every two weeks.

2.5 Data Analytic Strategy

The raw dataset downloaded from Qualtrics originally consisted of 376 participant responses. During the data cleaning process, I excluded responses from 16 participants who withdrew from the study without completing it; five participants who did not respond correctly to the IMC items; and two participants who declined to share their data with the researchers after being debriefed. No IP addresses were recorded in the dataset more than once, indicating that no participants provided multiple responses. Furthermore, I excluded responses from 12 participants

who listed social groups that were not relevant to subsequent questions and from one participant who did not list any close peers. In total, the data cleaning process resulted in the removal of 36 participant responses, or 9.57% of all responses. The final dataset used in the study consisted of 340 participant responses.

Next, I obtained descriptive statistics, Pearson correlations, and Cronbach's alpha reliability estimates for all scales, using SPSS Version 25. I used the sum of disclosed high-contact social roles to calculate social network diversity for each participant and the individual scale items to compute the latent variables of perceived peer attitudes, personal attitudes, and violent extremist intentions. Next, I conducted a series of assumptions tests to (1) examine extreme multivariate collinearity; (2) identify case outliers; (3) examine homoscedasticity; and (4) analyze skewness and kurtosis of all variables in the model. Due to the severely skewed AOS items, I modeled violent extremist intentions as an ordinal outcome variable (see Results for more information on assumption testing and its results).

For the hypothesized models, I used structural equation modeling (SEM) to analyze the associations between perceived peer attitudes, personal attitudes, violent extremist intentions, and social network diversity. SEM is a multivariate statistical technique that is commonly used to determine structural relationships between measured variables and latent constructs (Kline, 2015a). This technique is a combination of confirmatory factor analysis, in which variables are assigned to a predetermined set of factors, and multiple regression analysis, in which several regression paths are fit within the same model. SEM has three major advantages over traditional multivariate techniques (Kline, 2015a). First, while other multivariate techniques do not explicitly assess measurement error in their models, SEM models estimate these error variance parameters for both independent and dependent variables. Second, SEM estimates latent

variables from observed variables. Thus, the creation of latent variables takes into account measurement error. Finally, SEM allows for testing fully developed models against the data and evaluating for the fit of the sample data.

For the goodness-of-fit analyses, Kline (2015a) recommends reporting the following indices: (1) the model chi-square (χ^2), (2) the comparative fit index (CFI), (3) the root mean square error of approximation (RMSEA) and (4) the standardized root mean square residual (SRMR). The model χ^2 assesses overall fit and the discrepancy between the sample and the fitted covariance matrices, with non-significant χ^2 values ($p > 0.05$) indicating good model fit. The χ^2 , however, is highly sensitive to sample size changes, and the χ^2 value is usually statistically significant for models with large sample sizes, or more than 300 cases (Kline, 2015a, pp. 270–272). Thus, I considered other fit indices (CFI, RMSEA, SRMR) in addition to the χ^2 .

The CFI analyzes the model fit by examining the discrepancy between the data and the hypothesized model while adjusting for sample size; CFI values range from 0 to 1, with higher values indicating better fit (Kline, 2015a, pp. 276–277). The RMSEA examines the discrepancy between the hypothesized model, with optimally chosen parameter estimates, and the population covariance matrix; RMSEA values range from 0 to 1, with smaller values indicating better model fit (Kline, 2015a, pp. 273–276). The SRMR refers to the square root of the difference between the residuals of the sample covariance matrix and the hypothesized model; SRMR values range from 0 to 1, with lower values indicating better model fit (Kline, 2015a, pp. 277–278). Hu and Bentler (1999) recommend the use of these absolute fit indices with the $CFI \geq 0.95$, the $RMSEA \leq 0.08$, and the $SRMR \leq 0.08$ as cut-off points indicating acceptable model fit. However, other researchers point out potential problems with the use of rigid cut-off values, which may be more appropriate for testing statistical significance than for evaluating model goodness-of-fit (Marsh

et al., 2004). Instead, Marsh et al. (2004) recommend that interpretations of the degree of misspecification should be based on substantive and theoretical issues specific to a particular study and on comparing the performance of alternative models.

Given the fact that the examined models included an ordinal outcome variable with more than two cases, I used an ordered probit regression to conduct the analyses. This particular estimation strategy models the inverse standard normal distribution of the probability as a linear combination of the predictors, which allows for the interpretation of Likert-type scale variables with non-discrete ranges and produces predicted outcomes for each potential response category (Aitchison & Silvey, 1957). An alternative method for conducting SEM with ordinal data is the ordered logit model, which applies the logistic regression model to dependent variables with more than two ordered response categories. The ordered logit regression models the log odds of the outcome as a linear combination of the predictor variables (Snell, 1964). In general, logit and probit models tend to produce similar results when applied in the same large samples, but they provide coefficients in different metrics (Torres-Reyna, 2012).

In Mplus, the weighted least squares mean- and variance-adjusted (WLSMV) estimator serves as a default for the probit model, while the maximum likelihood (ML) estimator is the default option for the logit model. The WLSMV estimator provides weighted least squares parameter estimates by using a diagonal weight matrix and robust standard errors, as well as a mean- and variance-adjusted χ^2 test statistic. In contrast, the ML estimates the parameters by finding the values that maximize the likelihood of making the observations (B. O. Muthén & Asparouhov, 2002). The WLSMV estimator provides model fit indices such as the CFI and the RMSEA, which are not available with the ML estimator. In contrast, the ML estimator computes estimates used for comparison and selection of non-nested models, such as the Akaike

information criteria (AIC) or the log-likelihood ratio test. The present study focuses on model fit, rather than model comparison: the first model (Model 1) assesses the first hypothesis, while the subsequent model (Model 2) examines the second hypothesis. The comparison of these two models is not necessary to evaluate the study hypotheses. Thus, I decided to use the probit model with the WLSMV estimator for Model 1 and Model 2.

Measurement model. Before testing any structural models, I analyzed the goodness-of-fit of the measurement model. The measurement model is a confirmatory factor model consisting of all factor indicators regressed on their associated latent factors (Kline, 2015a, pp. 352–361). When the measurement model testing demonstrates a poor fit to the data, indicators with low factor loadings can be systematically removed to improve the fit. Per recommendations (Tabachnick & Fidell, 2013), I set the standardized factor loadings of 0.55 as cut-off points for acceptable factor loadings. I also used the measurement model analysis to determine whether participants correctly differentiated perceived peer attitudes from their own personal attitudes. Specifically, I examined whether the measured indicators were conceptually distinct by determining if the indicators of perceived peer attitudes loaded onto a different factor than indicators of personal attitudes. I used three separate figures to depict the measurement model in order to make it more coherent and understandable: Figures 4-6 illustrate the hypothesized factor loadings for perceived peer attitudes, personal attitudes, and violent extremist intentions, respectively.

In factor analysis, Pearson correlation coefficients indicate expected relationships between variables. Since mean and covariance cannot be accurately calculated for ordinal data, however, Pearson correlations are not appropriate to measure the associations between ordinal variables. Instead, Yang-Walletin et al. (2010) recommend the use of polychoric correlations for

a factor analysis with continuous and ordinal data. Polychoric correlation coefficients estimate the association for ordinal variables based upon the assumption of an underlying joint continuous distribution (Yang-Wallentin et al., 2010).

Research question 1. Model 1 represented an attempt to replicate the findings from previous research (e.g., Dahl & Van Zalk, 2014; Kuhn, 2004) and test whether perceived peer attitudes were significantly and positively associated with violent extremist intentions through the mediating role of personal attitudes (see Figure 1). Several researchers recommend SEM as the preferred approach to mediation analysis, as it allows for estimating and testing the entire structural model simultaneously and for comparing different models using goodness-of-fit statistics (e.g., Danner et al., 2015). I used bootstrapping to generate estimates for the effect of the mediator (i.e., personal attitudes). Bootstrapping refers to a non-parametric resampling procedure used to get more precise estimates by constructing 95% confidence intervals. If zero lies outside the confidence intervals, then one can reject the null hypothesis of no direct effect (Preacher & Hayes, 2008). For this study, I used the bootstrap estimates based on 5,000 bootstrap samples, per recommendations (Preacher & Hayes, 2008).

Importantly, Kline (2015b) notes that a cross-sectional design cannot directly support a causal inference. When the variables in the mediation model are measured at the same time, it is difficult to establish whether the presumed causal variables have a subsequent effect on the outcome variable. The theory of planned behavior offers a strong rationale for the directionality assumption, as changes in perceived peer attitudes and personal attitudes precede changes in intentions (e.g., Van De Ven et al., 2007). Research findings using experimental or longitudinal designs provide additional evidence for the mediation effect of personal attitudes on the relationship between perceived peer attitudes and behavioral intentions for several violent

outcomes (e.g., Dahl & Van Zalk, 2014; Kim & Hunter, 1993; Seddig, 2014). Nevertheless, one should not make any definite conclusions about the causality of the observed relationships based solely on the findings of cross-sectional studies. Instead, such studies can establish that a relationship exists between the examined variables; further longitudinal research is needed to assess their causality.

Research question 2. Models 2-3 examined the hypothesis that social network diversity moderated the relationship between perceived peer attitudes and personal attitudes (see Figures 2-3), using the latent moderated structural equation method (LMS; Klein & Moosbrugger, 2000). The LMS method is built into Mplus software and requires the estimation of only one additional parameter. However, the LMS models do not produce traditional model fit indices, standardized coefficients, or effect sizes for the latent interaction. To address this limitation, Maslowsky et al. (2015) offer a two-step procedure for estimating latent moderated structural equations, using the XWITH command in Mplus.

In the first step of the LMS method, I included the observed variable, social network diversity, in Model 2 and assessed its relative fit (see Figure 2). I estimated the latent interaction term in a subsequent step (see Figure 3) and, therefore, did not include it in the measurement model. The latent interaction term does not have a mean, variance, or covariance with other parameters and, therefore, should not affect the fit of the measurement model. To assess the overall fit of each LMS model, I first obtained the χ^2 , CFI, RMSEA, and SRMR values for Model 2. Using a log-likelihood ratio test, I compared the relative fit of Model 2 (the model where the interaction is not estimated and therefore assumed to be zero) and Model 3 (the model with the estimated interaction). Based on this test, I determined whether the more parsimonious Model 2 represented a significant loss in fit relative to the more complex Model 3. If Model 2

fits well and represents a significant loss in fit relative to Model 3, then one can conclude that Model 3 is also a well-fitting model. If the log-likelihood ratio test is not significant, then Model 2 does not result in a significant loss of fit relative to Model 3. This method, however, cannot assess whether the fit of Model 3 is equal to or worse than the fit of Model 2.

I calculated the test statistic for a log-likelihood ratio test (D), as the difference between the log-likelihood for Model 2 and the log-likelihood for Model 3. The values of D are approximately distributed as χ^2 . I calculated the degrees of freedom (df) to determine the significance of D by subtracting the number of free parameters in Model 2 from the number of free parameters in Model 3. Then, I compared the D statistic obtained from the log-likelihood ratio test to a χ^2 distribution using df .

The LMS method requires the use of maximum likelihood (ML) estimation in Mplus to test a latent variable interaction and obtain the log-likelihood values necessary to compare the fit of the two models. Thus, I used the ML estimator to specify Model 3; I also conducted a second analysis of Model 2 using the ML estimator to obtain the log-likelihood value necessary to compare its relative fit to Model 3. Since Mplus sets logistic regression as the default for ML, I used the LINK=PROBIT function for a probit model with the ML estimator (see Appendix E for full Mplus syntax used in the study).

To plot and examine the latent interaction, I followed the procedure outlined by Swartout (2013). First, I calculated the simple slopes by saving the latent factor scores. Using these scores, I ran a multiple linear regression in SPSS Version 25 with social network diversity, perceived peer attitudes, and their interaction predicting personal attitudes. Finally, I used the resulting coefficients to test the effect of perceived peer attitudes on personal attitudes at the mean, -1 standard deviation, and +1 standard deviation levels of social network diversity.

Figure 4. Measurement model for perceived peer attitudes

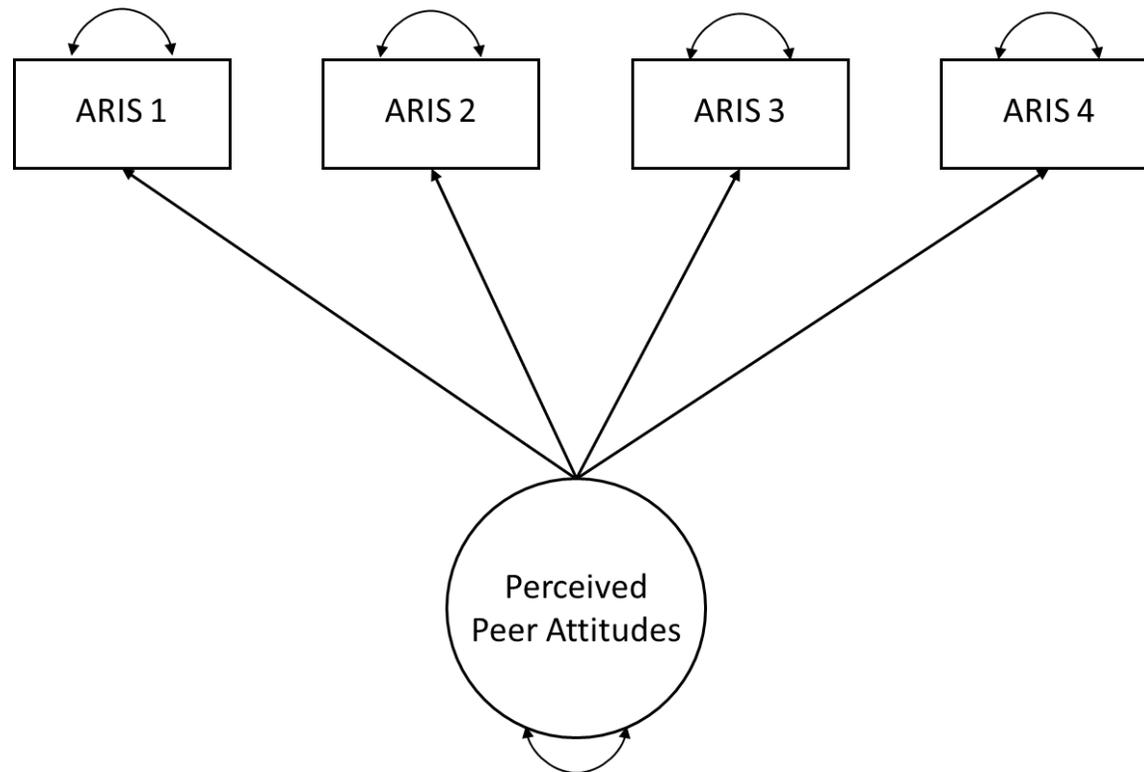


Figure 5. Measurement model for personal attitudes

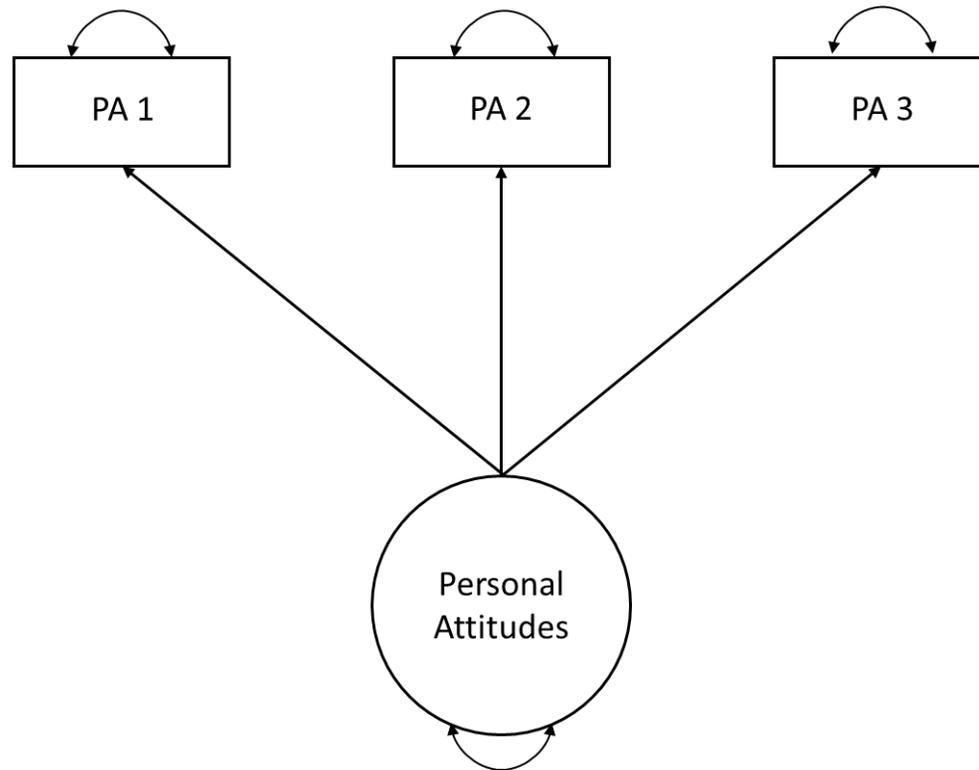
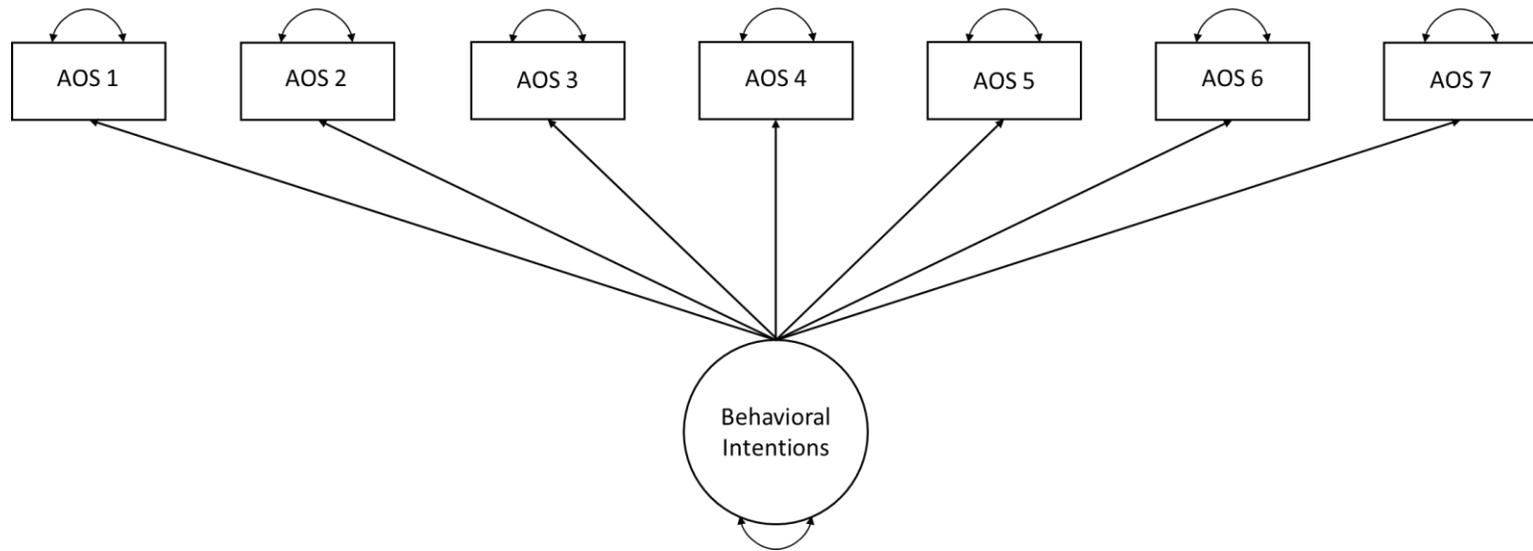


Figure 6. Measurement model for behavioral intentions



3 RESULTS

3.1 Descriptives

Table 2 provides means, standard deviations, and Pearson correlations for all study variables. The mean scores for the ARIS items assessing perceived peer attitudes ranged from 3.04 to 3.94 ($SD=1.74-1.87$)—noticeably higher compared to scores from previous studies using the same scale but examining personal attitudes (Moskalenko & McCauley, 2009). The mean scores for AOS items measuring violent extremist intentions ranged from 0.43 to 0.59 ($SD=0.69-0.77$), while the mean scores for PA items assessing personal attitudes varied from 1.64 to 2.37 ($SD=0.98-1.24$). The mean score for social network diversity, or the total number of high-contact social roles, was 5.04, with a standard deviation of 1.76. The inter-item correlations ranged from 0.58 to 0.73 for violent extremist intentions (AOS); from 0.43 to 0.74 for perceived peer attitudes (ARIS); and from 0.50 to 0.71 for personal attitudes (PA). The correlations for all items from the three scales were statistically significant at $p<0.001$. Social network diversity was negatively, but not significantly, correlated with all other items, with correlations ranging from -0.02 to -0.16. Notably, the correlations of social network diversity with PA items were slightly higher than for other items, ranging from -0.12 to -0.16. In comparison, the correlations of social network diversity with AOS items ranged from -0.02 to -0.09, while its correlations with ARIS items varied from -0.04 to -0.08.

Table 2. Means, Standard Deviations, and Zero-Order Correlations for Study Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. AOS1	--														
2. AOS2	0.64*	--													
3. AOS3	0.62*	0.61*	--												
4. AOS4	0.66*	0.58*	0.63*	--											
5. AOS5	0.69*	0.64*	0.67*	0.69*	--										
6. AOS6	0.65*	0.63*	0.61*	0.63*	0.73*	--									
7. AOS7	0.69*	0.68*	0.68*	0.67*	0.71*	0.73*	--								
8. ARIS1	0.35*	0.30*	0.29*	0.35*	0.33*	0.35*	0.35*	--							
9. ARIS2	0.39*	0.40*	0.34*	0.39*	0.37*	0.37*	0.43*	0.71*	--						
10. ARIS3	0.40*	0.41*	0.34*	0.34*	0.43*	0.38*	0.40*	0.63*	0.74*	--					
11. ARIS4	0.40*	0.40*	0.42*	0.46*	0.48*	0.42*	0.44*	0.43*	0.53*	0.54*	--				
12. PA1	0.36*	0.36*	0.37*	0.42*	0.34*	0.36*	0.41*	0.27*	0.35*	0.33*	0.35*	--			
13. PA2	0.38*	0.40*	0.35*	0.38*	0.37*	0.31*	0.42*	0.39*	0.39*	0.45*	0.50*	0.55*	--		
14. PA3	0.39*	0.40*	0.40*	0.44*	0.43*	0.37*	0.42*	0.39*	0.45*	0.46*	0.51*	0.50*	0.71*	--	
15. SNI	-0.04	-0.05	-0.02	-0.09	-0.05	-0.03	-0.09	-0.05	-0.07	-0.08	-0.04	-0.14	-0.16	-0.12	--
Mean	0.51	0.43	0.55	0.47	0.59	0.57	0.53	3.94	3.12	3.44	3.04	1.64	2.15	2.37	5.04
St Dev	0.74	0.69	0.73	0.69	0.75	0.77	0.78	1.80	1.74	1.79	1.87	0.98	1.24	1.23	1.76

Note. * $p < 0.001$ AOS=Activism Orientation Scale; ARIS=Activism and Radicalism Intention Scale; PA=Personal Attitudes; SNI=Social Network Index

3.2 Assumption Testing

Using SPSS Version 25, I conducted a series of assumption tests prior to model analysis. First, I examined extreme multicollinearity by calculating the tolerance ($1-R^2$) and the variance inflation factor (VIF, or $1/(1-R^2)$) statistics for all items. Per recommendations (Tabachnick & Fidell, 2013), I set the values of tolerance < 0.10 and VIF > 10.0 as thresholds to indicate extreme multivariate collinearity. Overall, tolerance values ranged from 0.31 to 0.61 and VIF values from 1.64 to 3.28, indicating that multicollinearity was not a concern.

Next, I identified case outliers (scores ± 3.0 standard deviations away from the mean) using Mahalanobis distance. I carried out an exploratory regression with variables for perceived peer attitudes, personal attitudes, and violent extremist intentions. I found the probability for each Mahalanobis score and removed all outliers with less than a $p < 0.001$ probability, as per recommendations (Finch, 2012). Overall, the Mahalanobis scores ranged from 0.09 to 17.30, with the lowest probability at 0.002.

For examining homoscedasticity, or the level of variability across levels of the predictors, I conducted the Cook-Weisberg test and inspected the partial plots for all univariate relationships (Tabachnick & Fidell, 2013). Since SPSS does not offer a direct option for performing the Cook-Weisberg test, I used an indirect procedure to conduct the test (Fávero & Belfiore, 2019, pp. 525–529). First, I calculated the square of the residuals and the residual sum of squares. I computed a new variable, *RESUP*, as the square of the residuals divided by the residual sum of squares over sample size. Finally, I calculated the *RESUP* regression and examined the sum of squares due to regression, obtained via the ANOVA table, to test the null hypothesis, or that all error variances were equal. Overall, the non-significant χ^2 score ($\chi^2=0.12$, $p>\chi^2=0.72$) indicated that the null hypothesis could not be rejected. A visual inspection of the plots confirmed this

finding, showing visibly similar levels of variability across levels of the predictors and indicating homoscedasticity.

Finally, I inspected frequency distributions, histograms, and normal probability plots to examine the skewness and kurtosis of all variables in the model. I used the skewness ratio (i.e., skew index over its standard error) and the kurtosis ratio (i.e., kurtosis index over its standard error) to detect severe skewness or kurtosis. I set the skewness ratio values higher than ± 3.0 and the kurtosis ratio values higher than ± 10.0 as cut-off points indicating severe skewness and kurtosis, respectively (Kline, 2015a, pp. 76–77). Based on previous research findings, the items used to assess perceived peer attitudes, personal attitudes, and violent extremist intentions were likely to be positively skewed (e.g., Kunst et al., 2018), as the examined attitudes and intentions tend to be relatively uncommon in the general population.

The analysis of skewness and kurtosis of all variables in the model confirmed this belief. The skewness ratios for AOS and PA items were all higher than 3.0, ranging from 3.38 (PA3) to 13.31 (AOS2) and indicating severe skewness. Notably, no ARIS items had a skewness ratio higher than 3.0, with values ranging from -1.69 (ARIS1) to 2.85 (ARIS4). Regarding kurtosis, one item (AOS2) had a kurtosis ratio of 11.50, indicating severe kurtosis. No other items from the three scales had kurtosis ratios higher than 10.0. Table 3 provides the skewness and kurtosis indexes, standard errors, and ratios for all study variables.

Past research recommends the use of one of the normalizing transformations, such as the log-transformation, to address the severe skewness and kurtosis of items assessing violent extremist attitudes and intentions (Kunst et al., 2018). Thus, I first conducted the log-transformations for all PA and AOS items in the model (Table 3 further includes skewness and kurtosis scores for the variables following the log-transformation). The data transformation

significantly improved the normality of PA items, with their skewness ratios ranging from -0.85 (PA3) to 2.85 (PA1). However, there was still a noticeable deviation from normality for AOS items, with values ranging from 4.09 (AOS7) to 7.78 (AOS2).

Consequently, I decided to handle severely skewed AOS items as ordinal categorical variables based on predetermined cut-off points. Given that the AOS items are measured on a four-point Likert scale, such an approach would be appropriate for this data and would not lead to the loss of any information (Royston et al., 2006). To analyze the data with categorical variables, I used an ordered probit model with weighted least squares with mean- and variance-adjusted (WLSMV) estimator, which does not assume normally distributed variables (B. O. Muthén & Asparouhov, 2002). For the predetermined ordinal cut-off points, I used the four Likert scale categories.

Table 3. Skewness and Kurtosis Scores for Study Variables

	Skewness	SE	Skewness/SE	Kurtosis	SE	Kurtosis/SE
AOS1	1.41	0.13	10.85*	1.59	0.26	6.12
AOS2	1.73	0.13	13.31*	2.99	0.26	11.50**
AOS3	1.25	0.13	9.62*	1.11	0.26	4.27
AOS4	1.49	0.13	11.46*	1.96	0.26	7.54
AOS5	1.13	0.13	8.69*	0.75	0.26	2.88
AOS6	1.13	0.13	8.69*	0.40	0.26	1.54
AOS7	1.39	0.13	10.69*	1.15	0.26	4.42
ARIS1	-0.22	0.13	-1.69	-1.28	0.26	-4.92
ARIS2	0.31	0.13	2.38*	-0.99	0.26	-3.81
ARIS3	0.24	0.13	1.85	-1.15	0.26	-4.42
ARIS4	0.37	0.13	2.85	-0.94	0.26	-3.62
PA1	1.01	0.13	7.77*	1.36	0.26	5.23
PA2	0.75	0.13	5.77*	-0.65	0.26	-2.50
PA3	0.44	0.13	3.38*	-0.98	0.26	-3.77
ln (AOS1)	1.42	0.21	6.76*	0.45	0.42	1.07
ln (AOS2)	1.79	0.23	7.78*	1.64	0.45	3.64
ln (AOS3)	1.44	0.20	7.20*	0.51	0.40	1.28
ln (AOS4)	1.62	0.22	7.36*	1.11	0.43	2.58
ln (AOS5)	1.36	0.20	6.80*	0.29	0.39	0.74
ln (AOS6)	0.91	0.20	4.55*	-0.81	0.40	-2.03
ln (AOS7)	0.90	0.22	4.09*	-0.80	0.43	-1.86
ln (PA1)	0.37	0.13	2.85	-0.50	0.26	-1.92
ln (PA2)	0.24	0.13	1.85	-1.45	0.26	-5.58
ln (PA3)	-0.11	0.13	-0.85	-1.44	0.26	-5.54

Note. * Value $\geq \pm 3.0$ indicates severe skewness; ** Value $\geq \pm 10.0$ indicates severe kurtosis

3.3 Measurement Model

Before testing any structural models, I first examined the goodness-of-fit of the measurement model (see Figures 4-6). Overall, tests of the measurement model demonstrated a good fit to the data, $\chi^2(74)=230.10$ $p<0.001$, CFI=0.97, SRMR=0.03, RMSEA=0.08 (90% CI = 0.07, 0.09). As previously mentioned, the χ^2 is highly sensitive to changes in sample size and tends to be statistically significant for models with large sample sizes, or more than 300 cases (Kline, 2015a, pp. 270–272). While both the CFI and SRMR values indicated good model fit, the obtained RMSEA value was near the recommended cut-off value of 0.08, and the upper limits of its 90% confidence interval exceeded this value.

Items measuring perceived peer attitudes loaded onto a different factor than items assessing personal attitudes, confirming that the measured indicators were conceptually distinct. Standardized factor loadings ranged from 0.68 (ARIS1) to 0.84 (ARIS2) for perceived peer attitudes, from 0.70 (PA1) to 0.79 (PA2) for personal attitudes, and from 0.85 (AOS3) to 0.91 (AOS7) for violent extremist intentions. Since all items loaded significantly onto their respective latent variables and the model fit indices demonstrated good to acceptable model fit, I carried forward the measurement model in subsequent analyses. Table 4 provides the measurement model parameters with standard errors and standardized estimates, including factor loadings, residual variances, intercepts, thresholds, and factor variances. Figures 7-9 also depict the latent variables with its standardized factor loadings: perceived peer attitudes (Figure 7), personal attitudes (Figure 8), and violent extremist intentions (Figure 9).

Table 4. Measurement Model Parameters with Standard Errors and Standardized Estimates

Relation/Variable	Estimate	SE	Ratio	<i>p</i>	Std
Factor Loadings					
Violent Extremist Intentions by					
AOS1	1.00	--	--	--	0.88
AOS2	0.91	0.10	8.95	<0.001	0.86
AOS3	0.88	0.09	10.03	<0.001	0.85
AOS4	1.09	0.13	8.46	<0.001	0.90
AOS5	1.16	0.11	10.52	<0.001	0.91
AOS6	1.02	0.09	10.98	<0.001	0.88
AOS7	1.16	0.17	6.93	<0.001	0.91
Perceived Peer Attitudes by					
ARIS1	1.00	--	--	--	0.68
ARIS2	1.20	0.13	9.60	<0.001	0.84
ARIS3	1.18	0.12	10.11	<0.001	0.82
ARIS4	1.09	0.14	7.60	<0.001	0.72
Personal Attitudes by					
PA1	1.00	--	--	--	0.70
PA2	1.31	0.18	7.13	<0.001	0.79
PA3	1.54	0.22	7.05	<0.001	0.73
Residual Variances					
ARIS1	1.73	0.19	9.27	<0.001	0.53
ARIS2	0.89	0.13	7.10	<0.001	0.29
ARIS3	1.05	0.14	7.36	<0.001	0.33
ARIS4	1.71	0.16	10.70	<0.001	0.49
PA1	0.12	0.01	9.06	<0.001	0.51
PA2	0.13	0.02	7.97	<0.001	0.38
PA3	0.26	0.03	10.32	<0.001	0.47
Intercepts					
Perceived Peer Attitudes					
ARIS1	3.91	0.10	38.74	<0.001	2.18
ARIS2	3.14	0.11	29.98	<0.001	1.79
ARIS3	3.43	0.10	34.16	<0.001	1.93
ARIS4	3.00	0.12	24.87	<0.001	1.60
Personal Attitudes					
PA1	0.36	0.04	8.55	<0.001	0.74
PA2	0.60	0.03	17.83	<0.001	1.04
PA3	0.76	0.05	15.12	<0.001	1.04
Thresholds					
Violent Extremist Intentions					

AOS1						
T1	0.57	0.16	3.70	<0.001	0.27	
T2	2.80	0.23	12.40	<0.001	1.33	
T3	4.29	0.29	15.07	<0.001	2.04	
AOS2						
T1	0.80	0.15	5.20	<0.001	0.41	
T2	2.92	0.24	12.00	<0.001	1.49	
T3	3.89	0.31	12.48	<0.001	1.98	
AOS3						
T1	0.36	0.14	2.64	<0.001	0.19	
T2	2.39	0.19	12.48	<0.001	1.26	
T3	3.88	0.27	14.40	<0.001	2.03	
AOS4						
T1	0.71	0.17	4.08	<0.001	0.32	
T2	3.15	0.30	10.38	<0.001	1.40	
T3	4.58	0.42	10.92	<0.001	2.04	
AOS5						
T1	0.31	0.17	1.84	<0.001	0.13	
T2	2.86	0.24	11.71	<0.001	1.21	
T3	4.96	0.37	13.42	<0.001	2.10	
AOS6						
T1	0.45	0.15	2.92	<0.001	0.21	
T2	2.31	0.22	10.71	<0.001	1.08	
T3	4.49	0.35	12.78	<0.001	2.10	
AOS7						
T1	0.77	0.19	4.01	<0.001	0.33	
T2	2.62	0.31	8.40	<0.001	1.10	
T3	4.28	0.41	10.38	<0.001	1.80	
Means/Intercepts						
Perceived Peer Attitudes						
ARIS1	3.91	0.10	38.74	<0.001	2.18	
ARIS2	3.14	0.11	29.98	<0.001	1.79	
ARIS3	3.43	0.10	34.16	<0.001	1.93	
ARIS4	3.00	0.12	24.87	<0.001	1.60	
Personal Attitudes						
PA1	0.36	0.04	8.55	<0.001	0.74	
PA2	0.60	0.03	17.83	<0.001	1.04	
PA3	0.76	0.05	15.12	<0.001	1.04	
Factor Variances						
Violent Extremist Intentions	3.44	0.59	5.79	<0.001	1.00	

Perceived Peer Attitudes	1.51	0.33	4.62	<0.001	1.00
Personal Attitudes	0.12	0.03	4.32	<0.001	1.00

Figure 7. Perceived peer attitudes with standardized factor loadings

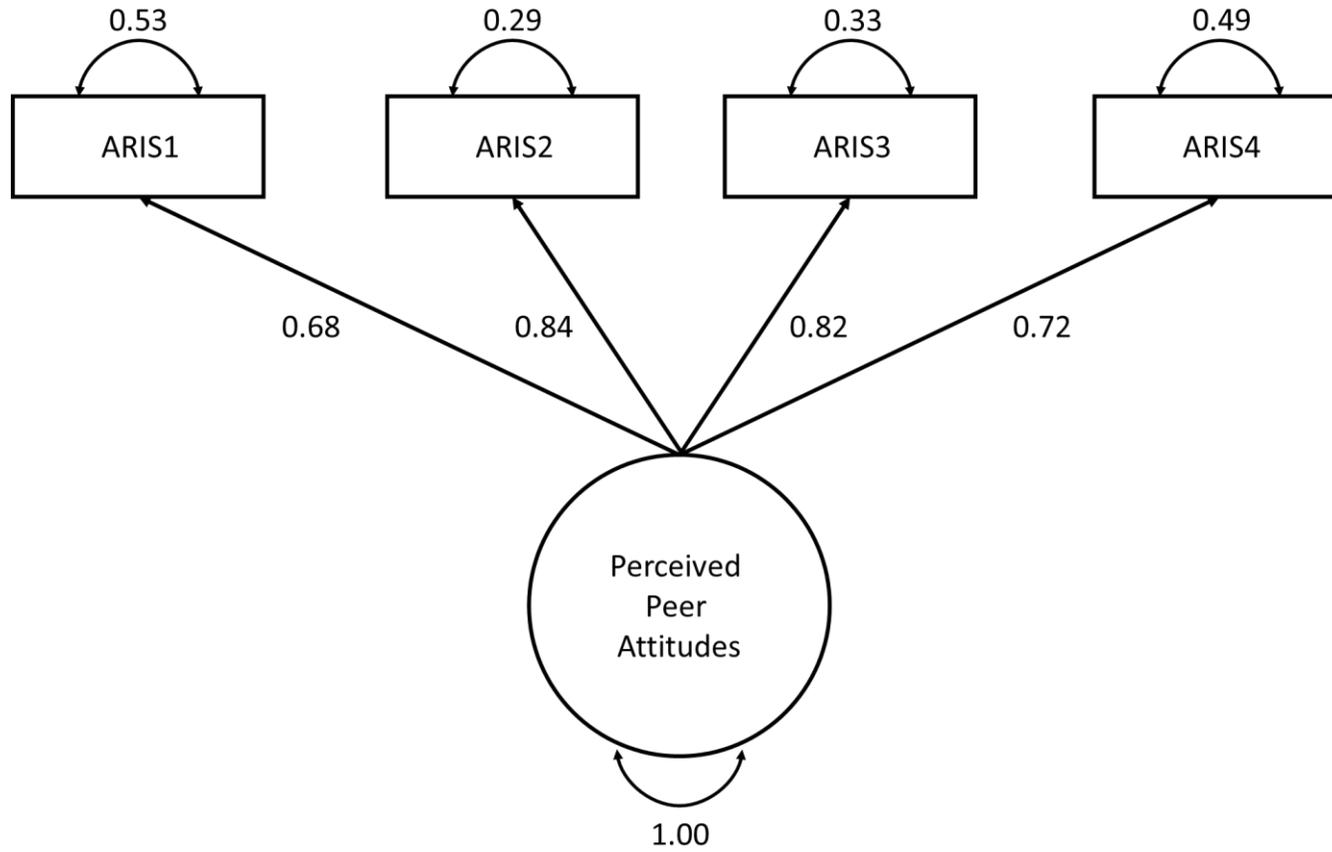


Figure 8. Personal attitudes with standardized factor loadings

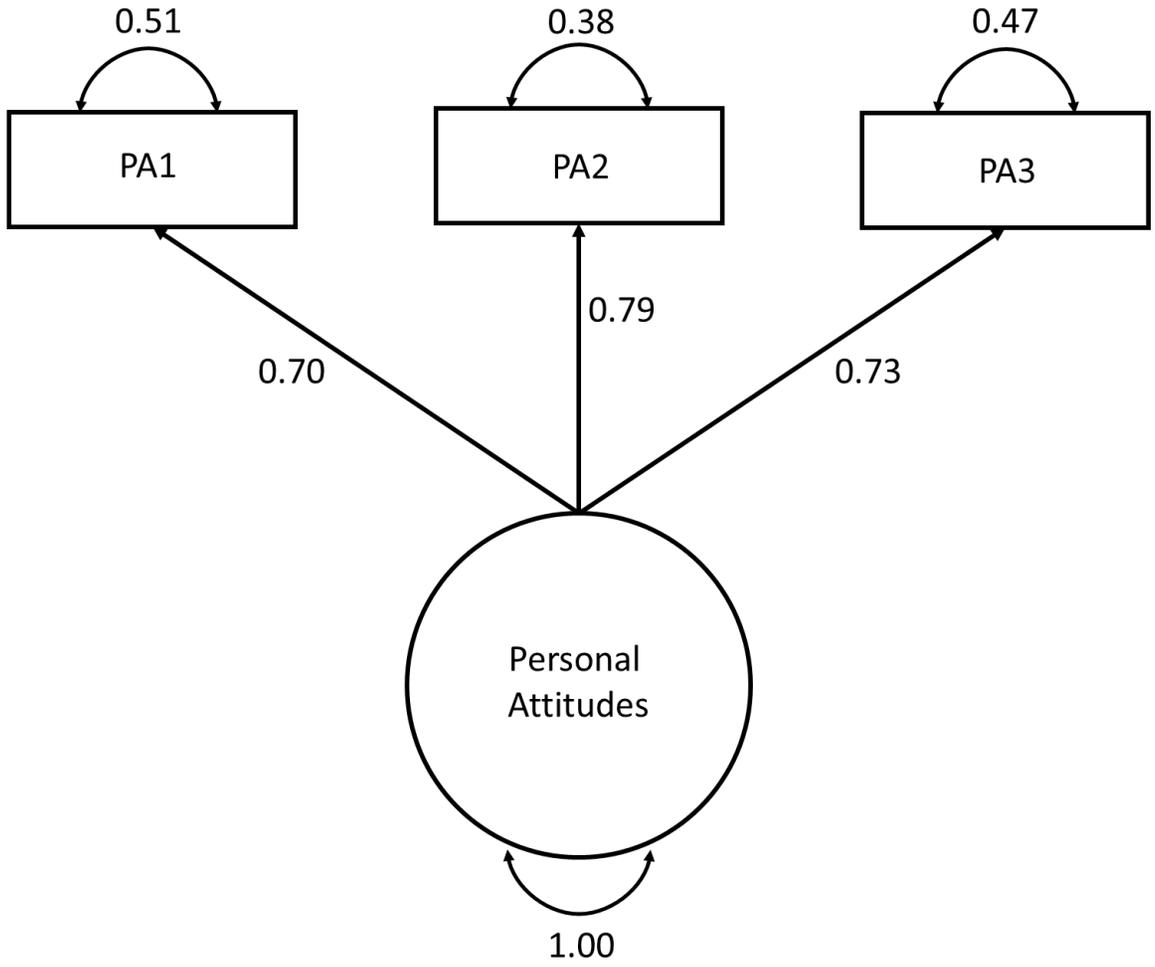
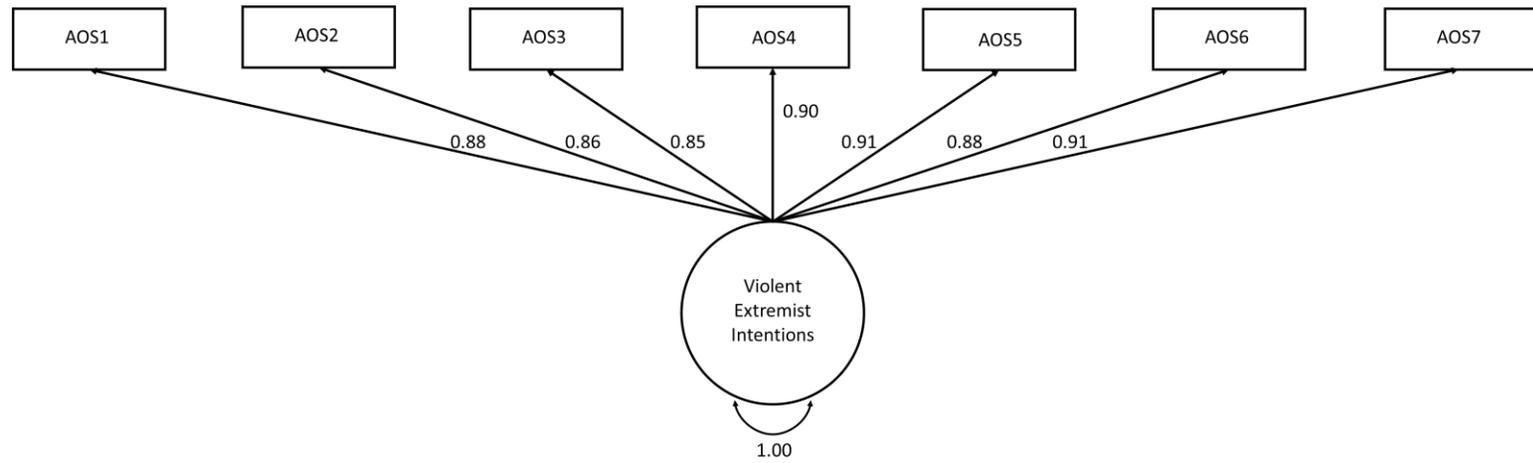


Figure 9. Violent extremist intentions with standardized factor loadings



3.4 Research Question 1

Model 1 examined the hypothesized relationships between perceived peer attitudes, personal attitudes, and violent extremist intentions. To scale the latent variables, I fixed the loadings of the first items to 1.0. Table 5 provides fit statistics for all structural models examined in the study. The model fit statistics indicated good model fit, $\chi^2(74)=230.11, p<0.001$, CFI=0.97, SRMR=0.03, RMSEA=0.07 (90% CI = 0.06, 0.08).

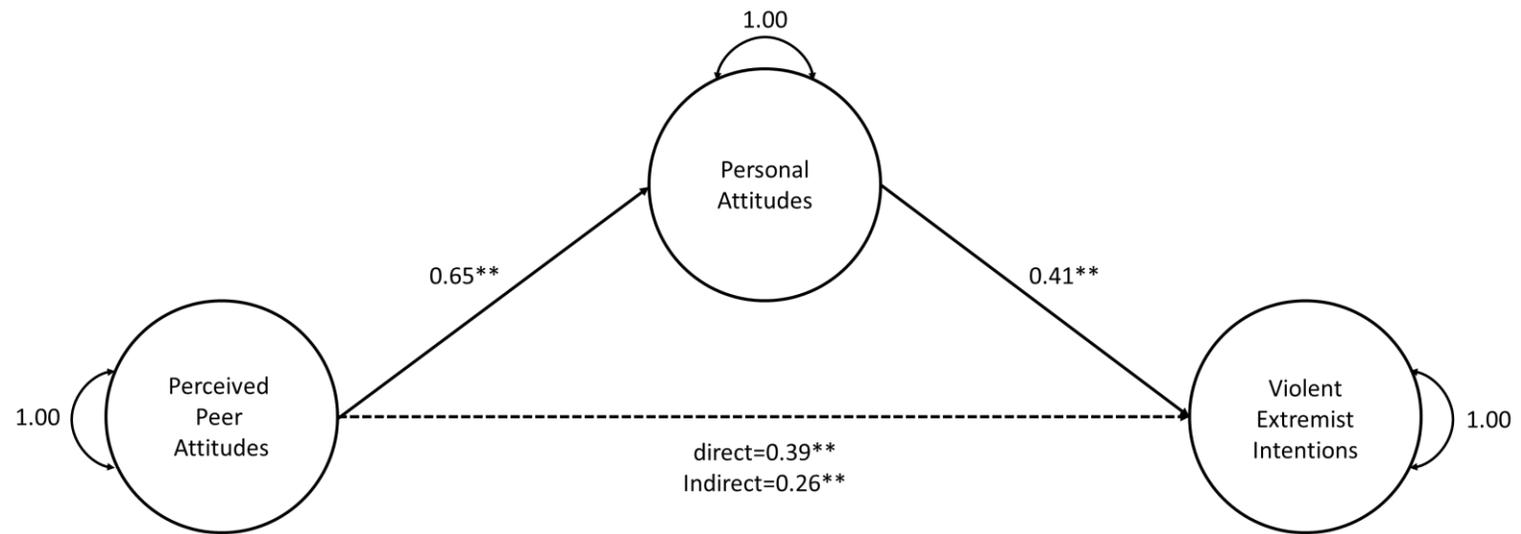
Figure 10 depicts Model 1 with standardized estimates. Perceived peer attitudes were positively and significantly related to personal attitudes ($b=0.65, SE=0.03, p<0.001$), and personal attitudes were positively and significantly related to violent extremist intentions ($b=0.41, SE=0.05, p<0.001$). The total association of perceived peer attitudes with violent extremist intentions was also positive and statistically significant ($b=0.65, SE=0.04, p<0.001, 95\% CI = 0.58, 0.72$). The direct association was still statistically significant ($b=0.39, SE=0.06, p<0.001, 95\% CI = 0.29, 0.50$), even after accounting for the indirect effect of personal attitudes ($b=0.26, SE=0.04, p<0.001, 95\% CI = 0.18, 0.35$). Personal attitudes, therefore, partially mediated the relationship between perceived peer attitudes and violent extremist intentions. Overall, participants who perceived their peers to be more supportive of violent extremist attitudes held similar attitudes and expressed greater willingness to engage in violent extremism themselves.

Table 5. Tests of Model Fit

Model Name	χ^2	df	p	CFI	SRMR	RMSEA	90% CI RMSEA	Comparison				Note
								H ₀	ΔH_0	Δdf	p	
Model 1	230.11	74	<0.001	0.97	0.03	0.07	0.06-0.08	--	--	--	--	--
Model 2	231.53	86	<0.001	0.98	0.04	0.07	0.06-0.08	-5202.36	--	--	--	--
Model 3	--	--	--	--	--	--	--	-5222.47	20.12	2	<0.001	v. Model 2

Note. CFI = Comparative Fit Index; SRMR = Standardized Root Mean Square Residual; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; H₀= Log-likelihood

Figure 10. Model 1 with standardized estimates



Note: **Significant at $p < 0.001$
Mean structures not shown

3.5 Research Question 2

In the first step of the LMS method, I estimated Model 2 and assessed its fit. Model 2 included social network diversity in addition to all the Model 1 variables, but it did not estimate the interaction and therefore assumed it to be zero. To scale the latent variables, I fixed the loadings of the first items to 1.0. The model fit the data well: $\chi^2(86)=231.53, p<0.001, CFI=0.97, SRMR=0.04, RMSEA=0.07$ (90% CI = 0.06, 0.08). Social network diversity was negatively related to personal attitudes, but this association did not reach statistical significance ($b=-0.07, SE=0.06, p=0.21$). Figure 11 depicts Model 2 with standardized estimates, while Table 5 includes fit statistics for Model 2.

Next, I estimated Model 3, which included the interaction term. As previously mentioned, the LMS method does not provide traditional model fit indices. Instead, I used the log-likelihood ratio test to determine the relative fit of Model 3, compared to Model 2. The log-likelihood (H_0) value for Model 3 was equal to -5222.48, yielding a log-likelihood difference value of $D=20.12$ when compared to the log-likelihood (H_0) value of Model 2 (-5202.36). Based on the number of free parameters of Model 2 (56) and Model 3 (54), the difference in free parameters was equal to 2, which represented the df value used for the log-likelihood ratio test. The log-likelihood ratio test was statistically significant ($p<0.001$), indicating that Model 3 was significantly better in fit relative to Model 2.

Figure 12 depicts Model 3 with standardized estimates, while Table 4 provides the full model parameters with standard errors and standardized estimates, including factor loadings, residual variances, means/intercepts, thresholds, and factor variances. The perceived peer attitudes by social network diversity interaction effect was statistically significant at $p<0.05$ ($b=-0.17, SE=0.02, p=0.01$). To examine the latent interaction, I conducted the simple slopes analysis

using the latent factor scores. The simple slope was positive and statistically significant for the mean level of social network diversity ($b^*_m=0.21$, $SE=0.06$, $p<0.01$), as well as for the low level ($b^*_{-1sd}=0.34$, $SE=0.05$, $p<0.001$). However, the simple slope was no longer statistically significant for the high level of social network diversity ($b^*_{+1sd}=0.04$, $SE=0.03$, $p=0.72$). Overall, the effect of perceived peer attitudes on personal attitudes decreased as social network diversity increased. Figure 13 depicts the effect of the interaction of perceived peer attitudes and social network diversity on personal attitudes.

Table 6. Full Model Parameters with Standard Errors and Standardized Estimates

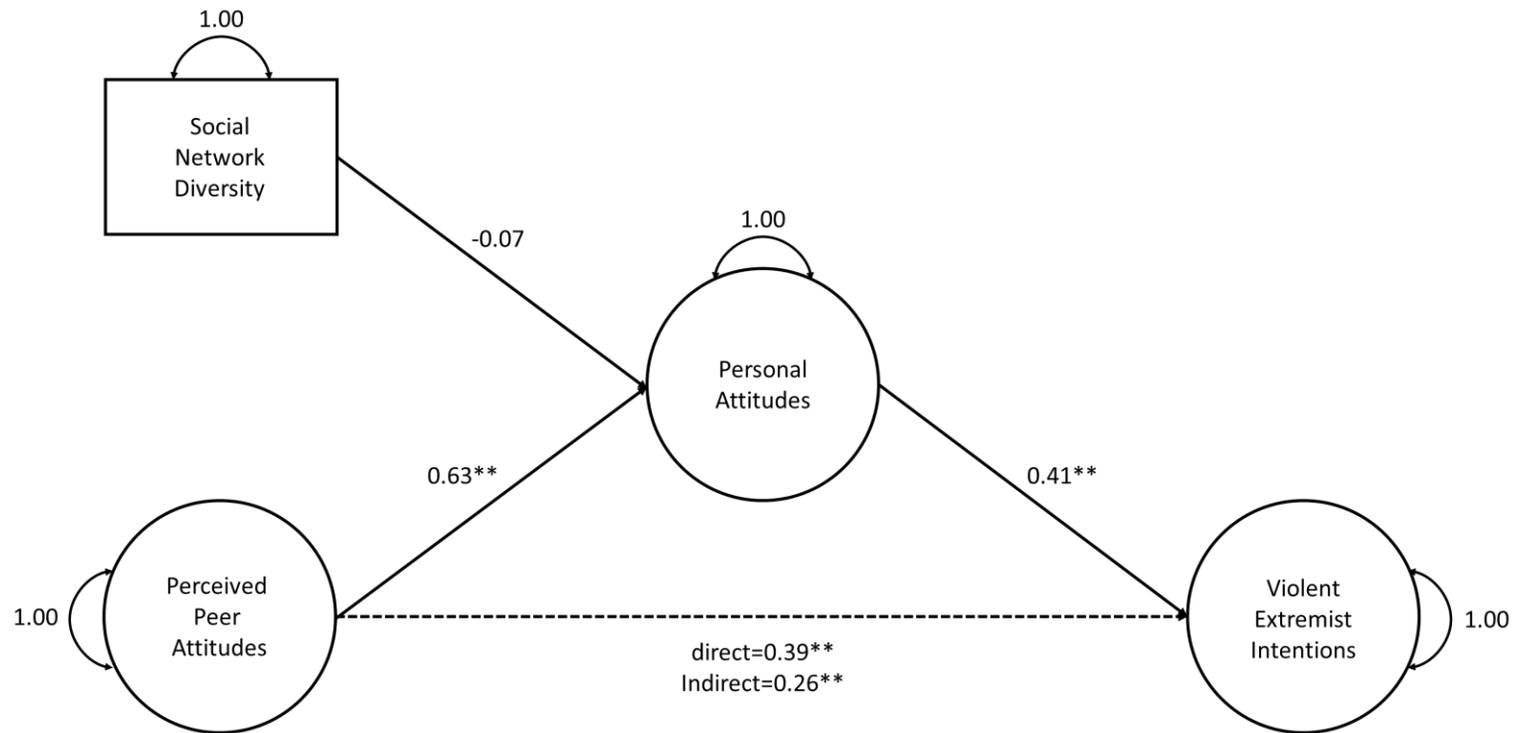
Relation/Variable	Estimate	SE	Ratio	<i>p</i>	Std
Regressions					
VEI on PA	1.03	0.14	7.19	<0.001	0.41
PA on PPA	0.18	0.03	5.73	<0.001	0.63
PA on PPAxSNI	-0.03	0.02	7.90	<0.05	-0.17
PPA-VEI Effect					
Total	0.46	0.05	9.60	<0.001	0.64
Indirect (PA)	0.18	0.04	5.29	<0.001	0.26
Direct	0.28	0.05	5.77	<0.001	0.39
Factor Loadings					
Violent Extremist Intentions by					
AOS1	1.00	--	--	--	0.88
AOS2	0.98	0.03	36.26	<0.001	0.86
AOS3	0.97	0.02	40.39	<0.001	0.85
AOS4	1.02	0.03	40.73	<0.001	0.90
AOS5	1.03	0.02	49.90	<0.001	0.91
AOS6	1.00	0.02	49.24	<0.001	0.88
AOS7	1.03	0.03	35.87	<0.001	0.91
Perceived Peer Attitudes by					
ARIS1	1.00	--	--	--	0.68
ARIS2	1.20	0.13	9.58	<0.001	0.84
ARIS3	1.18	0.12	10.09	<0.001	0.82
ARIS4	1.09	0.14	7.58	<0.001	0.72
Personal Attitudes by					
PA1	1.00	--	--	--	0.70
PA2	1.30	0.18	7.16	<0.001	0.78
PA3	1.55	0.22	7.05	<0.001	0.73
Residual Variances					
Perceived Peer Attitudes by					
ARIS1	1.72	0.19	9.27	<0.001	0.53
ARIS2	0.88	0.13	6.81	<0.001	0.29
ARIS3	1.04	0.15	7.20	<0.001	0.33
ARIS4	1.72	0.16	10.74	<0.001	0.49
Personal Attitudes by					
PA1	0.13	0.01	9.01	<0.001	0.51
PA2	0.13	0.02	8.09	<0.001	0.39
PA3	0.25	0.03	9.94	<0.001	0.47
Means/Intercepts					

SNI	5.02	0.10	51.22	<0.001	2.80
Perceived Peer Attitudes by					
ARIS1	3.91	0.10	38.74	<0.001	2.18
ARIS2	3.14	0.11	29.98	<0.001	1.79
ARIS3	3.43	0.10	34.16	<0.001	1.93
ARIS4	3.00	0.12	24.87	<0.001	1.60
Personal Attitudes by					
PA1	0.54	0.06	9.88	<0.001	1.09
PA2	0.83	0.07	12.62	<0.001	1.43
PA3	1.04	0.08	12.32	<0.001	1.41
Thresholds					
Violent Extremist Intentions by					
AOS1					
T1	0.09	0.09	0.99	0.32	0.09
T2	1.14	0.11	10.41	<0.001	1.14
T3	1.85	0.17	11.09	<0.001	1.85
AOS2					
T1	0.23	0.09	2.47	0.01	0.23
T2	1.31	0.12	10.58	<0.001	1.31
T3	1.80	0.16	10.98	<0.001	1.80
AOS3					
T1	0.01	0.09	0.14	0.89	0.01
T2	1.08	0.11	9.89	<0.001	1.08
T3	1.86	0.17	11.15	<0.001	1.86
AOS4					
T1	0.13	0.09	1.42	0.16	0.13
T2	1.22	0.12	10.53	<0.001	1.22
T3	1.86	0.17	11.16	<0.001	1.85
AOS5					
T1	0.06	0.09	0.62	0.53	0.06
T2	1.02	0.11	9.71	<0.001	1.02
T3	1.91	0.17	11.20	<0.001	1.91
AOS6					
T1	0.03	0.09	0.31	0.76	0.03
T2	0.90	0.10	8.70	<0.001	0.90
T3	1.92	0.17	11.20	<0.001	1.92
AOS7					
T1	0.14	0.09	1.50	0.13	0.14
T2	0.91	0.11	8.56	<0.001	0.91
T3	1.61	0.15	10.89	<0.001	1.61

Factor Variances

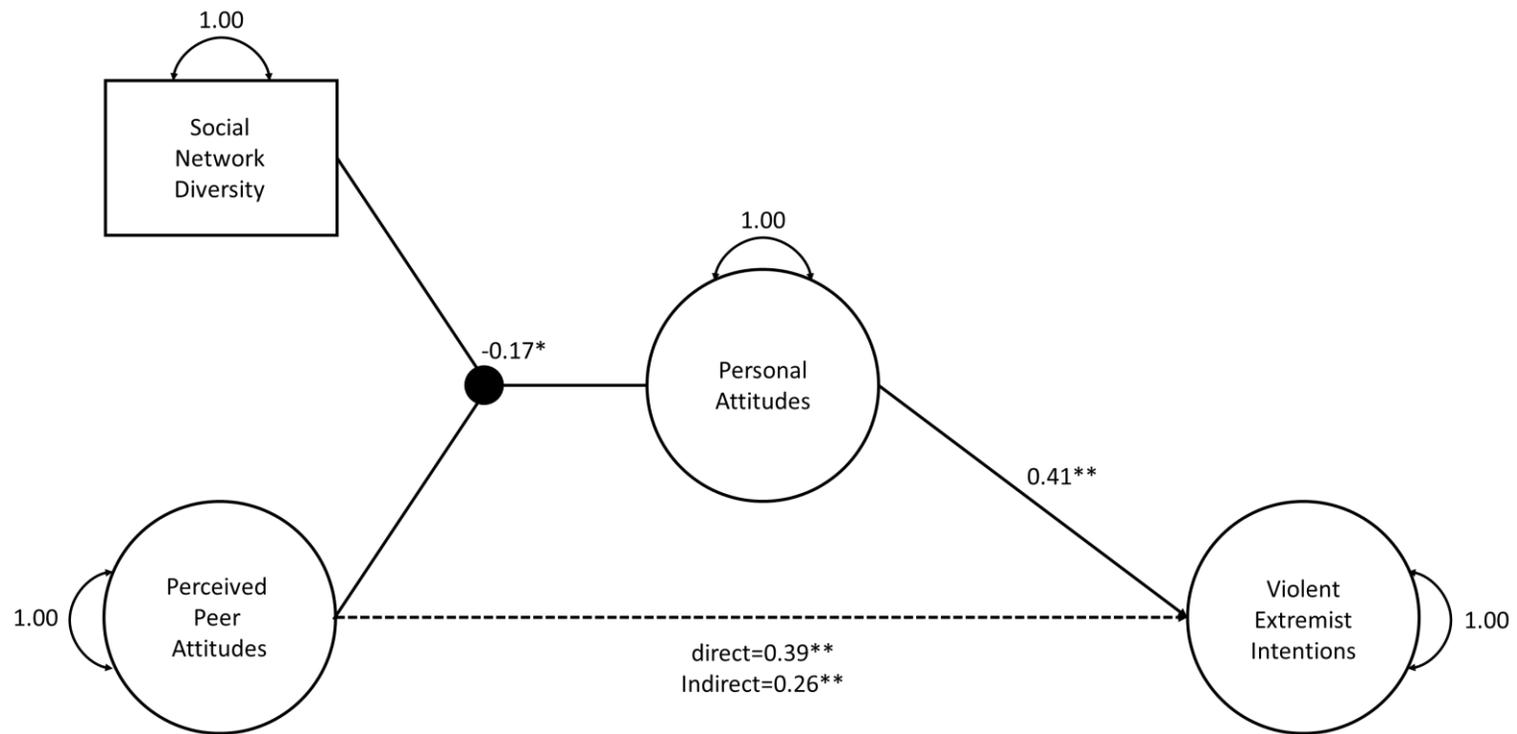
Violent Extremist Intentions	3.44	0.59	5.79	<0.001	1.00
Perceived Peer Attitudes	1.51	0.33	4.62	<0.001	1.00
Personal Attitudes	0.12	0.03	4.32	<0.001	1.00

Figure 11. Model 2 with standardized estimates



Note: ** Significant at $p < 0.001$
Mean structures not shown

Figure 12. Model 3 with standardized estimates

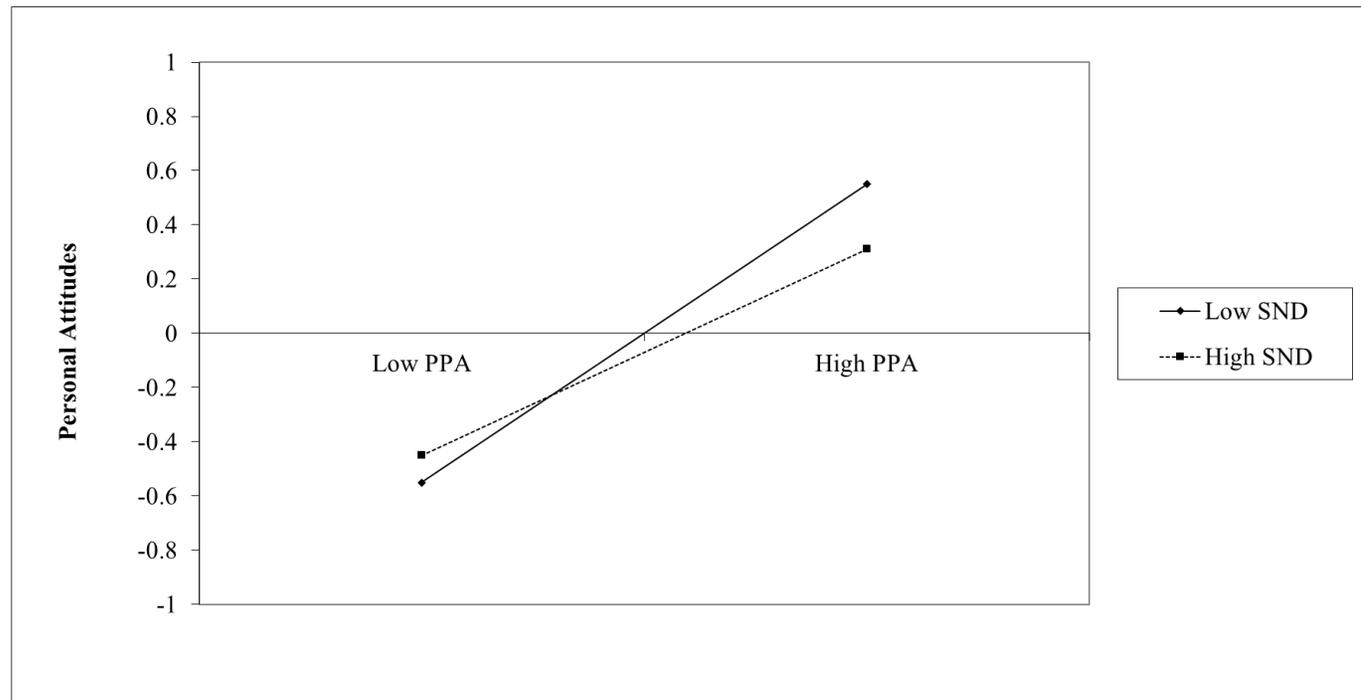


Note: Black dot indicates interaction term

*Significant at $p < 0.05$

**Significant at $p < 0.001$

Figure 13. Interaction effect graph



Note: PPA=Perceived peer attitudes
SND=Social network diversity

4 DISCUSSION

The present study sought to answer the following questions: (1) To what extent are perceived peer attitudes, personal attitudes, and violent extremist intentions related to each other? (2) To what extent does the relationship between perceived peer attitudes and violent extremist intentions differ at various levels of social network diversity? Overall, the study findings supported the initial hypotheses. Perceived peer attitudes were positively and significantly associated with violent extremist intentions through their relationship with personal attitudes. In other words, participants who thought their peers were more supportive of violent extremism held similar attitudes and, consequently, reported greater willingness to engage in violent extremist behaviors themselves. The mediating effect, however, was partial: personal attitudes did not account for the total association between perceived peer attitudes and violent extremist intentions. Furthermore, social network diversity moderated the relationship between perceived peer attitudes and personal attitudes. In other words, participants with more diverse social networks were less likely to hold personal attitudes similar to their perceived peer attitudes.

The study findings correspond with past research on other violent outcomes, which suggests that perceived peer attitudes serve as an important factor contributing to the development of violent attitudes and intentions (Ali et al., 2011; Mesch et al., 2003), while structural features of peer networks, such as their diversity, influence the strength and direction of this relationship (Jose et al., 2016). The current study, however, is one of the first to examine the role of perceived peer attitudes and social network diversity in the formation of violent extremist attitudes and intentions. Thus, study findings expand on the current research on violent extremism by highlighting the importance of attitudinal and structural features of peer networks in this process.

Research question 1. Participants who thought their peers were more supportive of violent extremism held similar attitudes and, consequently, were more willing to engage in such behaviors themselves. This finding is in line with past research, which indicates that perceived peer attitudes can serve as a strong predictor of violent extremist attitudes and intentions (Dahl & Van Zalk, 2014; Kuhn, 2004). According to the theory of peer influence, the observed relationship between perceived peer attitudes and personal attitudes results from the social need to maintain peer relationships (Albert et al., 2013). Young men use their perceptions of peer attitudes to determine which attitudes are socially acceptable among their close friends. They consolidate their attitudes with the widely held beliefs as a way of gaining peer approval, since they are usually rewarded for expressing beliefs in line with the majority opinion (Schachter, 1951). The current study appeared to reflect this process: participants were more likely to approve of violent extremist attitudes if they thought that such attitudes were socially acceptable within their peer groups.

The observed mediation effect was partial, meaning that personal attitudes accounted for some, but not all, of the relationship between perceived peer attitudes and violent extremist intentions. Partial mediation implies not only a significant relationship between personal attitudes and violent extremist intentions but also some direct relationship between perceived peer attitudes and personal intentions (Field, 2013, p. 409). For example, some people may conform their intentions and behaviors to their perceptions of peer norms due to the need to maintain social relationships, as they can be socially ostracized for not behaving in line with peer expectations (Schachter, 1951). However, they may not necessarily adopt such norms as their own. Likewise, additional variables can potentially influence this relationship. For instance, perceived peer attitudes may impact perceived behavioral control (Ajzen, 1991): people may find

it easier to engage in violent extremism if they think that their peers would support such actions. Overall, the study indicates that the development of violent extremist attitudes and intentions is not a result of a single factor, but rather the product of a complex interaction of a multitude of variables across socio-ecological systems. Perceived peer attitudes are a significant feature contributing to this process, although not the only one.

Research question 2. The study also found a moderating effect of social network diversity on the relationship between perceived peer attitudes and personal attitudes. In other words, participants with more diverse social networks were less likely to express support for violent extremism, even when they thought their closest peers would approve of such beliefs. This finding corresponds with studies on other violent outcome, which indicate that social network diversity can serve as a protective factor against sexual violence perpetration (Kaczkowski et al., 2017) or the endorsement of xenophobic beliefs (Walter et al., 2017). People with more diverse social networks are more likely to form their own opinions rather than adopt the beliefs of their peers (Quintelier et al., 2012). Greater network diversity exposes people to a broader range of norms and attitudes; thus, they experience less pressure to adopt group beliefs and do not base their sense of personal identity or self-worth entirely on in-group membership (Putnam, 2001). Simply put, people with diverse social networks do not necessarily feel the need to adopt violent extremist attitudes in order to be accepted into their peer group. They may also be less willing to support such beliefs when they contrast them with other attitudes shared within their more extensive networks. Since exposure to diverse peer networks also tends to promote civic engagement (e.g., Eveland & Hively, 2009; Quintelier et al., 2012; Scheufele et al., 2004), further research may possibly explore whether social network diversity fosters non-violent and legal political engagement in place of violent extremist actions.

4.1 Limitations and Future Directions

Sample. The study sample was not necessarily representative of the overall population. First, the study was limited to men between the ages of 18 and 29 years old. I chose to focus on this particular population due to the association of age and gender with the likelihood of engagement in violent extremism. Young men are at a significantly greater risk for endorsing violent extremist attitudes and behaviors (Kimmel, 2018). They are also more susceptible to peer influences that encourage aggressive and risk-taking behaviors, compared to both older adults and women in the same age group (McCoy et al., 2019). The limited focus of the study, however, makes it difficult to determine whether the strength of the observed associations is, in fact, higher for young adult men. Therefore, future research should examine whether current study findings can be replicated using a more generalizable and nationally representative sample.

Likewise, additional studies should focus on specific political, religious, or racial/ethnic groups. For instance, past research has examined the impact of social marginalization and peer influences on engagement in violent extremism among East German young adults (Kuhn, 2004) or Muslim immigrants in Western Europe and North America (Doosje et al., 2013; Lyons-Padilla et al., 2015). Research, however, has not yet assessed the impact of structural features of social networks, such as their diversity, on violent extremist attitudes and behaviors within the populations hypothesized to be at a heightened risk for violent extremism. In the future, such studies may be especially beneficial to counter violent extremism programs by identifying specific communities where network diversity can serve as a protective factor against the rise of violent extremism.

The use of an online sample could also be considered a limitation for this study. Research notes some fundamental differences between the MTurk worker pool and the general population.

For example, the majority of MTurk workers are young, unmarried men; they are more educated, less religious, more interested in political issues, and more likely to be unemployed than the general population (Goodman et al., 2013). The current study sample also had some distinctive characteristics. More than half of the participants self-identified as atheist or agnostic. This proportion is considerably higher compared to national surveys, which estimate the irreligious population in the United States at 3-9% (Pew Research Center, 2014). The sample was also not particularly racially or ethnically diverse: 76% of participants identified as White, non-Hispanic/Latino. When asked about their most salient social group, 12.35% of participants listed their ethnic/racial group, while only 2.06% (i.e., seven participants) named their nationality. Notably, “American” was the only listed nationality. In a more diverse sample, one would expect more participants to select their race/ethnicity or nationality, as the minority status tends to make one’s racial, ethnic or national identity more salient (Smith, 1991). Thus, future studies need to examine the observed impact of perceived peer attitudes and social network diversity while utilizing other forms of participant recruitment, including community-based samples.

Measures. The study assessed perceived, rather than actual, peer attitudes. Personal perceptions of peer attitudes do not always reflect the peers’ *actual* attitudes but can still have a significant impact on personal attitudes and behaviors (Jose et al., 2016; Martens et al., 2006). Still, the focus on perceived peer attitudes limits the possible implications of the current study regarding the role of actual peer attitudes in the development of violent extremist attitudes and intentions. For instance, study participants considered their peers to be more supportive of violent extremism than themselves: scores on items assessing perceived peer attitudes were noticeably higher than scores on items measuring personal attitudes. Researchers need to examine whether this discrepancy between perceived peer attitudes and personal attitudes

reflects an accurate assessment of peers' actual attitudes, rather than self-serving or social desirability bias at the hands of participants.

On a similar note, the current study used behavioral intentions, rather than actual behavior, as an outcome of interest. Previous research offers considerable evidence for the applicability of behavioral intentions in predicting antisocial and health-related behaviors (for review, see Godin & Kok, 2016). Researchers still consider behavioral intentions to be a useful proxy for assessing violent extremist behavior, as the accurate assessment of such behavior in a large and representative sample is often difficult (e.g., Corning & Myers, 2002; Doosje et al., 2013; Moskalenko & McCauley, 2009). Such data, however, may be vulnerable to self-serving biases, as participants are often reluctant to disclose their willingness to engage in illegal behaviors (Furnham, 1986). In the present study, for instance, participants were more likely to indicate that their peers held violent extremist attitudes than to state their own willingness to engage in such behaviors. Participants may have been more comfortable sharing their perceptions of their peers' opinions rather than their own violent extremist intentions. Future research should replicate the current study's findings with actual behavior, rather than intentions, to address this possible limitation. Since participants are often unwilling to disclose their engagement in violent extremism, past studies have instead assessed related behaviors, such as voting for extremist political parties (e.g., Kuhn, 2004).

Data analysis. The present study utilized a cross-sectional design, which cannot directly support causal inference (Kline, 2015b). Because the variables in the mediational effect model (Model 1) were measured at the same time, it is difficult to establish whether the presumed causal variables (i.e., perceived peer attitudes, personal attitudes) had a subsequent effect on the outcome variable (i.e., violent extremist intentions). On a similar note, the lack of longitudinal

analysis makes it unclear whether the observed association between perceived peer attitudes and peer attitudes is a result of peer influence, rather than peer selection. One may interpret the study findings by inferring that participants changed their attitudes and, consequently, intentions to conform to their perceptions of their peers' attitudes. However, one cannot entirely discount an alternative hypothesis that participants selected peers who shared their beliefs about political issues and violent extremism.

The theory of planned behavior offers a strong rationale for the directionality assumption since the changes in perceived peer attitudes and personal attitudes tend to precede changes in behavioral intentions (for review, see Kim & Hunter, 1993). Furthermore, Dahl and Van Zalk (2014) found in their longitudinal study that peer support for illegal political violence predicted increases in personal support for such actions; study participants did not select peers with similar attitudes towards illegal political violence, but rather adjusted their beliefs to those of their current peers. Still, a longitudinal follow-up study should be conducted to fully examine the causality of the observed relationships. In such a study, the participants' violent extremist attitudes and intentions, as well as their perceived peer attitudes and social network diversity, should be measured at multiple time intervals. This design would not only allow researchers to observe the causality of the examined associations but also to detect developments and changes in attitudes and intentions of the studied population at both the group and the individual levels.

4.2 Implications

Research implications. The present study highlights the value of integrating findings from research on other forms of violent behavior into the study of violent extremism. The study replicated the relationship between perceived peer attitudes and personal attitudes and intentions, as well as the moderating effect of social network diversity, observed in research on alcohol and

substance abuse (S. Cohen & Lemay, 2007; Martens et al., 2006), delinquent behaviors (Ali et al., 2011; Mesch et al., 2003) or sexual violence perpetration (Kaczkowski et al., 2017; Swartout, 2013). Given the results, researchers should consider examining whether other findings on the role of peer networks in violence perpetration can also be incorporated into the study of violent extremism.

First, the study found that perceived peer attitudes serve as a potential risk factor for the development of violent extremist attitudes and intentions. Other research, however, suggests that perceived peer attitudes may also function as a protective factor against violent outcomes. When young men believe that their peers would disapprove of violent attitudes and behaviors, they are less likely to perpetrate such actions themselves (Dahl, 2017). Furthermore, prosocial and politically engaged peer networks facilitate non-violent civic engagement (Šerek & Machackova, 2015), generate positive attitudes towards political institutions (Putnam, 2001), and aid in the formation and cultivation of non-violent social movements (Lee & Chan, 2010). In other words, such peer networks help expose young men to a broader range of political beliefs and provide different opportunities for political activism and self-expression. Therefore, future research needs to examine whether prosocial and non-violent perceived peer attitudes can protect young men against the development of violent extremist attitudes and intentions, as well as whether social network diversity also plays a moderating role in this process.

The current project serves as one of the first studies to examine the role of structural features of peer networks in the formation of violent extremist attitudes and intentions. Given its findings, future research needs to examine the potential role of other dimensions of network structure in this process. For instance, researchers may focus on network centrality (i.e., the extent to which a social network revolves around a single node, or individual) and density (i.e.,

the extent to which network members know one another). Peer network density interacts with perceived peer attitudes to predict hostile masculinity and, consequently, sexual aggression (Swartout, 2013). The strength of peer influence on intimate partner violence is also greater in larger, more centralized peer networks (Ramirez et al., 2012). Further research should explore whether peer network centrality and density have a similar effect on the development of violent extremist attitudes and intentions.

Some researchers also highlight the capacity of social network analysis in the study of violent extremism (Perliger & Pedahzur, 2011; Ressler, 2006). Social network analysis aims to understand a community through the mapping of the relationships that connect them as a network and identifying the key individuals, associations between them, and the network subcomponents (Wasserman et al., 1994). This approach is especially suited for the examination of structural network features and their impact within small informal groups, such as violent extremist organizations. In other words, social network analysis can identify which group structures are more vulnerable, which actors are crucial for the continuing existence of the group, and how the network subcomponents communicate with each other. Such information can be crucial for designing and implementing effective counter violent extremism programs. Consequently, research on violent extremism has begun to implement social network analysis more widely in recent years (for review, see Perliger & Pedahzur, 2011). The current study highlights the need for more research on the role of social networks in radicalization and violent extremism, given its findings on the role of peer networks and their structural features in the development of violent extremist attitudes and intentions.

Policy implications. The study has several implications for prevention and countering violent extremism (P/CVE) programs. Currently, P/CVE does not have a universally accepted

definition, as it may require various approaches and perspectives, depending on the individuals, settings, and specific objectives (National Academies of Sciences, Engineering, and Medicine, 2017). Broadly speaking, P/CVE refers to a multitude of prevention and intervention approaches intended to “increase the resilience of communities and individuals to radicalization toward violent extremism, to provide non-violent avenues for expressing grievances, and to educate communities about the threat of recruitment and radicalization to violence” (National Academies of Sciences, Engineering, and Medicine, 2017, p. 1).

In recent years, social-ecological approaches to P/CVE have begun to emphasize the role of contextual and environmental factors in the development of violent extremist attitudes and behaviors (Stephens et al., 2019). This approach shifts focus from the individual to the dynamic interactions between the individuals and their social environments. Multiple factors across socio-ecological systems interact in complex ways to result in attitudinal and behavioral changes, to varying degrees (Stephens et al., 2019). The current study identifies peer networks as having a substantial influence on this process and explores their interactions with other factors.

Specifically, the study findings inform three types of P/CVE interventions: (1) social-ecological intervention, (2) peer mediation, and (3) intergroup contact. First, social-ecological interventions seek to prevent or counter extremist behaviors by offering help within social environments, with an emphasis on family relations, peer associations, school performance, housing, and employment (Lub, 2013). According to this perspective, enhancing and improving social ties of at-risk individuals reduces feelings of social deprivation, which in turn decreases the risk of engagement in violent extremism. For example, Building Resilience Against Violent Extremism (BRAVE), the World Organization for Resource Development and Education’s (WORDE) community-based approach to CVE, focuses on generating public awareness about

the risk factors for violent extremism and empowering “gatekeepers,” or community stakeholders, to provide support to at-risk individuals (Horgan et al., 2018; Mirahmadi, 2016).

Based on the study findings, peer gatekeepers can serve two crucial roles for social-ecological P/CVE initiatives. First, people’s violent extremist attitudes are often in line with their perceived peer attitudes. As a result, potential perpetrators may share their grievances, ideologies, or intentions with their peers. Past research offers additional support for this assumption: studies of lone-actor terrorists have revealed that, in the majority of cases, their family or friends were aware of their violent intentions but did not report this information to authorities (Gill et al., 2014). Thus, close peers are well-positioned to identify at-risk persons and reach out to other community members or appropriate social services for help. P/CVE efforts, however, need to educate peer gatekeepers about accurately recognizing indicators of violent extremism and reporting this information to appropriate authorities.

Second, perceived peer attitudes can serve as an important protective factor against violent extremism. Study findings suggest that at-risk individuals may be less likely to embrace extremist attitudes when they believe that their peers would not approve of such beliefs. Thus, social-ecological P/CVE initiatives need to foster prevention skills and resources within peer networks. As P/CVE service providers are often unable to reach out to all at-risk individuals, peer networks may mitigate violent extremist attitudes within communities with limited access to such services. Consequently, the current study suggests that P/CVE programs need to alter their prevention efforts to encourage proactive attitudes among young men, protecting them and their peers from violence perpetration.

According to the peer mediation approach, peers have a better understanding of the issues of young adults and, consequently, can exert a stronger influence on them (Lub, 2013). Thus,

peer mediation programs employ adolescents and young adults in conflict mediations between hostile youth groups. For example, the Department of Homeland Security's (DHS) Peer to Peer (P2P): Challenging Extremism program includes college students designing and implementing social and digital P/CVE tools designed to educate their peers about the risks of violent extremism (Moffett & Sgro, 2016). The current study findings offer empirical support for the assumptions and causal pathways of the peer mediation approach. When individuals interact with peer mediators and learn relevant and accurate information about violent extremism, they may change their perceptions of what their peers think of this topic. In turn, the change in perceived peer attitudes influences their personal attitudes and intentions. Thus, the involvement of peers in P/CVE interventions may have a positive effect on the attitudinal and behavioral outcomes of participants through its impact on perceived peer attitudes.

Finally, intergroup contact interventions aim to improve contact and increase tolerance between youths of different racial, ethnic, or religious groups, as a way to promote mutual understanding and reduce prejudice and stereotyping (Lub, 2013). The central assumption underlying this approach is that hostility towards out-groups results from ignorance and lack of contact (Pettigrew & Tropp, 2006). The current study findings partially support this assumption, as social network diversity moderated the relationship between perceived peer attitudes and personal attitudes for violent extremism. In other words, contact with various out-group members can influence the individual's beliefs and protect against the potentially negative effect of peer networks. The study, however, did not examine hostility towards out-groups and, therefore, cannot fully determine whether inter-group contact reduces prejudices and stereotypes about other groups.

While exploring the possible role of peer groups in P/CVE initiatives, researchers and policymakers need to note the risk for iatrogenic effects of peer attitudes. Dishion et al. (1999) note that promoting interactions among youths with antisocial and proviolent attitudes may inadvertently reinforce related behaviors among group members through “deviancy training.” Thus, peer-focused P/CVE programs need to ensure that such networks do not unintentionally result in peer influence and promotion of proviolent attitudes and behaviors. Based on the current study findings, greater diversity within social networks may potentially alleviate this negative effect of peer attitudes.

The study findings can be implemented not only for prevention but also for exit programs. The term “exit programs” refers to various interventions aimed at de-radicalization (i.e., changing radical beliefs), disengagement (i.e., reducing violence perpetration), or rehabilitation of violent extremists (Horgan & Braddock, 2010). Researchers distinguish between “push” and “pull” factors for exiting violent extremist organizations: push factors (e.g., loss of faith in ideology) lead to dissatisfaction with the group, while pull factors (e.g., family ties) offer opportunities to leave the group (Vergani et al., 2018). Based on the current study findings, perceived peer attitudes and social network diversity can serve as potential pull factors in this process. For example, diverse social networks can offer an alternative to social marginalization and dependence on the violent extremist group. The study, however, has focused on attitudes and intentions within a general sample. Thus, its findings do not necessarily extrapolate to the population of former violent extremists. Therefore, further research should examine whether peer networks can serve as a pull factor for the processes of de-radicalization and disengagement from violent extremism.

4.3 Conclusion

The present study adds to the existing knowledge on the development of violent extremist attitudes and intentions by examining a positive and statistically significant relationship between perceived peer attitudes and violent extremist intentions, with personal attitudes partially mediating this association. Participants who considered their peers to be supportive of violent extremism were more likely to hold such attitudes themselves and to express readiness to engage in related behaviors. Social network diversity moderated the relationship between perceived peer attitudes and personal attitudes: participants with more diverse social networks were less likely to hold positive attitudes towards violent extremism, even when they thought their peers were supportive of such attitudes. The study findings are in line with past research exploring the effects of perceived peer attitudes and social network structure on the development of violent attitudes and intentions. Thus, future studies need to explore the potential role of other aspects of peer networks in the process of engagement in violent extremism. Regarding its policy implications, the current study highlights the need for P/CVE programs that offer young men opportunities for positive relationships, community involvement, and growth of social ties. Study findings provide empirical evidence for social-ecological approaches to P/CVE, such as social-ecological interventions, peer mediation, and intergroup contact interventions.

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APPENDICES

Appendix A. Activism Orientation Scale (AOS)

Please respond to the following questions by circling how likely it is that you would engage in each of the following activities.

0 = Extremely unlikely

1 = Unlikely

2 = Likely

3 = Extremely likely

High-Risk Activism Scale

1. Engage in a political activity in which they knew they would be arrested?
2. Engage in a physical confrontation at a political rally?
3. Engage in a political activity in which they feared that some of their possessions would be damaged?
4. Engage in an illegal act as part of a political protest?
5. Engage in a political activity in which they suspect there would be a confrontation with the police or possible arrest?
6. Block access to a building or public area with their bodies?
7. Engage in a political activity in which they feared for their personal safety?

Appendix B. Activism and Radicalism Intention Scale (ARIS)

For the following activities, PLEASE ANSWER ACCORDING TO WHAT YOUR FRIENDS THINK, specifically [names of the five friends that each participant listed at the beginning of the study]. If these friends were hanging out, honestly discussing each activity without you there, how likely is it that they would agree or disagree with each statement?

1 = Disagree strongly

2 = Disagree

3 = Disagree a little

4 = Neither agree nor disagree

5 = Agree a little

6 = Agree

7 = Agree strongly

Radicalism Intention Scale

1. You can continue to support an organization that fights for your group's political and legal rights even if the organization sometimes breaks the law.
2. You can continue to support an organization that fights for your group's political and legal rights even if the organization sometimes resorts to violence.
3. You can participate in a public protest against the oppression of my group even if you thought the protest might turn violent.
4. You can attack police or security forces if you saw them beating members of their group.

Appendix C. Personal Attitudes (PA)

Please respond to the following questions by circling how strongly you would agree or disagree with the following statements.

1 = Strongly disapprove

2 = Somewhat disapprove

3 = Neither approve nor disapprove

4 = Somewhat approve

5 = Strongly approve

1. Sending threats and intimidating letters to public figures in certain cases may be necessary in order to put a stop to a dangerous policy.
2. There are situations where there is no other alternative and even weapons must be used in order to stop the government from carrying out its policies.
3. When a political disaster is looming on the horizon, and all other means of protest have been exhausted and proved futile, a violent action can be forgiven.

5. How many other relatives (other than your spouse, parents & children) do you feel close to? (If '0', check that space and skip to question 6.)

0 1 2 3 4 5 6 7 or more

5a. How many of these relatives do you see or talk to on the phone at least once every 2 weeks?

0 1 2 3 4 5 6 7 or more

6. How many close friends do you have? (meaning people that you feel at ease with, can talk to about private matters, and can call on for help)

0 1 2 3 4 5 6 7 or more

6a. How many of these friends do you see or talk to at least once every 2 weeks?

0 1 2 3 4 5 6 7 or more

7. Do you belong to a church, temple, or other religious group? (If not, check 'no' and skip to question 8.)

no yes

7a. How many members of your church or religious group do you talk to at least once every 2 weeks? (This includes at group meetings and services.)

0 1 2 3 4 5 6 7 or more

8. Do you attend any classes (school, university, technical training, or adult education) on a regular basis? (If not, check 'no' and skip to question 9.)

no yes

8a. How many fellow students or teachers do you talk to at least once every 2 weeks? (This includes at class meetings.)

0 1 2 3 4 5 6 7 or more

9. Are you currently employed either full or part-time? (If not, check 'no' and skip to question 10.)

(0) no (1) yes, self-employed (2) yes, employed by others

9a. How many people do you supervise?

0 1 2 3 4 5 6 7 or more

9b. How many people at work (other than those you supervise) do you talk to at least once every 2 weeks?

0 1 2 3 4 5 6 7 or more

10. How many of your neighbors do you visit or talk to at least once every 2 weeks?

0 1 2 3 4 5 6 7 or more

11. Are you currently involved in regular volunteer work? (If not, check 'no' and skip to question 12.)

no yes

11a. How many people involved in this volunteer work do you talk to about volunteering-related issues at least once every 2 weeks?

0 1 2 3 4 5 6 7 or more

12. Do you belong to any groups in which you talk to one or more members of the group about group-related issues at least once every 2 weeks? Examples include social clubs, recreational groups, trade unions, commercial groups, professional organizations, groups concerned with children like the PTA or Boy Scouts, groups concerned with community service, etc. (If you don't belong to any such groups, check 'no' and skip the section below.)

no yes

Consider those groups in which you talk to a fellow group member at least once every 2 weeks. Please provide the following information for each such group: the name or type of group and the total number of members in that group that you talk to at least once every 2 weeks.

Total number of group members

Group that you talk to at least once every 2 weeks

1.

2.

3.

Appendix E. Mplus Code

```

TITLE: measure model;
DATA: file is Diss data (01.10.2020).txt;
VARIABLE: names are aos1 aos2 aos3 aos4 aos5 aos6 aos7
             aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;
             categorical are aos1 aos2 aos3 aos4 aos5 aos6 aos7;
             usevariables are aos1 aos2 aos3 aos4 aos5 aos6 aos7
             aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3;
             missing are all(-999);
ANALYSIS: parameterization=theta;
             estimator=wlsmv;
MODEL:
             vei by aos1@1 aos2 aos3 aos4 aos5 aos6 aos7;
             ppa by aris1@1 aris2 aris3 aris4;
             pa by lnpa1@1 lnpa2 lnpa3;
             aris1 aris2 aris3 aris4;
             lnpa1 lnpa2 lnpa3;
             vei ppa pa;
OUTPUT: sampstat stdyx;

```

```

TITLE: model 1 wlsmv;
DATA: FILE IS Diss data (01.10.2020).txt;
VARIABLE: names are aos1 aos2 aos3 aos4 aos5 aos6 aos7
             aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;
             usevariables are aos1 aos2 aos3 aos4 aos5 aos6 aos7
             aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3;
             categorical are aos1 aos2 aos3 aos4 aos5 aos6 aos7;
             missing are all(-999);
ANALYSIS: estimator=wlsmv;
             bootstrap=5000;
MODEL:
             vei by aos1@1 aos2 aos3 aos4 aos5 aos6 aos7;
             ppa by aris1@1 aris2 aris3 aris4;
             pa by lnpa1@1 lnpa2 lnpa3;
             vei on pa ppa;
             pa on ppa;
             vei;
             ppa;
             pa;
MODEL INDIRECT:

```

```
vei ind ppa;
```

OUTPUT:

```
tech1 tech4 sampstat standardized cinterval (bcbootstrap);
```

TITLE: model 2 wlsmv;

DATA: file is Diss data (01.10.2020).txt;

VARIABLE: names are aos1 aos2 aos3 aos4 aos5 aos6 aos7

aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;

usevariables are aos1 aos2 aos3 aos4 aos5 aos6 aos7

aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;

categorical are aos1 aos2 aos3 aos4 aos5 aos6 aos7;

missing are all(-999);

ANALYSIS: estimator=wlsmv;

bootstrap=5000;

MODEL:

vei by aos1@1 aos2 aos3 aos4 aos5 aos6 aos7;

ppa by aris1@1 aris2 aris3 aris4;

pa by lnpa1@1 lnpa2 lnpa3;

vei on pa ppa;

pa on ppa sni;

vei;

ppa;

pa;

sni;

MODEL INDIRECT:

vei ind ppa;

OUTPUT:

```
tech1 tech4 sampstat standardized cinterval (bcbootstrap);
```

TITLE: model 2 ml;

DATA: file is Diss data (01.10.2020).txt;

VARIABLE: names are aos1 aos2 aos3 aos4 aos5 aos6 aos7

aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;

usevariables are aos1 aos2 aos3 aos4 aos5 aos6 aos7

aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;

categorical are aos1 aos2 aos3 aos4 aos5 aos6 aos7;

missing are all(-999);

ANALYSIS: link=probit;

estimator=ml;

bootstrap=5000;

MODEL:

```

vei by aos1@1 aos2 aos3 aos4 aos5 aos6 aos7;
ppa by aris1@1 aris2 aris3 aris4;
pa by lnpa1@1 lnpa2 lnpa3;
vei on pa ppa;
pa on ppa sni;
vei;
ppa;
pa;
sni;

```

MODEL INDIRECT:

```
vei ind ppa;
```

OUTPUT:

```
tech1 tech4 sampstat standardized cinterval (bcbootstrap);
```

TITLE: model 3 ml;

```
DATA: file is diss data (01.10.2020).txt;
```

```
VARIABLE: names are aos1 aos2 aos3 aos4 aos5 aos6 aos7
aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;
usevariables are aos1 aos2 aos3 aos4 aos5 aos6 aos7
aris1 aris2 aris3 aris4 lnpa1 lnpa2 lnpa3 sni;
categorical are aos1 aos2 aos3 aos4 aos5 aos6 aos7;
missing are all(-999);
```

```
ANALYSIS: estimator=ml;
```

```
type=random;
```

MODEL:

```

vei by aos1@1 aos2 aos3 aos4 aos5 aos6 aos7;
ppa by aris1@1 aris2 aris3 aris4;
pa by lnpa1@1 lnpa2 lnpa3;
ppaXsni | ppa XWITH sni;
vei on pa ppa;
pa on ppaXsni;
vei;
pa;
ppa;
sni;

```

OUTPUT:

```
sampstat tech1 standardized;
```

SAVEDATA:

```
file is probing.sav;
save = fscores;
```