

Understanding the Overlap of Online Offending and Victimization: Using Cluster Analysis to Examine Group Differences

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Criminal offending and victimization often overlap in both the virtual and offline worlds. However, scholars are still unsure how the offending-victimization relationship plays out between the online and offline worlds. Using a sample of 2,491 adults, four clusters are discovered: 1) those unlikely to have offended or been victimized, 2) those who had online victimization and offending experiences, 3) Those who have been victimized offline and online, but who are unlikely to have offended, and 4) individuals who were victims both online and offline and offended online. Thus, the offending-victimization overlap may be common, but it is certainly not exclusive.

Keywords: Cybercrime, Cyberoffending, Cybervictimization, Cluster analysis, Overlap, Poly-victimization, Poly-offending

Introduction

In 2021, a majority of the world's population is connected online, and the numbers are steadily rising, with 74.6% of the population using internet in 2015, 85.5% in 2016, 87.3% in 2017, and 88.5% in 2018 (World Bank, 2019). Today, the world without the internet is unimaginable. As users engage in a wide range of online activities, it follows that more victimization and offending will happen online. Despite this highly anticipated trend, only a few studies explore the relationships between offline and online crime. For example, Buil-Gil and colleagues (Buil-Gil et al., 2021) examined whether cybercrime increased due to the displacement of crime opportunities from offline to online during the global COVID-19 pandemic and found a significant increase in cyber dependent crimes (offenses that can only be committed using computer systems or networks) while crimes such as burglary, larceny theft, criminal damage and arson, and violence decreased. Other studies found similar shifts from offline to online platforms (e.g., Payne, 2020; Lallie et al., 2020; Collier et al., 2020). However, these studies do not take into consideration the possible overlap between offline and online offending and victimization. Work focused solely on either victimization or offending ignores the fact that criminal offending and victimization often overlap, and this overlap appears to happen in both the virtual and offline worlds.

Indeed, the overlap between offending and victimization is seen so frequently that it is one of the most empirically established criminological facts in the literature (e.g., Baxter, 2020; Bossler & Holt, 2009; Bossler et al., 2012; Costello et al., 2016; Daday et al., 2005; Jennings et al., 2010; Jennings et al., 2012; Kranenbarg et al., 2019; Marcum et al., 2014; Reisig & Holfreter, 2018). Yet, despite our confidence that the relationship exists among those who commit and are victims of cybercrimes as well as traditional crimes, researchers are less sure about how the offending-victimization relationship plays out between the location of crime of either online and offline worlds.

That is, are those who commit crimes online victimized offline or do those who are victims of cybercrime commit offline crimes? We attempt to answer these types of questions.

Given the vast literature and theoretical work that has been done in research about the overlap, we will not attempt to create a systematic review of the literature in this paper. Instead, our research is an exploratory study that seeks to provide a typology of the overlapping characteristics of crime engagement in traditional and virtual spaces. We also look at the possible individual factors that predict victimization and offending. Finally, the study explores overlapping group characteristics between victimization and offending, both in the traditional and virtual spaces. This research adds to the literature a typology that takes locale (online/offline) and actor type (victim/offender) into consideration while most researchers only considered one of those variables. The manuscript begins by reviewing the literature examining the victim-offender overlap in conventional (offline) and virtual spaces. Then, after introducing the findings of our data collection on a large scale nationally representative sample of Americans, the results are interpreted considering the existing literature and theoretical and practical implications are offered.

Literature review

Victim-offender overlap

As noted above, the link between offending and victimization is one of the most robust findings in criminology. For example, a meta-analysis of studies spanning five decades that investigate the victim-offender overlap found that 31 of the 37 studies provided “considerable support” for the victim-offender overlap, with the others providing “limited support” for the relationship (Jennings et al., 2012). Indeed, there is

evidence that the victim-offender overlap applies to a variety of crimes, including but not limited to violent crimes (e.g., Broidy et al., 2006; Lauritsen & Quinet, 1995; Sampson & Lauritsen, 1990; Walters, 2020), sex trafficking (UNODC, 2012; UNODC, 2016; Baxter, 2020), economic crimes (Kerstens & Jansen, 2016), bullying (Marcum et al., 2014; Trajtenberg et al., 2021), dating violence (Reingle et al., 2012; Jennings et al., 2011), physical and psychological intimate partner violence (Paterson et al., 2007; Schokkenbroek et al., 2021), and a variety of cybercrimes (e.g., Bossler & Holt, 2009; Bossler et al., 2012; Choi & Lee, 2017; Costello et al., 2016; Daday et al., 2005; Jennings et al., 2010; Jennings et al., 2012; Kranenbarg et al., 2019; Marcum et al., 2014; Novo et al., 2014). With respect to cybercrimes, for example, Marcum and her associates found that in a sample of over 1,100 students, both males and females who had gossip posted about them were 3.2 and 3.6 times more likely to post to Facebook to hurt someone, respectively (Marcum et al., 2014). Similarly, being a victim of a malware infection to the point where one lost data was significantly related to being involved in deviant online behaviors oneself. Specifically, pirating media increased the likelihood of being a victim of malware infections by nearly 1.5 times, at least for males (Bossler & Holt, 2009).

The overlap has also been studied in a variety of populations. For example, the offender-victimization overlap has been studied within high-risk groups for decades, beginning with Wolfgang's (1958) study on Philadelphia's homicide victims who also tended to have a history of offending. Similarly, Broidy et al. (2006) found that 50% of homicide victims had a prior arrest. Dobrin (2001) found that homicide victims were four to ten times more likely to have been previously arrested for various property, violent crimes, and drug-related offenses than non-victims. The offender-victim overlap is also found in numerous other populations. The overlap has also been found in

samples of the general adult population, samples of those with mental disorders (Silver, 2002; Silver et al., 2011; Hiday et al., 2001), cross-cultural samples (e.g., Vega et al., 2009; Lara-Cinisomo et al., 2009), and international samples (e.g., Klevens et al., 2002; Regoeczi, 2000; Paterson et al., 2007). Thus, there is little doubt about the generalizability of observation that those who are victimized are often offenders themselves.

The relationship has also been studied among differing age groups. For example, Beckley et al. (2018) investigated the role of low self-control, adverse childhood experiences, and environmental factors in several victimization and offending scenarios. They included 20 nonviolent crimes (such as theft, fraud, vandalism, breaking and entering and selling drugs) and 13 violent offenses (such as assault, robbery, making threats, and carrying a weapon) in their interviews with adolescents who reported victimization and offending behaviors between the ages of 12 and 18. The respondents were about 1.5 times as likely to be victim-offenders compared to victims-only and offenders-only, and adolescents who were victimized were significantly more likely to offend (Beckley et al., 2018). Other studies also provide evidence for the victim-offender overlap among youth (e.g., Bossler et al., 2012; Fiegelman et al., 2000; Chang et al., 2003; Daday et al., 2005; Kerstens & Jansen, 2016), and the overlap has also been found in studies of adolescents and young adults (e.g., Costello et al., 2016; Novo et al., 2014; Regoeczi, 2000). The relationship holds even among older individuals, even though older adults tend not to be overly criminal. For example, Reisig and Holtfreter (2018) found that among those over 60, criminal offending was a significant predictor of victimization even after controlling for levels of self-control, depression, and spending time in bars and other drinking establishments. Again, although the overlap is far from perfect, there is little doubt the relationship

exists, it exists for a variety of groups, it exists for a variety of crimes, and it is generalizable across both time and space.

Theoretically, a significant amount of research on the victim-offender overlap is rooted in self-control theory (Gottfredson & Hirschi, 1990). According to the theory, low self-control leads to risk-taking, impulsivity, shortsightedness, insensitivity to others, and seeking immediate gratification. Thus, low self-control elevates the chances of offending (Gottfredson, 2009; Pratt & Cullen, 2000) and victimization as well (Baron et al., 2007; Higgins et al., 2009; Holtfreter et al., 2008; Jennings et al., 2010; Piquero et al., 2005; Schreck, 1999; Schreck et al., 2002; Stewart et al., 2006). According to research (Van Wilsem, 2011; Ngo & Paternoster, 2011; Bossler & Holt, 2010; Pratt et al., 2014; Kerstens & Jansen, 2016), low self-control is associated explicitly with noncontact crimes such as fraud and cybercrime, where some degree of victim cooperation is necessary for the perpetration to be successful.

General strain theory has also been used to explain the offender-victim overlap. Strain theory (Agnew, 1992) posits that experiencing strain can lead to negative emotions and, ultimately, crime (Agnew, 1992). Being victimized is a source of strain that, unless adequately coped with, can manifest in negative emotions such as anger, depression, or frustration, and consequently, crime (Agnew, 1992, 2006). In effect, for individuals who lack social support and means of coping, deviant activities can serve as coping mechanisms used to overcome strain. In this manner, the theory offers a time-ordered relationship between victimization and offending, where criminal activity follows victimization. However, crime itself can generate strain, which can manifest in subsequent offending (referred to as the “amplifying loop,” see Agnew, 1992), thereby creating a victim-offender overlap. The concept of an amplifying loop was tested and supported by scholars examining the “cycle of violence” in child abuse (Heyman &

Smith, 2002; Widom, 1989), intimate partner violence online and in traditional spaces (Walker, 1979/2017; Reingle et al., 2012), and bullying in both online and offline spaces (Cullen et al., 2008; Espelage & Swearer, 2003; Hinduja & Patchin, 2007). Hinduja & Patchin (2007) also found that strain mediates the relationship between cyberbullying victimization and offline delinquency.

Finally, subcultural theories can also help explain the victim-offender overlap. Subcultural theories emphasize the role of the environment in creating opportunities where both offending and victimization are highly possible. In structurally disadvantaged residential areas, for example, cultural norms that reinforce offending may prevail (Anderson, 1999). Such cultural and subcultural norms and the exposure to neighborhood violence they lead to can both reinforce participation in offending and increase the risk of victimization (Baskin & Sommers, 1997; Felson, 1992; Jacobs & Wright, 2006; Singer, 1987; Stewart et al., 2006). The overlap of subcultural values, morals, and activities has also been observed in the hacker community (Holt, 2007) and illustrated significant overlap in the experiences of individuals in cyberspace and the offline world since hackers were present in both social environments.

Location of crime overlaps

There is also ample evidence that the *location of crime* overlaps (online-offline offending). That is, crimes committed online are also committed offline (or vice versa). This overlap is well documented for a variety of crimes, especially violent crimes, and it occurs for poly-offenders as well as poly-victims.

Poly-locale offending

Criminals can commit their offenses solely offline (e.g., burglary), solely online (e.g., cyber-identity theft), or both offline and online (e.g., cyber and traditional bullying). Poly-locale offending is increasingly common, especially in terms of systematic and persistent acts of violence. Unlike traditional crimes that required the physical contact between the offender and victim, social media facilitates persistent acts of violence by allowing the offender greater access to the victim's life. That is, social media allows offenders to contact victims virtually any time from anywhere; it allows them to interact with victims synchronously and asynchronously, and it allows them to contact victims at work, at home, and while in the community. This level of contact was impossible when interactions were limited to physical contact.

Because of the virtual world is less temporally and spatially limited, violent offenders can now victimize their targets frequently and in multiple locations. For example, intimate partner violence often co-occurs online and offline (Schokkenbroek et al., 2021). Moreover, it is well documented that bullying simultaneously occurs online and offline or spillover from one locale to the other (e.g., Lazuras et al., 2017; Trajtenberg et al., 2021; Waasdorp & Bradshaw, 2015; Weinstein et al., 2021). The pattern of online-offline overlap is also seen in stalking behaviors. Cavezza and McEwan (2014) found that the majority of cyberstalkers also used off-line stalking tactics. Numerous scholars have also linked hate crimes to hateful speech and extremist ideas (Chan et al., 2016; Foxman & Wolf, 2013; Freilich et al., 2011; Singh & Singh, 2012; The New America Foundation International Security Program, n.d.). Indeed, online hatred is often the precursor of offline crimes (Chan et al., 2016; Williams, 2020). For example, Awan and Zempi (2016) found that the 2015 terrorist attacks in Paris and Tunisia and the activities of Islamic State militants triggered a significant increase in anti-Muslim attacks both online and offline, and victims feared that online

hatred would materializing in actual violence against them in the offline world (Awan & Zempi, 2016; Zempi, 2014). Similarly, misogyny and online abuse of women and girls often spills over to the traditional, offline environments and exist in continuity rather than isolated offenses (Lewis et al., 2019).

Thus, criminal activity seems to overlap in the cyber and offline worlds, and Akers' (1998; 2009) social learning theory (SLT) can help explain this overlap. According to SLT, individuals learn criminal behavior through interaction with others. Specifically, actors learn criminal behavior through differential association, differential reinforcement, the adoption of deviant definitions, and imitation (Akers 1998; 2009). The well-known and tested theory has ample empirical support for offline crimes, and it has been tested expansively on cyber-offending (Van Ouytsel et al., 2017; Higgins et al., 2006; Higgins & Makin, 2004; Higgins & Wilson, 2006; Hinduja & Ingram, 2008; 2009; Hollinger, 1993; Holt et al., 2010; Ingram & Hinduja, 2008; Miller & Morris, 2016; Morris & Blackburn, 2009; Morris & Higgins, 2009; 2010; Rogers, 2001; Skinner & Fream, 1997).

Indeed, social media may be amplifying the processes described in social learning theory by organizing communities and spreading antisocial ideas (see Hawdon, 2012). As the distinction between offline and online private networks become less apparent (McCuddy & Vogel, 2014), users now identify as strongly with their online communities as with their families (Lehdonvirta & Räsänen, 2011). Thus, online interactions mirror in-person interactions where differential association plays a crucial role in learning antisocial behaviors by rewarding (positively reinforcing) and imitating (modeling) them. Moreover, online criminal incidents that go unchecked, unrecognized or otherwise unchallenged by communities can lead to the normalization of such

behaviors and can quickly escalate and spill over into the physical world (see Hawdon, 2012; Feldman et al., 2013; Müller & Schwarz, 2020).

Poly-locale victimization

There is even more evidence supporting the overlap between offline and online victimization. For example, in a study of over 2,000 adolescents ages 10 to 17, over 95% of respondents who reported an online victimization in the past year also reported an offline victimization in the past year (Mitchell et al., 2011). It is well documented that victims of bullying frequently experience traditional forms of offline bullying and cyberbullying (e.g., Lazuras et al., 2017; Trajtenberg et al., 2021; Waasdorp, & Bradshaw, 2015; Weinstein et al., 2021). For example, Trajtenberg et al. (2021) studied poly-victimization bullying experiences of Chilean adolescents and identified three subgroups of victims. Most bully victims were victimized offline, a moderate number were victimized digitally, but a third type of victims, who were disproportionately young women, suffered both offline and online forms of bullying (Trajtenberg et al., 2021). As Wegge et al. (2014: 415), note that, “cyberbullying is an extension of traditional bullying as victims often face the same perpetrators offline and online.” Similarly, victims of intimate partner violence are attacked in both offline and online spaces (Schokkenbroek et al., 2021). This overlapping victimization across platforms also happens with hate speech as those targeted online frequently experience offline targeting as well (Awan & Zempi 2016).

Yet, once again, the pattern is not perfect. In a sample of 3,488 college students, being stalked offline increased students’ likelihood of being stalked online, but this only held for male students (Reyns & Fisher, 2018). Moreover, being cyberstalked did not predict offline victimization, and females who are cyberstalked were less likely to be

stalked offline, but cyberstalked males were more likely to be stalked offline (Reyns & Fisher, 2018). Thus, at least in terms of stalking, offline and online victimization are interrelated, but gender may moderate the relationship (see Reyns & Fisher, 2018). Nevertheless, people victimized online are often victimized offline too.

A criminological theory that offers explanations for victimizations in multiple locations is Cohen and Felson's (1979) Routine Activity Theory (RAT). According to LRAT (Cohen et al., 1981), individual lifestyles and routine activities put people in risky situations that create criminal opportunities. As a result, individuals become suitable targets through their lifestyles. Although the theory was mainly tested on physical crimes and victimization, research posits (Choi & Lee, 2017) that traditional and online behaviors can act in concert to induce criminal activity. An example of the poly-victimization overlap would be when interpersonal violence (e.g., harassment or bullying) starts online but later overflows to the physical world when the victim meets the bully/harasser at school or in the workplace. Following this logic, LRAT was successfully tested, applying its tenets to online lifestyles (e.g., Holt & Bossler, 2009; Holtfreter et al., 2008; Reyns, 2013). Recognizing that individual lifestyles are part of routine activities theory, Choi (2008) proposed an integrated theory of cyber-routine activities, according to which two causal factors are responsible for victimization: digital guardianship such as cyber-security, and online vocational and leisure activities.

Combinations of overlaps

If one considers the potential overlap of victimization, offending, and crime locale of online or offline, 10 theoretical combinations can be identified. These are presented in Table 1. The most obvious combination are individuals who are not involved in criminal activities and do not experience criminal victimization. These

individuals are represented in row (1) and are the “uninvolved.” Next, there are three types of victim-only individuals (rows 2 – 4). The first is victimized only online while the second type of victim-only individual is victimized only offline. The third type of victim-only individual is victimized both online and offline. The next three categories are the offender-only individuals (rows 5 – 7). Like with the victim-only categories, offender-only individuals can commit their offenses only offline (i.e., traditional criminal), only online (i.e., a cybercriminal), or both offline and online (i.e., a poly-locale criminal). The final three categories are the offender-victims (rows 8 – 10). These individuals are both involved in criminal activity and also experience criminal victimization. Their crimes and victimization can occur solely in online settings, solely offline, or both online and offline.

Insert Table 1 about here

The above research highlights the heterogeneity and complexity of traditional and online victimization and the possible overlap with offline crimes. Next, the sample and methods are discussed, and the paper closes with a discussion of the study’s implications for theory and practice. Two research questions (RQ) guide this study:

RQ1: What distinct groups (clusters) of participants, if any, can be identified considering seven online offending and victimization scenarios included in our survey?

RQ2: Are there any differences between the victim, offender, non-victim, non-offender clusters in terms of sociodemographic variables, political affiliation, computer skills, and internet use?

Materials and Methods

The authors conducted an online survey. Respondents were selected using online

sampling through both Dynata (formerly known as Survey Sampling International) and Qualtrics, global online market research firms that provide online sampling and data collection services for businesses and academics using samples from nationally representative panels. Using the criteria provided by the researchers (individuals 18 years of age and older, representative by race, age, and sex in the United States), Dynata and Qualtrics distributed the online survey created by the researchers to individuals in their panels who were selected to participate in research studies. Such panel samples are common in academic and business research (e.g., Gibson et al., 2021; Gershuny et al., 2021; Kobayashi et al., 2021) and can provide valid and reliable data (Ansolabehere & Schaffner, 2014; Callegaro et al., 2014; Craig et al., 2013; Simmons & Bobo, 2015). In total, 2,793 participants began the survey on October 15-21, 2020. Individuals who did not complete the survey or completed it in under three minutes (i.e., speeders) were dropped from the sample. This resulted in a total sample of 2,671 participants, out of which 2,491 answered the questions about victimization and offending. The online survey was part of a larger project and asked participants about their cyber victimization and offending experiences and a series of demographic questions. The research was approved by the Institutional Review Board of {institution name} under #19-1010.

Of particular interest in this survey were a series of questions related to cyber offending and cyber victimization. For cyber offending, ten questions about experiences in 12 months prior to being surveyed were asked. Example behaviors include, posting hurtful information about someone online, illegally uploading copyrighted files, and buying prescriptions (without a prescription) or other drugs from online pharmacies or websites. Online victimization was measured in a similar way, asking participants if they have experienced each of seven different cyber victimizations in the past 12 months. Examples of victimization questions included: lost money due to an email,

website, or other computer scam, had unknown transactions in their bank/investment account, credit card, or other online payment system, and experienced unwanted sexual comments or advances. All questions for both cyber victimization and offending can be found in Table 3.

Demographic questions were also asked. These include asking the respondents' gender, age, race, and political leanings. Demographics were well within the expected margin of error for a nationally representative sample. Our sample was 47% male, average age was 45 and, 28% described themselves as liberal, 33% as moderate and 39% as conservative. In addition to these common demographics, we also asked about support for President Trump. This variable is included because support for the former president has been shown to correlate with accepting online extremist views, independent of the individual's political affiliation and adoption of traditional conservative positions (Hawdon et al., 2020). In the current sample, 47% approved of the job performance of President Trump. For a descriptive breakdown of demographic variables see Table 2.

To answer the research questions, a cluster analysis using average linkage was conducted. Cluster analyses are conducted to find groups within data. While methods of clustering vary, the main idea is to find groups with high intra-class similarity and low inter-class similarity. In essence, clusters help organize data by finding patterns of similarity between variables and organizing respondents into clusters based on their answers to the variables so that respondents with similar patterns of responses are grouped into the same cluster. The authors reviewed the cluster tree to find distinct clusters and then considered the clusters by their nature of victimization and offending behaviors. Then, the clusters are analyzed to determine if they significantly differ by

various demographic and computer use variables, such as computer time, dark web use, age, and gender.

Results

Overall, 1,061 (41.43%) participants reported some form of online victimization. The most common experience was having unknown transactions in their financial accounts (20.38%). The least common was having experienced identity theft (13.53%). When asked about victimization experiences in general (“In the past 12 months, have you been a victim of a crime?”), 398 participants (15.98%) indicated they had been victims of a crime in the last 12 months. Although this group can overlap with online victimization, as we did not specifically ask about offline victimization, it must be noted that 68% of respondents reported online victimization but not general victimization. The potential overlap between “general” victims and online victims is further discussed in the limitation section below.

Unsurprisingly, fewer participants reported online offending behaviors than victimization. Out of all participants, 642 (25%) reported at least one type of cyber offending. The most common behavior was excluding someone from an online community (16.16%), and the least common was hacking (10.15%). For a full breakdown of offending and victimization, see Table 3.

Insert Table 3 about here

To examine the overlap between offending and victimization, hierarchical cluster analysis with average linkage using Stata version 16 was used. The variables included were a count variable of online victimization, a count variable of online offending, and a binary variable asking about crime victimization in general. Although

10 potential clusters were identified in Table 1 and numerous clusters were found, five main clusters were identified by viewing dissimilarity metrics.

We further examined the five clusters and found distinct patterns within each. Reviewing these clusters yielded the following groups: 1) Individuals who were unlikely to have any victimization experiences or online offending behaviors (n=2,091), 2) Individuals who were likely to have only online victimization experiences (n=45), 3) Individuals who were likely to have online victimization experiences and online offending behaviors (n=229), 4) Individuals who were likely to have both online and general victimization experiences and online offending behaviors (n=105), and 5) Individuals who were more likely to have online offending experiences but few victimization experiences (n=21). See Table 4 for the five distinct clusters.

Insert Table 4 about here

For further discussion, the groups were renamed with their respective victimization and offending as follows: 1) Uninvolved, 2) Online Victims, 3) Online Victim-Offenders, 4) Complete Victim-Offenders, 5) Online Offenders. Next, the group characteristics were examined with respect to standard demographic variables. A list of these variables and their respective descriptive statistics can be found in Table 5. Males were more likely to be part of the Complete Victim-Offender group ($X^2 = 70, p < .001$). The differences were dramatic, as the Complete Victim-Offender group comprised of 78% male, whereas the Online Victims group was only 40% male.

Insert Table 5 about here

Itt tartok Given the political climate during this survey in the United States (the data were collected just before the 2020 presidential election), we explored the impact of politics on groups using an ANOVA to consider political leaning (very conservative to very liberal). The overall model was significant ($f=31.47$, $p<.001$). Post-hoc analysis showed that the Online Victim-Offender and Complete Victim-Offender groups were more likely to be conservative, which was measured with the question, “Thinking about politics today, do you generally consider yourself to be very conservative, somewhat conservative, moderate, somewhat liberal, very liberal, or I don’t know/prefer not to answer.” In addition, the relationship between support for President Donald Trump and cluster membership was investigated. A binary variable was used for this analysis, simply asking if the participant approves or disapproves of President Trump’s job performance. A chi-squared test revealed significant differences ($X^2 =153$, $p<.001$). The highest support for President Trump was from the Complete Victim-Offender group at 87%. The lowest support was from the Online Victims group at 40%.

Due to some clusters and races having few participants, race was analyzed as a binary variable, white or nonwhite, and no significant difference between these groups was found ($X^2 =7.34$, $p=.117$). Next, there was a significant effect of age ($f=26$, $p<.001$), such that the highest average age was in the Uninvolved group at 46 years old, while the lowest was in the Online Victim-Offender group at 35 years old.

Finally, overall computer time was not significantly different across groups ($f=1.6$, $p=.172$). However, certain types of computer use were more likely across the groups. For example, dark web use was higher for both the Online Victim-Offenders and Complete Victim-Offender groups ($f=36$, $p<.001$). Interestingly, post-hoc analysis showed a stair-step, with two groups – Online Victim-Offenders, and Complete Victim-Offenders – using the dark web for an average of six to seven hours a week, and the

next two groups – the Online Victim, and Online Offender groups – using it between three to four hours per week. Finally, the Uninvolved group used the dark web for an average of 1.7 hours per week.

Discussion

The victim-offender overlap is a widely accepted empirical fact in criminology. Although the overlap is commonly tested in traditional, offline spaces, the offline-online overlap is less likely studied and hence, needs further examination. In addition, victim-offenders have differences in their victimization and offending patterns, and research produced inconsistent findings in terms of establishing theoretical explanations for the victim-offender overlap. Using data from a large nationally representative sample of 2,671 Americans, the current study aims at further exploring the victim-offender overlap in virtual and traditional spaces.

Our study finds evidence of the victim-offender overlap and their online and offline convergence. Of the ten possible iterations of victim-offender overlap, the cluster analysis revealed five distinct groups, 1) Uninvolved, 2) Online Victims, 3) Online Victim-Offenders, 4) Complete Victim-Offenders, and 5) Online Offenders. The following distinct characteristics are associated with the clusters. The group of non-involved individuals (individuals who were unlikely to have been victimized or offended), was the most numerous (n=2,091). The next largest group (n=229) contains online victim-offenders who engaged in cybercrime both on the offending and victimization sides. The third large cluster includes individuals who reported both online and traditional victimization and additionally some online offending (n=105). Only online victims comprise a smaller cluster (n=45), and the smallest cluster (n=21) includes online offenders with a few victimization experiences. The five distinctive

groups reveal the complexity of the victim-offender overlap in traditional and virtual spaces.

Criminological studies point to the historical overrepresentation of males in both offending and victimization (see Newburn & Stanko, 1994 for an overview). Although a mixed and inconsistent effect of sex on online offending and victimization has been found (e.g., Livingstone & Haddon, 2009; Brenner & Smith, 2013; Novo et al., 2014; Choi & Lee, 2017), males were most actively represented in the victim-offender group in the current analysis. Political association (i.e., the support of President Trump in the 2020 presidential elections) also indicated distinct features, contrasting the clusters heavily represented in offending who supported the President with the cluster representing only-victims showing significantly less support for President Trump. The data represents the polarized political opinions of the nation before the 2020 presidential election. This was the time when hate crime violence against individuals hit a 16-year high, even exceeding property crime (Shattuck & Risse, 2021; note that the actual number of hate crimes is estimated to be 35 times higher than that reported). The rise in hate crime is said to be in direct association with President Trump expressing anti-immigrant statements and publicly condoning white supremacist violence (Scott, 2019; Politico, 2017). These actions were evidently supported by voters with more conservative than liberal political views (Blee & Creasap, 2010). The overlap of conservative political views, the support of President Trump, and online offending appears to be supported by our sample: 26% (n=303) of those who approved of President Trump indicated they had posted hurtful information about someone else online, whereas only 7% (n=97) of those who disapproved of the President indicated as such. This finding is similar to what has been reported by Hawdon and his associates (Hawdon et al., 2020). Moreover, the clusters with victim-offender overlap (Online

Victim-Offender and Complete Victim-Offender) reported more conservative political views than the clusters without overlap (Online Victims, Online Offenders, Uninvolved) whose members expressed more liberal views.

Participants' racial difference were not significant, but age was related to offending and victimization in the expected direction, with younger ages being primarily represented in the cluster active in offending *and* victimization. Further, the lowest average age was in the cluster with online overlap of offending and victimization but no offline victimization. Due to younger people tending to have more vivid and diverse online routines, it was expected that they would be more likely to suffer and commit online crimes more than older individuals who have less active online lifestyles (Schokkenbroek et al., 2021).

Contrary to our expectations, however, overall computer time did not show a significant difference between groups. Nevertheless, risky online routine activities such as dark web use were higher in the clusters that reported high online and offline victimization and offending. Within that, the two victim-offender clusters (Online Victim-Offender and Complete Victim-Offender) were most active in using the dark web for six to seven hours a week, compared to the moderate dark web use of the only online offenders *and* only online victims. This corroborates previous findings suggesting that engaging in risky online lifestyles such as visiting dark web sites makes individuals more prone both to victimization and offending online (Choi et al., 2014; Choi et al., 2020).

Several criminology theories have been used to examine the relationship between victimization and offending. Routine activities and lifestyle exposure theories, the integrated cyber-routine activities theory, the general theory of crime, social learning, and subcultural theories offer explanations for a possible causality in the

victim-offender overlap. There is, however, less work devoted to the online-offline overlap. Although our victim-offender, online-offline overlap taxonomy does not imply any specific theory in the analysis, there are possible theoretical explanations that can be further examined in the future.

First, the authors find that online routines and lifestyles can expose individuals to both sides of the crime equation. Younger males who routinely use the dark web were more likely to be victimized and to offend online. Second, social learning theory can explain the victimization-offending overlap for those conservative political affiliations and those who supported President Trump. These groups were the most likely to be in the clusters where offending and victimization overlapped. When these individuals visit online platforms, they likely experience a dynamic cycle of violence where victimization and offending often co-occur and overlap (Cullen et al., 2008; Espelage & Swearer, 2003; Hinduja & Patchin, 2007; Navarro et al., 2018). It is possible they either used online platforms for offending and then experienced victimization (note that the most common offending behavior in our sample was excluding someone from an online community), or they were targeted and then learned to offend as retaliatory coping mechanism from other offenders and from fellow targeted individuals who were likely victimized online. Either way, they were the most likely to offend and be victimized repeatedly. This explanation is in line with existing research on online hate perpetration and offending (e.g., Costello & Hawdon, 2018; Hawdon et al., 2019a; Hawdon et al., 2019b). The above theories, together with subcultural and strain theories, must be further tested for their possible explanation of the victim-offender and the locale overlaps and their combinations.

Our sample only had 106 individuals who offended online but did not have any online victimization experiences. Most offenders had an active online lifestyle and

experienced some form of online victimization. Hence, our study finds evidence for the relative easiness of online offending (compared to traditional, offline offending) and that online offending usually comes combined with online victimization. Although most criminal policies and prevention programs approach offending and victimization as a one-way street (people are either offenders or victims: Lauritsen & Laub, 2007), it is evident that victimization and offending are, instead, often bidirectional. Our findings prompt suggestions for prevention programs that combine target hardening and awareness-raising, sensitizing individuals about the possible harmful effects of their online acts (Bowling, 2009; Schokkenbroek et al., 2021), and raising awareness of the cycle of violence they can experience online, due to their (retaliatory) offending.

The findings suggest that those who are victimized online may become offenders. This tendency can be conducive to the spread of online hate crime. These findings are in line with observed general trends (Bail et al., 2018; Boxell et al., 2017; Marks et al., 2019) pointing to the polarizing effect of the internet. A plausible policy implication of this finding is that experimental programs could be applied that confront users who are caught in echo chambers and ideologically cocooned networks (Gillani et al., 2018) to mitigate social media's polarization effect.

Another unsettling, although not surprising, finding of this study highlights the overrepresentation of young people in online crime, both as victims and offenders. While these age groups are both online victims and offenders, they are neither victims nor offenders in traditional, offline locations. This finding points to the possible deindividuation and disinhibition effects of digital platforms (Suler, 2004), that can work differently for younger and older age groups, independently of the length of online presence, and the diversity of online activities which did not show significant difference by age in our sample. This finding suggests policies and programs that develop age-

appropriate prevention and intervention efforts focusing on mitigating disinhibition effects of online platforms.

It should also be noted that suggesting victims deserve some degree of blame because they are likely offenders is incorrect. Not only is the premise of this incorrect, but the data does not support this conclusion. While most of the offenders in our sample had victimization experiences (83%) a smaller percentage of victims had offending experiences (51%). We see there are roughly an equal number of victims who have no offending experiences but are still victims.

Limitations

Our study has several limitations. First, there is the possibility of overlap resulting from individuals including their online victimization experience as a general victimization experience. To put it another way, while we asked about specific online victimization experiences, we did not specifically ask about offline victimization. However, two pieces of evidence provide confidence that our results are valid. First, 68% of participants who indicated they had been victimized online said they had not been victimized offline. It appears that a large proportion of participants did not include their online victimization as part of their general victimization. To examine the online versus general victimization conundrum, we also designed a second cluster analysis. In this second analysis, an offline victimization variable was created by only considering participants who said they did not have any online victimization experiences but did say they had general victimization (i.e., only offline victimization). The resulting clusters were similar, with the same categorization for the top five clusters.

Next, the clustering analyzed binary data, and traditional methods-related literature advises against utilizing clustering methods on binary data (for an overview, see Li, 2006). However, current studies support the application of binary data clustering

(Morlini, 2012), where binary attributes are generated from latent continuous variables dichotomized with a suitable threshold value and where the scores of the latent variables are estimated from the binary data. Although there are weaknesses of binary data clustering (Li, 2006), given its support in social science (e.g., Henry et al., 2015), medical studies (e.g., Abidin & Westhead, 2017), and big data analytics (Morlini, 2012) in recent literature, we consider our results to be valid.

Using self-report surveys to gather personal and often sensitive information, such as engaging in offending activities and being a victim, provides more reliability to the sample since there is no interviewer who would deter survey participants from admitting the truth (Bleijenbergh et al., 2011). The online form of survey-based data collection diminished the threat of internal validity by instrumentation due to the non-personal collection of data. However, there is still a possibility of participants hiding their true behavior and thus retaining inaccurate or misleading data due to question sensitivity. Notwithstanding, our survey being cross-sectional did not allow for making causal inferences. We could not assess the temporal order of victimization and offending, only the overlap. We were, thus, unable to evaluate whether victimization causes offending or vice versa. Future research should focus on the time order between victimization and offending, and the possible reoccurring patterns known as the “cycle of violence.” This can be achieved by panel data collections, and/or by adding time-sensitive questions in a survey.

The victim-offender overlap might vary across different criminal and deviant behaviors (see Jennings et al., 2012); yet our study did not detail the characteristics of the overlap in crime types. One thing is sure, that victimization and perpetration are more spurious, and the victim-offender overlap is more heterogeneous than many

studies revealed to date. Our study's novelty is to highlight that, indicating that future research must address the variety of underlying heterogeneous conditions.

Future research directions

Among the many theories tested, currently there are two main theories, routine activities theory and the general theory of crime, that dominate the field of understanding the victim-offender overlap (Jennings et al., 2012). In the future, more research is needed to better understand the causalities of the victim-offender overlap, especially concerning the online-offline overlap of victimization and offending. Researchers need to investigate the factors predicting the overlap of victimization and offending in the virtual and physical world. Investigators also need to further unpack the relationship among certain behaviors online and offline. It would be of particular interest to examine whether the experience of one type of victimization leads to specific forms of criminal offending, perhaps in a retaliatory manner, for example, if an online insult leads to an aggravated physical assault, and whether the victim rather strikes back online and/or offline. It would help predict crime if researchers could measure the risk of becoming an offender of a specific crime after experiencing harassment online. Unraveling victim-offenders' situational and individual characteristics and those who are neither victims nor offenders would further our understanding of the dynamics of victimization and offending. Longitudinal data sets should be collected to study the victim-offender overlap on subsequent datasets so that the sequence of offending and victimization, and the combination of those can be revealed. Data collection tools (e.g., surveys) also should ask about the sequence of victimization and offending, so that the relationships of the two can be measured.

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Declaration of Interest Statement

The authors report no potential competing interest.

PROOF

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PROOF

Table 1: Theoretical Overlap of Victim and Offender and Locale of Crime

	VICTIM	OFFENDER	ONLINE	OFFLINE	
1	0	0	0	0	Uninvolved in crime (Uninvolved)
2	1	0	1	0	Victim only ONLY ONLINE (OnlineVictim)
3	1	0	0	1	Victim only ONLY OFFLINE (OfflineVictim)
4	1	0	1	1	Victim only BOTH ONLINE AND OFFLINE (CompleteVictim)
5	0	1	0	1	Offender only ONLY OFFLINE (OfflineOffender)
6	0	1	1	0	Offender only ONLY ONLINE (OnlineOffender)
7	0	1	1	1	Offender only BOTH ONLINE AND OFFLINE (CompleteOffender)
8	1	1	1	0	Victim/offender overlap BUT ONLY ONLINE (OnlineVictimOffender)
9	1	1	0	1	Victim/offender overlap BUT ONLY OFFLINE (OfflineVictimOffender)
10	1	1	1	1	Victim/offender overlap BOTH ON AND OFFLINE (CompleteVictimOffender)

Table 2: Descriptive Statistics of Demographic Variables

Gender	Male	Female	LGBTQ/Non-Binary			
	1,209 (48%)	1,311 (52%)	12 (0%)			
Race	White	Black	American Indian	Asian	Pacific Island/Hawaiian	Other/Prefer not to Answer
	1,896 (72%)	382 (15%)	74 (3%)	149 (6%)	18 (0%)	112 (4%)
Political Orientation	Very Conservative	Somewhat Conservative	Moderate	Somewhat Liberal	Very Liberal	
	546 (23%)	390 (16%)	776 (32%)	346 (15%)	328 (14%)	
Age	Mean	Median	SD	Min	Max	
	45	42	17	18	94	
Support for Trump	Approve	Disapprove				
	1,185 (47%)	1,343 (53%)				

Table 3. Participant Reported Offending and Victimization

Types of Offending Behavior	Respondents Who Reported Engaging in Past 12 Months	
	Count	% of Total Sample (n=1,109)
Posted hurtful information about someone on the internet	408	16.04%
Threatened or insulted others through email or instant messaging	302	11.89%
Excluded someone from an online community	411	16.16%
Hacked into an unauthorized area of the internet	258	10.15%
Distributed malicious software	282	11.10%
Illegally downloaded copyrighted files or programs	348	13.69%
Illegally uploaded copyrighted files or programs	266	10.47%
Used someone else's personal information on the internet without their permission	293	11.54%
Bought prescriptions (without a prescription) or other drugs on online pharmacies or websites	312	12.27%
Posted nude photos of someone else without his/her permission	289	11.38%
Types of Victimization		
Lost money due to an email, website or other computer scam	473	18.66%
Had your identity used by someone else to start a bank account, credit card or loan	343	13.53%
Had unknown transactions in your bank/investment account, credit card, or other online payment system	517	20.38%
Received notification from a company or organization that your private information, such as name, social security, credit card or password, had been stolen or posted publicly?	496	19.60%
Experienced hurtful comments, pictures or videos about you posted online?	456	18.01%
Experienced unwanted sexual comments or advances online?	443	17.50%
Had a computer virus or malware that affected how your computer operated	438	17.28%

Table 4. Cluster Analysis Group Averages

Group Name	Count	Averages				
	n	Online Offending	Online Victimization	General Victimization	Weekly Hours on Computer	Weekly Hours on Dark web
Unlikely to have any victimization experiences or online offending behaviors (Uninvolved)	2,091	0.23	0.53	0	26.47	1.70
Individuals who were likely to have only online victimization experiences (OnlineVictim)	45	0.44	5.29	0	27.32	3.51
Individuals who were likely to have online victimization experiences and online offending behaviors (OnlineVictimOffender)	229	6.02	4.31	0	22.53	6.08
Individuals who were likely to have both online and general victimization experiences and online offending (CompleteVictimOffender)	105	9.75	6.90	1	23.61	6.90
Individuals who were more likely to have online offending experiences and few victimization experiences (OnlineOffender)	21	9.24	1.43	0	26.38	3.81

Table 5. Demographic Variables and Clusters

Cluster	n	% Male	% White	% Support for Trump	Average Political Leaning (1-7)	Average Age
Uninvolved	2,091	44.33	74.80	41.94	3	46.29
OnlineVictim	45	40.00	62.22	40.00	3	38.89
OnlineVictimOffender	229	62.45	72.93	72.07	2	35.36
CompleteVictimOffender	105	78.10	80.00	87.68	2	39.62
OnlineOffender	21	57.14	61.90	76.19	3	39.62