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Cybercrime, Differential Association, and Self-Control: Knowledge Transmission Through Online Social Learning

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Keywords: Social Learning, Cybercrime, Differential Association, Learning, Online Crime

Biographical Note
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Katalin Parti is assistant professor of sociology at Virginia Tech. Dr. Parti's research focuses on cybercrime and online bullying. She evaluated cyberbullying programs of the Massachusetts Aggression Reduction Center as a Fulbright Fellow. She was awarded the European Safety and Prevention Award for channeling academic research results to schools. She has published in peer-reviewed journals such as *Pediatrics*, *International Journal of Cybersecurity Intelligence & Cybercrime*, the *European Journal of Crime Criminal Law and Criminal Justice*, and the *Journal of Contemporary European Research*.

Abstract

In an increasingly digital world, our social interactions are increasingly moving online. Differential association and social learning theories suggest that we learn both moral definitions and the how-to of crime from those we associate with. In this paper we examine whether online or offline social learning leads to more self-disclosed forms of cyber-offending. Using a national online sample of 1,109 participants, we find both online and offline social learning are important correlates to cyber-offending. In addition, we predict that lower self-control will interact with social learning to further increase the likelihood of cyber-offending. Overall, we find that both social learning and self-control, individually and as an interaction, have a large effect-size in predicting cyber-offending.

Keywords Social Learning, Cybercrime, Differential Association, Learning, Online Crime

Our age is digital. More people are spending more time doing more things online than ever before. The number of people in the world using internet in 2020 was 5.05 billion, which means 64% of the world population was connected to the internet in 2020 (Internetworldstats, 2020). There were 3.8 billion social media users worldwide in 2020, 49% of the world, a 9% increase from 2019. The average internet user spends 6 hours, 43 minutes online a day. The US lags just one minute behind this average. In 2020, the US population will spend 40% of their waking lives online (Kemp 2020).

People learn by observing and imitating online

As people spend more time on social media, they have more opportunities to learn social norms online. We spend an average of 2 hours, 24 minutes a day using social media (GlobalWebIndex 2020). The US average is somewhat below this, where users spend 2 hours, 2 minutes on social media in 2020. These data indicate that online platforms became a preferential space of informal learning and social conditioning, especially in highly connected nations of the developed world, such as the US. According to the "homogenization" literature (Merkovity, 2015; Steger, 2013; Nicolaides, 2012), the global connectedness created a process whereby nation-states and their citizens are homogenized because of the use of social media. Since people from all over the world interact with each other in the same public spheres (popular social media platforms), it creates a homogenized persona. The learning process has never been easier than in the digital world, where most of the world's population is digitally connected.

Self-control affected by online communication

A crucial effect of our digital environment is the online lifestyle that shapes cognition. Attention span is decimated by hyperlinks online, with frequent fragmented information (Peng et al. 2018). Some negative impacts of digital technologies are a lower level of motivation and selfregulation and shallow engagement (Lodge and Harrison 2019). The multiple opportunities and functionalities available instantly online often make it difficult for users to focus on their tasks. According to research, self-control is affected by digital information consumption. The business models of tech companies incentivize design that nudges people into using services frequently to optimize advertising revenue. This "attention economy" also weakens self-controls (Davenport and Beck 2002; Duckworth et al. 2014; 2016) because it rewards fragmentation in attention, a key concept in the digital economy (van Zoonen 2013).

Digitization has multiple effects. As we are more likely do things online, our referential groups from whom we learn our norms and values shift to the digital. Simultaneously, we are conditioned to a space where self-control is weakened. But do we learn more effectively from online referential groups than from our offline friends? And how does self-control mitigate the effect of learning digital wrongdoing? Our study aims to investigate these questions.

The current study empirically examines the combined effect of peer interactions and the individual's self-control level in cyber-offending. We apply a measure of the social learning construct of differential association consisting of deviant peer associations (incorporating both traditional and virtual peers) and self-control on cyber-offending using data collected from a census-based nationally representative sample of American adults.

Literature review

Social Learning Theory (SLT) is the product of modifications and revisions of Burgess and Akers' Differential Reinforcement Theory (Burgess and Akers 1966), which contains a reformulation of Edwin Sutherland's Differential Association Theory (1947). According to social learning theory, we learn criminal behavior through interaction with others (Akers 1998; 2009).

SLT contains four theoretical concepts: differential association, definitions, differential reinforcement, and imitation or modeling. The probability that people engage in deviant activities increases when they differentially associate with others who favor criminal behavior, are exposed to criminal or deviant models, define it as desirable or justifiable, and anticipate or receive a greater reward than punishment for the behavior (Akers 1998).

Differential association is the process through which individuals are exposed to definitions favorable or unfavorable to illegal or deviant behavior. This exposure can be direct interactions with significant others, such as the family or the peer group, or indirect association with a more distant reference group. These associations are role models, the primary source of definitions favorable and unfavorable to the violations of the law.

Definitions are the person's evaluative judgment of the particular behavior. The more a person approves of an act, or the more effectively they neutralize moral prohibitions against the act, the greater the likelihood that the person will engage in the behavior. Imitation or modeling is engaging in a behavior the person observed previously. If one observes a role model engaging in a social behavior, it is more likely that the person will imitate the behavior.

Differential reinforcements—the presence or absence of positive (reward) and negative stimuli (punishment)—increase or decrease the likelihood of a behavior being repeated. The behavior is more likely repeated through rewards (positive reinforcements) and the avoidance of punishment (negative reinforcement). However, the behavior is less likely repeated through the presentation of aversive stimuli (positive punishment) and the loss of reward (negative punishment).

SLT has been tested and supported by self-report data on substance abuse (Pratt et al. 2010), gang membership and delinquency (Winfree et al. 1994; Gagnon 2018), adult criminality

(Burton et al. 1994), hard drug use (White et al. 1987), prescription drug misuse (Schroeder and Ford 2012), rape and sexual violence (Boeringer et al. 1991), intimate partner violence offending (Sellers et al. 2003; 2005), stalking (Fox et al. 2011), victimization (Bettencourt 2014; Cohran et al. 2011), revictimization in childhood sexual abuse (Tasheuras 2019), drug-related crime (Walters 2020), and academic dishonesty (Lanza-Kaduce and Klug 1986). Akers' SLT (Akers 1998) has been tested expansively on cyber-offending (Van Ouytsel et al. 2017; Higgins et al. 2006; Higgins et al. 2004; Higgins and Makin 2004; Higgins and Wilson 2006; Hinduja and Ingram 2008; 2009; Hollinger 1993; Holt et al. 2010; Ingram and Hinduja 2008; Miller and Morris 2016; Morris and Blackburn 2009; Morris and Higgins 2009; 2010; Rogers 2001; Skinner and Fream 1997).

Differential association theory (Sutherland et al. 1995), which became part of the domains in SLT, states that crime is learned through intimate interactions, and peer influence is among the strongest predictors of crime and delinquency (Warr 2002; Pratt et al. 2010). Multiple studies have shown support for social learning and differential association theories to explain various cybercrimes. Morris and Higgins (2009) claimed that differential association was the single best predictor in self-reported software piracy after testing various criminology theories, including strain, neutralization, social learning, and self-control. Subsequent studies examining online piracy supported this finding (Higgins et al. 2009; Higgins and Makin 2004a; Higgins and Makin 2004b; Ingram and Hinduja 2008). Marcum et al. (2014) investigated the hacking behaviors of high school students in a rural county of North Carolina and found that deviant peer association were responsible for hacking behaviors. Respondents who associated with deviant peers were more likely to log into another person's e-mail without permission and send an e-mail, log into another person's Facebook account without permission and post a message, or access a website with no authorization (Marcum et al. 2014). Hutchings and Clayton (2016) studied young males who operated "booter services," websites that illegally offer Denial-of-Service attacks for a fee. The researchers claim that would-be offenders learned the sophisticated techniques of this complex cybercrime through their associations with deviant online peers. Offenders also learned the definitions favorable toward offending and techniques of neutralization.

Social media plays a crucial role in disseminating ideas, and Hawdon emphasized the importance of its role in organizing communities and dispersing antisocial ideas (Hawdon 2012). Hawdon argues that social media amplifies the effect of hate groups that now predominantly operate online. Interaction with people associated with hate groups became much easier on social media. That reality provided an avenue for engaging in violent antisocial acts, more severe than software piracy. With visibility, immediacy (real-time communication), intimacy (identification with members of online communities as "friends"), and rationalization to violence, hatred is effectively learned online. Applying Hawdon's interpretation of differential associations in online social networking sites, McCuddy and Vogel (2014) state that the processes of traditional social interaction also characterize online interaction. McCuddy and Vogel found that online socialization triggers offline offending and that trust strengthens relationships online, facilitating differential association. McCuddy and Vogel (2014) believe that the distinction between offline and online private networks has become less apparent in recent years. As a result, users now identify as strongly with their online communities as with their families (Lehdonvirta and Räsänen 2011), which indicates a high level of trust in online relationships. The above research supports that idea that online interactions mirror in-person interactions, where differential association plays a crucial role in learning social and antisocial behaviors by rewarding (positively reinforcing) and imitating (modeling) them.

Studies show online social networking sites' capacity for influencing antisocial, hate-inspired behaviors (Hawdon 2012). These sites function as reinforcement of already existing attitudes. They allow regular and accessible communication, provide anonymity, and encourage others to become supporters of deviant behaviors. Online social networks provide avenues for a variety of deviant activities, beliefs, and biases. For our research, they offer a testing point to understand the impact of the internet on learning criminal behaviors. However, merely learning motives and techniques of crime does not lead to criminal behavior.

Self-control

According to Gottfredson and Hirschi (1990), self-control is responsible for keeping someone away from criminal opportunities. One factor contributing to low self-control is ineffective parenting, i.e., when parents fail to monitor, recognize, and punish deviant behavior. Parental deviance, low self-control, family size, having a single-parent family, and a mother working outside of the home all hinder socialization. These factors contribute to a low level of self-control in children and make them impulsive, insensitive, risk-taking, short-sighted, and non-verbal (Gottfredson and Hirschi 1990). Besides the abundance of studies supporting Gottfredson and Hirschi's arguments (Buker 2011; Hope et al. 2012), several studies examined self-control in children and adolescents in cyberspace. Baek (2018) found that low self-control works similarly in traditional and online crimes: it increases children's involvement in online deviant activities. Low self-control correlates with creating child sexual abuse material (Clevenger et al. 2014), misusing internet for personal purposes at work (Restubog et al. 2011), and cyberbullying (Vazsonyi et al. 2012; Shadmanfaat et al. 2018).

Although Gottfredson and Hirschi in their General Theory of Crime argued that self-control develops in early childhood and remains constant over the life course, recent studies found that self-control can change and might be dynamic over time (Burt et al. 2006; Hay and Forrest 2006). These studies are consistent with the Life-Course Theory of Crime, stating that one's propensity to commit crimes can vary over the life course and individuals can develop a desistance from crime by experiencing “turning points” even in late adulthood (Laub and Sampson 2003). Testing General Theory of Crime against Life-Course Theory, Na and Paternoster (2012) found that "self-control is malleable, is responsive to intentional attempts to change it, and continues to develop in response to changing level of social control/social bond at least up until the age of 17" (Na and Paternoster 2012: 454). The study provides evidence of the utility of prevention and intervention programs to increase the level of self-control in fighting adolescent delinquency. This finding becomes relevant in the current paper, as we attempt to examine cybercrimes committed by adults in correlation to the offenders’ differential associations to online and offline delinquent peers.

Interaction between differential association and self-control

The concept of self-control also appears to be important from a theoretical perspective; it has no direct influence on cyber-offending and only appears to influence this behavior when combined with SLT constructs. Several studies of self-control and cyber-offending have found correlations between the two (Donner et al. 2014; Higgins et al. 2007; Malin and Fowers 2009; Moon et al. 2010). Studies integrated self-control and social learning (Morris and Higgins 2009; McGloin and Shermer 2009; Meldrum et al. 2009) and found that both low self-control *and* deviant peers are criminogenic risk factors, operating in concert. In other words, as it was found concerning software piracy (Higgins and Makin 2004b), low self-control does not correlate with online deviant behavior in individuals who do not associate with delinquent peers, only in those who have many delinquent peers. Similarly, self-control conditions the effect of differential association and differential reinforcement on music piracy (Hinduja and Ingram 2008; Burruss et al. 2012). McGloin and Shermer (2009) found that those with lower self-control will be more active members of a deviant group and self-control has a more significant effect on delinquency when a direct measure of cyber delinquency is considered (Meldrum et al. 2009). In examining cyberbullying in middle school students, Li and colleagues (2016) found that both self-control and social learning predicted cyberbullying perpetration. However, the social learning process mediated the effect of low self-control. Therefore, low self-control can explain the association to delinquent friends, and indirectly to cyberbullying (Li et al. 2016).

Despite the evidence of the two measures related in effect, only a handful of studies examine the interaction between self-control and differential associations. According to these studies (Meldrum et al. 2009; Shadmanfaat et al. 2018; Nodeland and Morris 2020), the effect of self-control on deviant behavior decreases as peer delinquency decreases. In particular, in a sample of Iranian college students, Shadmanfaat et al. (2018) found that low self-control and association with deviant peers interacted in predicting cyberbullying engagement against sports rivals. Nodeland and Morris (2020) indicated that associating with peers, either online or offline, who support cyber-offending significantly influences cyber-offending behavior. However, they suggest that self-control may not be as important a consideration in the commission of cyber offenses as deviant peers; nevertheless, it moderates the effect of delinquent peers' interactions. As individuals spend more time online, investing in establishing new and maintaining existing online relationships, the opportunities for exposure to ideas, motivations, methods, and techniques for engaging in crime and deviance are continually expanding. Nodeland and Morris

(2020) advocate for an age-graded approach in suggesting that interactive technology is mainly preferred by younger people, who are also the most crime-prone population. They posit that merely being comfortable around computers does not determine cyber-offending. Instead, it is primarily influenced by spending time with a deviant peer group.

Online socialization

With a vast majority of the population communicating online, social media can serve as a platform of socialization (Acar 2008), despite the differences between traditional and online social networks. According to Acar (2008), one such difference is that traditional networks tend to be smaller than online ones. Pempek and colleagues (2009) propose that users mostly spend their time observing content that others have generated rather than creating content themselves. Users tend to communicate with existing friends rather than with newly acquired online contacts (Pempek et al. 2009). Since online networks are more expansive than traditional networks, they increase exposure to a broader range of behavior. Meldrum and Clark (2013) posited that the presence of peers, the lack of authority figures, and unstructured time spent online increased the likelihood of delinquent behavior. These results support the concept of unstructured socialization (Osgood et al. 1996; Osgood and Anderson 2004), according to which the amount of virtual time spent socializing with deviant peers elevates the risk of substance use and delinquency in middle school students (Meldrum and Clark 2013).

Although there is a dearth of research supporting the role of socialization processes in cybercriminal activities, most of the aforementioned studies examine how socialization processes in traditional interactions manifest in online offending. The criminogenic effects of social media have received little attention (e.g., Hawdon 2012; Weerman et al. 2013; Meldrum and Clark 2013; McCuddy and Vogel 2014). Additionally, other than Weerman et al.'s (2013) research, suggesting that online interactions on self-reported deviant activity had a significantly weaker effect than offline forms of interactions, there is little research on examining the effects of online versus offline social interactions on delinquency. Furthermore, the interaction between self-control and social learning was only analyzed on samples of middle school or college students—young people whose self-control levels are still malleable. However, similarly to adolescents, adults can be affected by social learning and differential association to deviant friends, primarily because of their increasing online presence. Our study aims at filling these gaps.

Hypotheses

H1: Online social learning predicts cybercrime offending.

H2: Offline social learning will be a better predictor of cyber-offending than online social learning.

H3: An interaction between self-control and differential association will occur. Self-control and differential association will exponentially increase the likelihood of committing cyber-offending.

Method

Data was collected via a Dynata online panel between November 24 and November 29, 2019. Dynata randomly selects panel members from recruitment pools, offering small incentives for completed surveys. We balanced the survey according to the 2019 US census data with regards to sex, ethnicity, and race. Overall, 1,315 respondents began the survey, but 1,109 usable participants completed it. One hundred twenty-five were dropped because they did not complete the first question and 81 dropped as “speeders” since they completed the survey unreliably fast.

While not without its criticisms (e.g., MacInnis et al. 2018), online proportional sampling has been found to yield results similar to probability-based samples (Weinberg et al. 2014; Simmons and Bobo, 2015). Techniques are employed to ensure data validity, such as using attention checks and eliminating individuals speeding through the survey (Wansink 2001; Evans and Mathur 2005). In addition, the incentives offered by Dynata increase participant interest and response rate (see Wansink 2001). Recent studies have highlighted the value of online panel samples, empirically showing only a small variation (0.7-2.5%) between the panel sample and benchmark data (Lehdonvirta et al., 2020).

Measures

Our primary *dependent variable* was the total of 10 self-reported cyber-offending behaviors. In creating our survey, we were informed by Nodeland and Morris' (2020) differential association cyber-offending measures. The behaviors ranged from cyberbullying to identity theft. All 10 behaviors can be found in Table 2. The number of reported behaviors ranged from 0 to 10. Over 81% (892) participants reported no cyber-offending behaviors in the last 12 months. The most reported cyber-offending behavior was "excluding others from an online community" (11%) and the least common was "distributed malicious software" (5%).

We included two *independent variables* for social learning. For online social learning we asked participants if (1) they talked about pirating techniques in online chat rooms or social media and (2) they discussed how to hack things online in chat rooms or social media. For offline social learning, we asked the same questions, but instead of online chat rooms or social learning, we included offline friends. Scores ranged from 0 to 2 with most participants engaging in 0 behaviors (89% offline and 90% online). Offline behaviors were slightly more common (11% compared to 10%).

We included self-control as measured by Vazsonyi et al.'s (2012) three-question scale: I get very angry often and lose my temper, I do dangerous things for fun, and I do exciting things, even if they are dangerous. Scores ranged from 0 to 6, with a mean of 1.17.

We also included demographics, such as self-reported gender, age, education, and race. All variables were similar to the U.S. census, well within the expected margins of error (US Census Bureau, 2019). For a complete breakdown of all demographic variables, please see Table 1.

Table 1 about here

Analytical Strategy

We examine the hypotheses in order. First, we utilize a logistic regression with a 1 representing having committed any of the 10 cyber-offenses. While we attempted to include online and offline social learning in the same model, unsurprisingly multicollinearity (r=.82) between the two social learning variables made this inappropriate. We use two logistic regressions, with either online or offline social learning as a predictor. To further explore our first hypothesis, we then examine each individual cyber-offending behaviors using a series of logistic regressions. Next, we examine the effect of social learning and self-control. We conclude by examining cyber-offending in a logistic regression with all social learning, self-control, and demographic variables.

Results

Our first hypothesis examined whether differential association generally was related to self-disclosed cyber-offending. We used two logistic regressions, with the dependent variable as having committed any cyber-offense in the last 12 months as predicted by either offline or online social learning. Two models were created because of multicollinearity between the social learning variables (r=.82). Both models were significant with strong predictive value (offline

Pseudo R^2 = .23 and online Pseudo R^2 = .19). Both online and offline learning were positively associated with self-disclosed cyber-offending ($p<.001$).

Our second hypothesis explored the role of offline and online learning. We suggest that offline learning will still be more valuable than online learning. Our models used in hypothesis one supports this conclusion. The odds ratio (OR) for offline learning was 12.5 and the OR for online learning was 8.4. Furthermore, the Pseudo R^2 was slightly higher in the offline model (.23 compared to .19, though we recognize that Pseudo R^2 is generally not comparable). While both online and offline learning were significant and had extremely high OR, it appears that offline learning was slightly more powerful in its predictive power.

To further understand the role of social learning, we examined individual self-disclosed cyber-offending behaviors as well. Utilizing a series of logit regressions, we wanted to understand if different types of cyber-offending were related to offline and online learning. All behavior measured was explained via social learning. The highest pseudo R^2 was for uploading copyrighted material (Pseudo R^2 = 0.39). The lowest explained behavior was excluding someone from an online community (Pseudo R^2 = 0.18). Offline social learning was not significant in one model (p=.95), using someone else’s personal information (i.e., identity theft). It is worth noting that Pseudo coefficients should not be directly compared as they are rough estimates. For further model breakdown, see Table 2.

Table 2 about here

From here we created two additional models using the composite self-reported online offending measure as our dependent variable. The first model included a composite of both offline and online social learning measures but also appended the self-control measure. Social learning and self-control were both significant ($p<.001$). It is worth noting that their OR decreased substantially, from between 8.4-12.4 to 2.5. Self-control was also significant ($p<.001$) with an OR of 1.6. This suggests that as self-control scores decreased, total self-reported cyber-offending increased. This model also included additional demographic control variables. These were: a binary indicator for male gender, a binary indicator for white race, education, income, and age. Only white race and age were significant. Both being white and increasing in age decreased the likelihood of self-reported cyber-offending. See Table 3 for all logistic regression models.

Table 3 about here

To examine the last hypothesis, we conducted a logistic regression which included a fully factorial interaction between self-control and social learning. Overall, the model was significant ($p<.001$). All variables were significant except for the interaction term. It appears that, while social learning and self-control are both predictive, they do not interact in our model.

Discussion

The goal of this study was to examine any relationships between SLT, self-control, and cyber-offending, with a special focus on the moderating role of differential association to delinquent peers. The application of traditional criminological theories to cyber-offending is a first step in determining whether such theories can explain participation in cyber-offending in a similar manner as traditional crime types. The current study adds to the SLT literature by utilizing a combined measure of traditional and virtual peer influences in its measure of differential association and in relation to self-control.

Although the logistic regressions were significant both for offline and online social learning, offline social learning predicted cybercrime offending slightly more strongly than online social learning. Individuals learned more about cyber deviant behaviors from traditional, offline relationships than from online peers. This is in concert with previous findings (Weerman et al. 2013) according to which online interactions on self-reported deviant activity had a significantly weaker effect than offline forms of interactions. However, our study did not support the findings of previous literature claiming an interaction effect between differential association and self-control in cyber-offending (Meldrum et al. 2009; Shadmanfaat et al. 2018; Nodeland and Morris 2020).

All online deviant behaviors were explained by social learning, including the highest explained distribution of illegally uploading copyrighted files, and the lowest explained excluding someone from an online community. Looking closer, we can see that cyber-offenders had their own "preferences" of social learning platforms; most cyber-offending behaviors were more likely to be learned online, while a few were offline. Looking at each deviant behavior, using someone's personal information without permission, malicious software distribution, uploading copyrighted files or programs, posting nude images without permission, unauthorized hacking, threatening or insulting someone via instant messaging, and buying prescriptions or drugs illegally were more influenced by online social learning; however, posting hurtful information, excluding someone online, and downloading copyrighted files or programs were rather explained by offline social learning (Table 2). From all these cyber-deviances, malicious software distribution, nude image posting, uploading copyrighted material, and hurtful information posting were explained most strongly in our model. These different preferences suggest that more technology-dependent crimes are more likely to be learned online. For example, hacking and disturbing malware require more computer skills than posting hurtful information and excluding someone on the internet; the latter being rather relationship-focused, thus, more likely to be learned through offline interactions.

From here, we progressed by creating two models: the first model included social learning, self-control, and additional demographic variables. Self-reported cyber-offending increased as self-control decreased. While our two primary independent variables, social learning and self-control, were significant, only race and age in the demographic controls maintained significance. Being white and increasing in age decreased the likelihood of self-reported cyber-offending (Table 3).

Previous studies identified differential association as the single best predictor in self-reported delinquency (Morris and Higgins, 2009; Higgins et al., 2009; Higgins and Makin, 2004a; Higgins and Makin 2004b; Ingram and Hinduja, 2008). As a follow-up of these above studies, we chose to test only differential association out of all SL components as a predictor of self-reported online delinquency. To date, the predictive power of differential associations and the interaction between social learning and self-control were examined only on student (K-12 and college) populations. Our findings provide support that differential associations can predict online offending in adults. Our analysis suggests that adult offenders learn online deviances through offline or online conversations. These platforms of communications function variously. While some cyber-deviances were conditioned through traditional offline interactions, others were through online platforms of communications. Further, low self-control was also correlated with online offending.

Associating with peers, either on- or offline, who support involvement in cyber-offending significantly influences participation in this behavior; nonetheless, offline relationships moderate the effect of low self-control better, when compared to online relationships. Despite the fact that individuals foster new relationships, develop existing relationships, have access to a growing number of resources, and spend increasing amounts of time online, in-person relationships are stronger predictors of online offending. This is especially the case at certain types of cybercrime, such as distributing malicious software, illegally uploading copyrighted material, posting nude depictions, and posting hurtful information. This indicates that these online wrongdoings require offline rather than online associations to delinquent friends. Although the first type of cybercrimes requires intensive knowledge transmission and learning details about the know-how, the second type of online malice is rather simple to commit. Perhaps a more general and viable explanation is the intertwined nature of online and offline communications. As McCuddy and Vogel (2014) found, with increasing digitization, the distinction between offline and online socialization platforms became less apparent, and as a result, users can identify as strongly with their online networks as with their offline friends and families (Lehdonvirta and Räsänen 2011).

Also known as the information richness theory, media richness theory (MRT) (Daft & Lengel, 1986) states that the media's ability to transmit information depends on richness (or clarity and certainty of information), and equivocality (or ambiguity) (Daft, Lengel, Trevino, 1987). The media can be ranked in the following descending order in terms of richness: face-to-face, video systems, audio systems, and text systems. If, for example, an interview happens face-to-face, there is an added advantage of observing facial expressions, body language, and understanding when the information is being withheld and when a person is lying. According to the MRT, lean media (emails) is best used to reduce uncertainty and rich media (face-to-face) is best used for reducing equivocality. Ishii et al. (2019) reviewed the theory's validity with recent communications channels and concluded that rich online platforms were more effective in conveying information than traditional, face-to-face learning experiences. Binker, Gastil, and Richards (2015) found that the use of multiple channels of varying richness was more effective in reaching audiences who had different levels of knowledge depending on the topic being learned. Media channels such as video and text were more effective in expanding educational knowledge, whereas video chat aided participants' ability to build social ties and formulate personal opinions.

Although media richness theory has not yet been tested on cybercriminal activity, it is possible that some online criminal activities are better 'learned' online than offline, in contrast to others. For example, it is possible that technology-dependent criminal activities such as hacking and software piracy that require technical knowledge and the ability to follow meticulous rules (in other words, richness and unequivocally) can be better learned from offline friends where the context is rich with verbal and nonverbal cues and the communication is clearer. On the other hand, relationship-focused criminal activities such as cyberbullying, harassment, or stalking that require immediacy in communication but no technical sophistication might be best learned using media that provide these features (e.g., texting, IM, online synchronous chat applications). All this suggests that online or offline learning platforms and channels cannot equally facilitate learning, and different channels of online and offline communication enhance different types of learning. It is also possible that people choose a combination of multiple online and offline platforms for a blended learning experience where different platforms and learning channels convey different type of information. Future research must examine the effectiveness of various online and offline media in engaging users in learning (i.e., informing, listening, and coordinating) different types of online activities, including different types of online crimes. Finally, our study reveals that being young and non-white predict stronger associations with deviant peers and more intensive online deviant activities. Younger adults in particularare spending a greater amount of time using interactive technology and also traditionally comprise the most crime-prone population, which would further suggest the importance of considering all types of peer associations with regard to offending. However, offline relationships play a more vital role in interaction with low self-control as a factor in engaging in cybercrimes.

Our findings suggest the importance of considering a combined measure of in-person and virtual peers in measuring differential association. SLT confounds the effect of computer knowledge on cyber-offending, suggesting that the persons who we spend time with are more important than our initial computer knowledge, which did not predict online offending alone. Finally, differential association appears to have a significant impact on cyber-offending independent and separate from the effects of self-control.

Limitations and Conclusions

Although the current study posits that online offenders learn crime-prone attitudes primarily from traditional (offline) discussions with their friends, we could not tell whether users communicate with the same group of friends offline and online. Hence, we cannot claim that differential association with offline friends influence online offending more than online friends' discussions. We only can claim that offline discussions are more successful in conveying definitions than online.

Future studies should focus on additional components of social learning. A replication of this study could include variables on peer offending behavior, possibly online and offline, in order to disentangle the effects of peer offending on deviant behavior. Additional replication studies should be conducted on different populations, including international samples. In addition, a survey which includes all four measures of SLT in the model instead of concentrating on differential association as a single component would be important to better understand the full value of SLT.

Additional studies could examine different types of online communities. Comparing communications with friends on chat applications and personal messaging vs. social media sites might allow researchers to show the strengths of each type of online communications platforms in learning antisocial behaviors. This could provide additional understanding for which platforms provide stronger social learning support, especially for criminal networks.

Finally, future studies are suggested to cover the effect of prevention and intervention programs targeting adults. Although we know much about social learning online among youth, and that level of self-control can change even in adolescence and over the life-course (Burt et al. 2006; Hay and Forrest 2006; Na and Paternoster 2012), instead of the assumption that self-control evolves by the age of 10 (see Gottfredson and Hirschi 1990), the concept that online presence can alter self-control must be examined in adult samples, too. This is of special concern in the digital age, when the "attention economy" conditions social media users (Davenport and Beck 2002; Duckworth et al. 2014; 2016), young and old, to attention fragmentation and shallow engagement, and as a consequence, the level of self-control decreases. In conclusion, further research is needed to better understand the mediators and moderators involved in SLT, as well as how the combined effect of SC and SL lead to an overlap in cyber-offending and cybervictimization.

Social learning and differential association provide theoretical consideration for learning from peers. This paper examines learning from both offline and online communities. We find that both offline and online social learning correlate with self-reported cyber-offending. Further, we did not find that self-control interacted with social learning. Finally, it generally appears that offline social learning is more important (i.e., higher effect size as measured by OR) in leading to cyber-offending.

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Table 1: Demographic Variables

			Count Measures				
Gender	**Male** 546 (50%)	**Female** 541 (49%)	**LQBTQ/Non-Binary** 16 (1%)				
Education	**Less than High School** 30 (3%)	**High School** 236 (21%)	**Some College** 265 (24%)	**College Degree** 387 (35%)	**MA/ Professional/ PhD** 187 (17%)		
Race	**White** 787 (71%)	**Black** 157 (14%)	**American Indian** 13 (1%)	**Asian** 70 (6%)	**Pacific Island/Hawaiian** 9 (1%)	**Other/Prefer not to Answer** 71 (6%)	
Household Income	**< $25k** 189 (18%)	**$25k-$50k** 273 (26%)	**$50k-$75k** 173 (17%)	**$75k-$100k** 179 (17%)	**$100k-$150k** 138 (13%)	**$150k-$250k** 70 (7%)	**>$250k** 26 (2%)
			Continuous Measures				
Age	**Mean** 43	**Median** 42	**SD** 13.68	**Min** 18	**Max** 80		

Table 2: Logit Regressions for Cyber-offending Behaviors and Social Learning

	Offline Social Learning			Online Social Learning			Model	
Logit Dependent Variable (in the past 12 months have you. . .)	OR	Std. Err	P	OR	Std. Err	P	LR χ^2	Pseudo R^2
Posted hurtful information about someone on the internet (n=876)	4.68	1.40	<.001	4.26	1.10	<.001	164	.38
Threatened or insulted others through email or instant messaging (n=874)	3.48	1.09	<.001	4.45	1.19	<.001	141	.35
Excluded someone from an online community (n=876)	2.91	.80	<.001	2.53	.63	<.001	91	.18
Hacked into an unauthorized area of the internet (n=876)	2.78	.96	.003	3.68	1.10	<.001	94	.29
Distributed malicious software (n=877)	3.50	1.36	.001	4.10	1.39	<.001	97	.38
Illegally downloaded copyrighted files or programs (n=874)	5.29	1.48	<.001	2.02	.52	0.006	116	.29
Illegally uploaded copyrighted files or programs (n=875)	2.59	.97	.011	5.51	1.76	<.001	117	.39
Used someone else's personal information on the internet without their permission (n=876)	.98	.39	.953	10.10	3.47	<.001	115	.37
Bought prescriptions or other drugs without a prescription on online pharmacies or websites (n=874)	2.65	.90	.004	3.22	.90	0.004	81	.24
Posted nude photos of someone else without his/her permission (n=876)	1.99	.73	.062	5.94	1.85	<.001	114	.35

Table 3: Logistic Regressions of Cyber-offending Behaviors

Variable	Model 1 Offline (n=1022)				Model 2 Online (n=913)				Full Model (n=808)			
	B	*SE(B)*	*P*	OR	*B*	*SE(B)*	*p*	*OR*	*B*	*SE(B)*	*p*	*IRR*
Offline Social Learning	2.53	.21	<.001	12.5								
Online Social Learning					2.12	.21	<.001	8.4				
Total Social Learning									.92	.14	<.001	2.5
Self-Control									.48	.08	<.001	1.6
Male (gender binary)									.41	.25	.107	1.5
Education									.12	.14	.376	1.1
White (race binary)									-.54	.26	.035	.58
Income									-.12	.09	.187	.88
Age									-.02	.01	.022	.97
Constant	-2.2	.11	<.001	.11	-2.6	.15	<.001	.13	-1.66	.54	.002	0.19
Pseudo R^2		.23				.19				.32		
LR Chi^2		207				161				225		

Table 4: Interaction effects between Self Control and Social Learning (n=871)

Variable	Interaction Model			
	B	*SE(B)*	*p*	OR
Social Learning	1.21	.21	<.001	3.35
Self-Control	.53	.08	<.001	1.70
Interaction	-.06	.08	.468	.95
Constant	-2.89	.18	<.001	.06
Pseudo R^2	.29			
LR Chi^2	222			