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Using Routine Activity Theory to Predict Technology-Facilitated Violence Among U.S. Adults During COVID-19

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Abstract

Using routine activity theory (RAT), the present study investigated predictors of two types of technology-facilitated violence: cyber obsessional pursuit victimization (COPV) and Cyber Aggression in Relationships Scale (CARS), during COVID-19 among a sample of U.S. adults ($N = 2,975$). Results revealed that target attractiveness in terms of gender, age, and racial/ethnic background predicted both intimate (CARS) and nonintimate (COPV) cyber violence. For target exposure, technology use and the perceived ability to protect one's privacy predicted both types of cyber violence. Previous experience of in-person intimate partner violence explained the largest amount of variance in both types of technology-facilitated violence victimization.

Keywords

cyber violence, victimization, relationships

Online communication technology has rapidly become an important facet of everyday life for nearly all American adults (Pew Research Center, 2021). While there are many positive impacts of utilizing online technologies to facilitate professional and social endeavors, the online world can also foster abuse and persecution. Technology-facilitated violence encompasses a broad array of online abuse including harassing, stalking, threatening, or sexually soliciting someone via the use of electronic technology (Burke Winkelman et al., 2015). These unwanted online behaviors can be related to interpersonal violence, such as online sexual harassment and online dating abuse (Henry et al., 2020).

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These crimes can also include discrimination based on gender, race/ethnicity, and sexual orientation (Dunn, 2020). Recent national data estimates prevalence of online harassment to be as high as 41% among American adults (Atske, 2021). Of those who were victimized in 2020, nearly a third report having experienced cyber harassment due to their race or ethnicity (Atske, 2021). Younger generations and sexual minority individuals are subject to even higher rates of online harassment (Atske, 2021). Alarmingly, the prevalence of severe types of cyber harassment, such as sexual solicitation and stalking, has increased by about 10% in the last 6 years (Atske, 2021).

Regardless of the type of cybercrime, there are many harmful consequences for victims (Stevens et al., 2021). A recent systematic review reported that 97% of studies on the well-being of cyber harassment victims found evidence of worsening mental health due to the abuse they faced (Stevens et al., 2021). These harmful effects can range from victims reporting greater symptoms of depression and anxiety, to more serious mental health impacts such as suicidal ideation or panic attacks (Stevens et al., 2021). Negative impacts of cyber victimization are not limited to mental health, but also include a mistrust of the legal system and a fear for one's personal safety (Burke Winkelman et al., 2015; Stevens et al., 2021).

In light of the increasing rates of cyber harassment victimization and its various negative impacts, understanding how to intervene is a crucial next step. Specifically, greater knowledge of who is most at risk of becoming victims of technology-facilitated violence is needed to inform prevention. Routine activity theory (RAT) is an approach that has been used in recent studies to understand various cybercrimes such as online harassment (Cohen & Felson, 1979; Vakhitova et al., 2016). Through the application of this theory, research is beginning to understand what makes potential victims vulnerable to online perpetrators of abuse, with the goal of ultimately preventing the occurrence of these crimes. However, this growing body of research still needs further evidence to understand how characteristics of potential victims and offenders are unique to technology-facilitated violence. In the next section, we outline the current literature on this theory and what has been left unanswered within the context of cyber abuse and violence.

RAT and Cyber Harassment

RAT (Cohen & Felson, 1979) was first applied in the field of criminology to assess the factors in one's environment and the characteristics of one's identity that impact victimization. Specifically, RAT asserts that crime occurs at the intersection of the following three dimensions: (a) target attractiveness, (b) exposure to offender, and (c) lack of guardianship (Cohen & Felson, 1979; Vakhitova et al., 2016). When individuals' daily activities place them in positions of high attractiveness, high exposure, and low guardianship—victimization is more likely to happen (Cohen & Felson, 1979; Johnson & Nikolovska, 2022). RAT can be applied to a variety of crimes in which specific victim and perpetrator characteristics are defined as predictors. For instance, a substantial body of research has used RAT to predict in-person intimate partner violence (IPV) victimization (Hayes et al., 2021; Mannon, 1997). Previous studies suggest cyber harassment may be similarly predicted by RAT, though the unique nature of the online sphere requires specific addendums (Vakhitova et al., 2016).

Effect of COVID-19 on Cyber Abuse

In addition to needing investigation in the online sphere, there is a large gap in the RAT literature related to how COVID-19 impacted the nature of cyber violence. A fundamental aspect of the RAT model is the suggestion that changes in one's daily activities may cause disruptions that increase crime prevalence when they impact attractiveness, exposure, and guardianship. The COVID-19 pandemic impacted individuals' on- and off-line routines, subsequently influencing crime rates through new victim and perpetrator daily behaviors (Johnson & Nikolovska, 2022). For instance, certain crimes significantly decreased, such as robberies, while others increased, like domestic violence and online abuse (Mohler et al., 2020). With an increase in use of technologies during the COVID-19 pandemic (Vargo et al., 2021), cyber security has become an important concern (Lallie et al., 2021).

These fluctuations in crime during the COVID-19 pandemic crime may be linked to changes in people's daily activities—including reduced in-person activities, in turn increasing at-home and online crimes such as domestic violence and online abuse (Mohler et al., 2020). In addition, the COVID-19 pandemic led to notable shifts in the demographics of people frequently online in the United States, expanding both the variety of people connecting and the intensity of their internet use. For example, internet usage increased among racial-ethnic minority groups in the United States as work, education, and essential services shifted online (McClain et al., 2021). To this effect, this study aims to investigate the extent to which previous applications of RAT to cyber violence hold true within the context of the COVID-19 pandemic, a time in which diverse individuals' routines included greater time spent online compared to before the pandemic (De' et al., 2020).

Target Attractiveness

In terms of cyber violence crimes, the RAT concept of target attractiveness has been operationalized in terms of the individual characteristics (e.g., age, race, and ethnicity) that make targets more likely to be victims (Vakhitova et al., 2016; Wick et al., 2017). Specifically, younger individuals (compared to older individuals, Burke Winkelman et al., 2015; Näsi et al., 2017) and racial and ethnic minorities (Mahoney et al., 2022) have systematically been found to be more likely victims of cyber harassment. While target attractiveness for IPV has been related to gender, only some studies of cyber violence found women to be more likely than men to be victims (Strawhun et al., 2013; Vakhitova et al., 2016; Wick et al., 2017).

To the best of our knowledge, studies that have applied RAT to technology-facilitated violence victimization have not investigated sexual orientation specifically as an aspect of target attractiveness. However, people who identify as sexual and/or gender minority identities have been found to experience higher rates of technology-facilitated violence (Vogler et al., 2023), such as cyber harassment perpetrated by a stranger, compared to heterosexual individuals (Finn, 2004). Sexual minorities may experience higher rates of online abuse due to a combination of societal prejudices, the nature of online anonymity, and specific targeting strategies used by perpetrators (e.g., Fox & Ralston, 2016). Likewise, research has also shown that sexual minority individuals are more likely to be victims of IPV, sexual assault, and stalking (Mahoney et al., 2022). Taken together, these findings suggest that sexual orientation can play a role in both intimate and nonintimate cyber violence.

Previous experience of abuse is another aspect of potential victims that can make them more attractive to perpetrators. Polyvictimization is a known phenomenon in which individuals who were previously victims of abuse are likely to be subject to further abuse later in life (Walker et al., 2019). To this effect, a person's lived experiences of violence can be viewed as a target attractiveness component. Within the context of technology-facilitated violence, researchers have begun to investigate in-person abuse as a predictor of cyber violence (Eaton et al., 2023) . Though the research is sparse, some evidence suggests previous experiences of IPV may make targets more attractive to online perpetrators of violence (Mahoney et al., 2022). One study found physical abuse to be linked with more severe cyber harassment (e.g., online stalking), while in-person emotional abuse was correlated with less severe forms of cyber harassment (e.g., online monitoring by partners; Mahoney et al., 2022). Further research is needed to understand whether target attractiveness and exposure differently predict different technology-facilitated crimes, specifically in terms of intimate compared to nonintimate cyber violence.

Exposure to Offenders

The dimension of exposure can be understood in terms of potential offenders' motivation to enact a crime as a function of their degree of accessibility to victims (Cohen & Felson, 1979). While this dimension is often understood in the context of physical space, exposure to offenders within the context of technology-facilitated violence rather focuses on the degree to which a person's use of the internet makes them available to potential perpetrators (Yar, 2005). Previous research on technology-facilitated violence has been successful at translating this dimension of RAT to the online sphere (Näsi et al., 2017; Vakhitova et al., 2016; Wick et al., 2017). Specifically, individuals who spend more time on the internet systematically make themselves more accessible to perpetrators by increasing their motivation to enact violence (Näsi et al., 2017; Vakhitova et al., 2016; Wick et al., 2017). Most prior work has investigated exposure online in terms of potential victims' use of social networking sites and text messaging. As information about individuals is often publicly available online, unknown perpetrators can easily utilize this information to perpetrate cyber abuse (Obada-Obieh et al., 2022). Similarly, the likelihood of technology-facilitated IPV occurring is related to the degree to which the victim spends time online and receives text messages (Melander & Hughes, 2018). However, studies that used RAT to predict cyber victimization have failed to understand exposure beyond social networking presence or general cellphone use (Näsi et al., 2017; Vakhitova et al., 2016). Little is known about whether using certain types of technology (e.g., using social networks compared to texting) impacts potential victims' exposure to offenders.

An important aspect of a potential victim's exposure to offenders online is related to the degree to which online users are able to protect their privacy online. When users are able to prevent others from accessing information about themselves online, perpetrators have in turn less avenues for cyber abuse (Obada-Obieh et al., 2022). Through increased privacy, online users may reduce their exposure to potential offenders, specifically for unknown perpetrators (Obada-Obieh et al., 2022; Wick et al., 2017). However, many people use technology with little knowledge on how to best protect themselves from dangers online, such as hacking or being harassed by strangers. Self-efficacy related to one's use of technology (i.e., feeling competent about how to protect one's privacy on the online sphere) has been found to be directly related to actual safety behaviors online (Boerman et al., 2021). Such competency related to protecting one's presence online can provide greater distance between potential victims and offenders by enhancing the privacy of potential victims, in turn reducing exposure to perpetrators of technology-facilitated violence.

Guardianship

The final component of RAT is guardianship, often operationalized as the presence of capable third-party individuals who can intervene before the occurrence of a crime (Cohen & Felson, 1979; Hayes et al., 2021). This component has been debated in terms of its application to cyber abuse victimization (Cohen & Felson, 1979; Vakhitova et al., 2016). Studies that have attempted to measure this concept in terms of cyber violence have failed to find a significant effect on victimization prediction (Näsi et al., 2017). One explanation may be due to an inability to accurately measure guardianship in the online sphere (Vakhitova et al., 2016). However, some studies have noted that a *lack* of guardianship is an inherent feature of cyber communication (i.e., there is rarely any sense of guardianship in online platforms (Vakhitova et al., 2016). In other words, guardianship is not as plausible on online platforms, demonstrating one of the aspects of technology that facilitates abuse (Obada-Obieh et al., 2022). For instance, perpetrators online have easier access to information about victims while remaining anonymous, and even concealing their true identity (Obada-Obieh et al., 2022). While there may be monitoring practices that can be put in place to guard someone's online presence, these safety practices are often geared toward minors' use of online technology, not adults.

In the present study, we will specifically focus on two facets of the RAT model, namely exposure to offenders and target attractiveness, as measured during the COVID-19 pandemic. These two aspects of the model have received the most robust support from previous studies predicting cyber violence using RAT (Wick et al., 2017). While exposure to perpetrators is evidently related to a target's use of online technologies as demonstrated by the current body of research, this finding could benefit from greater details in terms of what types of technology behaviors predict victimization, especially during COVID-19. With this study, we hope to address this shortcoming by investigating how self-efficacy when using online technology as well as different types of online presence impact a potential victim's exposure. In terms of target attractiveness, we aim to understand how different characteristics such as race/ethnicity, gender, and sexual orientation predict victimization differently depending on the perpetrator. We will further investigate how in-person experiences of violence, specifically IPV, influence victimization.

Intimate and Nonintimate Cyber Violence

Our study examined the co-occurrence of sexual and nonsexual online violence because these forms of violence are often intertwined and can provide insights into broader patterns of aggression and victimization. It is well-established that people who experience one form of violence are at increased risk of experiencing other forms, a phenomenon called polyvictimization (Wolfe, 2018). Similarly, previous research on predictors of violent behavior among perpetrators found that sadism and psychopathy predicted both the occurrence of sexual and nonsexual crimes (Robertson & Knight, 2014). Importantly, research has found that measures from routine activities theory can significantly differentiate single-type victims from polyvictims (Snyder et al., 2021). By studying the co-occurrence of sexual and nonsexual violence, researchers can identify patterns and assess whether certain populations are disproportionately affected by multiple types of violence, informing targeted prevention efforts.

Studying the co-occurrence of sexual and nonsexual violence helps clarify misconceptions about violence, such as the belief that sexual and nonsexual violence are entirely distinct phenomena. Indeed, sexual violence research often narrowly focuses on IPV without assessing instances of other types of violence (Krebs et al., 2011). By exploring their overlap, research can contribute to more nuanced understandings of violence, which can, in turn, reduce stigma around reporting and seeking help. Such frameworks have been studied in other areas of violence of research with the goals of increasing awareness and preventing abuse. For instance, research on elderly abuse encourages intervention to take on a polyvictimization lens to understand the layered and complex experiences of abuse faced by elders (Hamby et al., 2016). In turn, understanding polyvictimization by sexual and nonsexual violence can inform policy efforts. Policy responses to violence can be more effective when they are informed by a comprehensive understanding of how different forms of violence intersect.

Current Study

The aim of this study is to further understand (a) what identity characteristics of U.S. adults were risk factors for cyber violence during COVID-19 (assessing the "target attractiveness" feature of RAT), and (b) how the technology use and self-efficacy of U.S. adults relate to the likelihood of their victimization during COVID-19 (assessing the "exposure to offenders" facet of RAT). Specifically, we expect to find that racial/

ethnic minority individuals, younger individuals, those who identify as women or sexual identity minorities, and those who have been previously victimized by in-person IPV will be more likely to have experienced cyber violence, consistent with previous research on cyber harassment (Vakhitova et al., 2016; Wick et al., 2017). We will also conduct exploratory analyses to investigate whether intimate (vs. noninitimate) forms of technology-facilitated violence are differently predicted by these RAT dimensions. Our hypotheses were as follows:

H1: Racial and ethnic minorities will be more likely than White participants to have experienced cyber pursuit and aggression during COVID-19.
H2: Younger individuals will be more likely than older individuals to have experienced cyber pursuit and aggression during COVID-19.
H3: Women will be more likely than men to have experienced cyber pursuit and aggression during COVID-19.
H4: Sexual minority individuals will be more likely than heterosexual individuals to have experienced cyber pursuit and aggression during COVID-19.
H5: Individuals who experienced IPV before COVID-19 will be more likely to experience cyber pursuit and aggression during COVID-19.
H6: Those who used information and communication technologies (ICTs) more during COVID-19 will be more likely to experience cyber pursuit and aggression.
H7: Those with greater levels of ICT self-efficacy will be less likely to experience cyber pursuit and aggression during COVID-19.

Method

Data Collection

Data were collected between January and March 2021 using Qualtrics panels. A total of 3,198 U.S. participants were recruited using proportional quota sampling in terms of age, gender, sexual orientation, U.S. region, and race/ethnicity. For the sake of ensuring enough power per racial/ethnic group, we oversampled racial and ethnic minority identities. Participants answered an online survey largely related to their use of online technologies as well as online and in-person IPV before and during COVID-19.

Measures

The current study will investigate cyber violence in terms of demographic variables, specifically gender, age, sexual orientation, and race/ethnicity, as well as several well-established established scales. The total sample ($N = 2,975$) was made up of slightly more men (54.0%) than women (46.0%), see Table 1. Racial and ethnic background was about equally divided between White or European (non-Hispanic) participants (52.8%) and racial/ethnic minorities (11.3% Black, Afro-Caribbean, or African; 14.1% Latino/a or Hispanic, 9.9% Asian, 9.3% Native American or Alaskan Native, and 2.6% another race/ethnicity). About 82.5% of the sample identified as

Table 1. Sample Demographics for Sample at Large ($N = 2,975$).

	n (%)
Gender	
Woman	1,368 (46.0)
Man	1,607 (54.0)
Sexual orientation	
Heterosexual	2,632 (88.5)
Gay	82 (2.8)
Lesbian	51 (1.7)
Bisexual	162 (5.4)
Other	48 (1.6)
Race/Ethnicity	
White or European (non-Hispanic)	1,571 (52.8)
Black, Afro-Caribbean, or African	337 (11.3)
Latino/a or Hispanic	418 (14.1)
Asian	295 (9.9)
Native American or Alaskan Native	277 (9.3)
Other	77 (2.6)
Partner before COVID-19	
Yes	1,906 (64.1)
No	1,069 (35.9)
Partner since COVID-19	
Yes	1,841 (61.9)
No	1,134 (38.1)

heterosexual, 2.8% as gay, 1.7% as lesbian, 5.4% as bisexual, and 1.6% as another orientation. We outline below the scales used to measure cyber violence, previous experience of in-person IPV, and technology use.

Cyber violence. The Cyber Aggression in Relationships Scale (CARS; Watkins et al., 2018) asked participants to rate the frequency of their partner's aggressive online behaviors toward them during COVID-19, with a Cronbach's $\alpha = .97$ for this sample. We adapted the wording of the scale to ask participants to rate cyber aggression in their relationship specifically "since the COVID-19 pandemic occurred (e.g., March 2020)." This scale ranges from 0 (*never happened or has not happened since COVID-19*) to 7 (*this happened more than 20 times*). Sample items include "My partner asked me online for sexual information about myself when I did not want to tell" and "My partner checked or tracked my Internet activity without my permission." The three-factor structure of this scale has been investigated to understand the three subscales of psychological cyber aggression, sexual cyber aggression, and stalking; which demonstrated adequate model fit (Watkins et al., 2018). Note that only participants who indicated having a partner during the COVID-19 pandemic received this questionnaire, hence a specific subset was created for analyses with this outcome.

In terms of general cyber violence, the Cyber-Obsessional Pursuit Victimization (COPV) Scale (Spitzberg & Hoobler, 2002) was used to assess this concept, Cronbach's $\alpha = .96$ for this sample. This scale asked participants whether anyone had ever undesirably and obsessively perpetrated a series of online behaviors since the start of the COVID-19 pandemic. A total of 24 cyber violence behaviors were asked about, including for instance, "sending pornographic/obscene images or messages" and "obtaining private information without permission" (in terms of someone else perpetrating these acts on the participant).

Intimate partner violence. Three subscales from the Revised Conflict Tactics Scale (CTS-2; Straus et al., 1996) were used to assess in-person IPV prior to the COVID-19 pandemic, Cronbach's $\alpha = .94$ for this sample. These subscales specifically investigated the frequency of a partner's behaviors that constitute psychological aggression (e.g., "My partner insulted or swore at me."), physical assault (e.g., My partner threw something at me that could hurt."), or sexual coercion (e.g., "My partner made me have sex without a condom."). Answers ranged from "this never happened before the pandemic" to "more than 20 times before the pandemic." Note that only participants who indicated having a partner during the COVID-19 pandemic received this questionnaire, hence a specific subset was created for analyses with this predictor.

Technology usage. Lastly, two scales were used to investigate experience with technology (i.e., target exposure). The ICT scale (Rosen et al., 2013) assessed the frequency which participants use a variety of technologies including cell phones and computers, as well as specific online activities such as using online video communication or social networks. Responses ranged on a 7-point scale from "I did not know this technology" to "I used this technology very often." This scale was given twice to participants, once in relation to their use prior to COVID-19, Cronbach's $\alpha = .87$ for this sample, as well as a second time to assess their use during the pandemic, Cronbach's $\alpha = .88$ for this sample. In our analysis, we used both composite scores for ICT frequency of use before and during the pandemic, as well as specific single items since COVID-19 (social network use, chat software, video software, and online gaming).

In addition to usage, the ICT self-efficacy scale (Musharraf et al., 2018) specifically investigated people's sense of agency and ability to protect themselves when using technology, Cronbach's $\alpha = .93$ for this sample. Participants indicate the degree to which they agreed or disagreed on a 7-point Likert scale with 18 items related to their ability to safely use technology. Items included "I can easily judge whether the information that someone has provided on social networking sites is correct." and "I can easily control privacy settings of social networking sites that I mostly use (i.e., Facebook, Twitter, Skype, WhatsApp, Viber, etc.)."

Analysis Plan

Four sets of hierarchical linear regressions were conducted to test the research predictions. The same sets of analyses were investigated for each predictor, COPV and CARS.

The first sets of analyses focused on target attractiveness and exposure to offender predictors in the sample at large ($N = 2{,}975$) for COPV and in a sample of individuals with a partner during COVID-19 ($n = 1{,}815$) for CARS. In the first step, known predictors were introduced: age, gender (*man* = 0 and *woman* = 1), race (five dummy coded variables with White non-Hispanic as comparison group), and ICT use during COVID-19. The second step introduced a conceptually novel predictor within target attractiveness: sexual orientation (*heterosexual* = 0 and *sexual minority* = 1). Two additional predictors of target exposure were investigated: the difference in ICT use before and during the pandemic, and ICT self-efficacy, respectively.

Secondly, types of previous experiences of IPV were assessed as predictors above and beyond known predictors. Due to this predictor relating to people's experiences in romantic relationships before COVID-19, only participants who reported having had a partner before the pandemic were included to predict COPV ($n = 1{,}874$), and those who had a partner before *and* during COVID-19 ($n = 1{,}667$) to predict CARS, respectively. The first step introduced the following known predictors: race/ethnicity, gender, sexual orientation, ICT use since the pandemic, and ICT self-efficacy. In the second step, the sexual coercion subscale of CTS-2 was introduced, followed by psychological assault, and lastly psychological in subsequent steps.

Results

Descriptive Statistics

The average COPV and CARS scores for the sample were relatively low ($M_{\text{COPV}} = 6.08$, $SD_{\text{COPV}} = 12.6$, $M_{\text{CARS}} = 5.34$, $SD_{\text{CARS}} = 14.8$). There was a slight, significant, increase in ICT use during COVID-19, $M_{\text{before}} = 45.8$, $M_{\text{since}} = 47.6$, $t(2974) = 14.01$, $p < .001$. Correlations between continuous variables for the sample at large, as well as means and standard deviations, can be found in Table 2.

Table 2. Means, Standard Deviations, and Correlations for Sample at Large ($N = 3{,}067$).

Variable	*M*	*SD*	1	2	3	4	5	6
1. Age	46.94	16.39						
2. TechSE[a]	68.82	13.02	−.21**	.22**				
3. COPV[a]	6.08	12.65	−.24**	.21**	−.02			
4. Tech use before[a]	45.80	12.77	−.31**	.5**	.35**	.28**		
5. Tech use since[a]	47.58	13.56	−.35**	.51**	.38**	.26**	.87**	
6. Income	66,478.16	67,152.21	.05**	.03	.02	.02	.19**	.19**

Note. Tech ICT SE = information and communication technology self-efficacy; COPV = cyber obsessional pursuit victimization; TechICT Before= information nd communication technology; ICT use before COVID-19; TechICT Since = technologyICT use since COVID-19

[a]ICT SE = information and communication technology self-efficacy, COPV = cyber obsessional pursuit victimization, ICT Before= ICT use before COVID-19, ICT Since = ICT use since COVID-19.

**$p < .01$

Hierarchical Regressions Predicting COPV

In the first set of hierarchical regressions using RAT to predict COPV, all four models were significant, as shown in Table 3. Model 4 significantly explained more variance (about 3%) than model 3, $\Delta R^2 = .03, p < .05$. As such, Model 4 which regressed COPV onto race, gender, age, ICT use, sexual orientation, ICT difference in use, and ICT self-efficacy was concluded to be the best model. This model specifically explained a relatively small (15%) amount of the variance in COPV, $R^2 = .15, p < .001$. Looking more closely at this chosen model, the strongest predictor of COPV was ICT use since COVID-19, $\beta = .31$, $p < .001$, followed by age, $\beta = -.18$, $p < .001$. ICT self-efficacy and the difference in use before compared to during the pandemic both predicted COPV, $\beta = -.17$, $p < .001$ and $\beta = -.11$, $p < .001$, respectively. Race significantly predicted COPV for Black, $\beta = .07$, $p < .001$, Asian, $\beta = -.09$, $p < .001$, and Native

Table 3. Regression Model Comparisons Using Demographics and Technology Use to Predict Cyber Obsessional Pursuit Victimization in a Sample of U.S. Adults During COVID-19.

Model Comparisons

	R^2	ΔR^2
Model 1	.12***	
Model 2	.12***	.001*
Model 3	.13***	.008***
Model 4	.15***	.03***

Parameters for best model (Model 4)

	B	95%CI[UL, LL]		SE B	β
Intercept		13.18	9.63	10.30	1.81
Black	2.67	1.25	4.08	0.72	.07***
Latino/a	−0.51	−1.78	−0.77	0.65	−.01
Asian	−3.79	−5.28	−2.32	0.75	−.09***
Native	2.73	−1.24	4.22	0.76	.06**
Other	−0.45	−3.12	2.21	1.36	−.006
Age	−0.14	−0.17	−0.11	0.01	−.18***
Gender	−1.72	−2.59	−0.86	0.44	−.07***
Tech usesince COVID-19	−0.28	0.25	0.32	0.02	.31***
Sexual orientation	1.75	0.42	3.08	0.67	.04**
Tech usedifference	−0.19	−0.26	−0.13	0.03	−.11***
Tech self-efficacy	−0.17	−0.20	−0.13	0.02	−.17***

Note. tech = information and communication technology; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Predictor variables are uncentered, race/ethnicity dummy coded with White as reference group, gender dummy coded with man as reference group, tech use difference = tech use during COVID-19 – tech use before COVID-19.

***p < .001
*p < .05
**p < .01

American participants, $\beta = .06$, $p < .01$. Sexual orientation also predicted COPV, $\beta = .04$, $p < .01$.

In the second set of analyses, previous experiences of IPV were assessed in a subset of participants who reported having had a partner at some point before the start of COVID-19 ($n = 1{,}815$), see Table 4. The fourth model which included all three types of IPV was retained as it explained significantly more variance than Model 3, $\Delta R^2 = .02$, $p < .001$. This model explained the largest amount of variance, nearly 60%, in COPV, $R^2 = .59$, $p < .001$. When controlling for known predictors (i.e., age, race, gender, sexual orientation, ICT use, and ICT self-efficacy), the physical assault subscale of CTS-2 was the strongest predictor, $\beta = .58$, $p < .001$; followed by sexual coercion, $\beta = .19$, $p < .001$, and lastly psychological aggression, $\beta = .04$, $p < .001$.

Table 4. Regression Model Comparisons Using Previous Experiences of IPV to Predict Cyber Obsessional Pursuit Victimization in a Sample of U.S. Adults During COVID-19.

Model comparisons

	R^2	ΔR^2
Model 1	.16***	
Model 2	.26***	.10***
Model 3	.58***	.32***
Model 4	.59***	.02***

Parameters for best model (Model 4)

		B	95% CI [LL, UL]		SE B	β
Step 1	Intercept	4.70	1.42	7.98	1.67	
	Black	2.05	0.72	3.37	0.68	.05**
	Latino/a	0.19	−0.88	1.26	0.54	.006
	Asian	−1.78	−3.09	−0.47	0.67	−.04*
	Native	1.97	0.75	3.19	0.62	.05**
	Other	3.62	1.18	6.06	1.25	.05**
	Age	−0.06	−0.09	−0.04	0.01	−.08***
	Gender	−0.21	−0.96	0.54	0.38	−.009
	Sexual orientation	0.50	−0.72	1.72	0.62	.01
	Tech use	0.10	0.07	0.13	0.02	.12***
	Tech self-efficacy	−0.06	−0.09	−0.03	0.02	−.07***
Step 2	Psychological IPV	−0.09	−0.17	−0.01	0.04	.04*
Step 3	Physical IPV	1.20	1.10	1.30	0.05	.58***
Step 4	Sexual IPV	0.88	0.69	1.08	0.10	.19***

Note. IPV = intimate partner violence; CI = confidence interval; *LL* = lower limit; *UL* = upper limit. Predictor variables are uncentered, race/ethnicity dummy coded with White as reference group, gender dummy coded with man as reference group.
***$p < .001$
**$p < .01$
*$p < .05$

Table 5. Regression Model Comparisons Using Demographics and ICT Use to Predict Cyber Aggression in Relationships in a Sample of U.S. Adults During COVID-19.

Model comparisons

	R^2	ΔR^2
Model 1	.10***	
Model 2	.10***	.001
Model 3	.11***	.01***
Model 4	.13***	.02***

Parameters for best model (Model 4)

		B	95%CI [LL,UL]		SE B	β
Step 1	Intercept	16.42	10.9	21.9	2.82	
	Black	0.19	−2.03	2.41	1.13	.004
	Latino/a	−1.61	−3.44	0.22	0.93	−.04
	Asian	−5.65	−7.91	−3.39	1.15	−.11***
	Native	0.34	−1.74	2.43	1.06	.007
	Other	0.53	−3.63	4.71	2.12	.006
	Age	−0.16	−0.21	−0.11	0.02	−.17***
	Gender	−2.33	−3.61	−1.04	0.65	−.08***
	Tech use since COVID-19	0.29	0.23	0.35	0.03	.28***
Step 2	Sexual orientation	1.52	−0.50	3.53	1.03	.03
Step 3	Tech use difference	−0.25	−0.35	−0.15	0.05	−.12***
Step 4	Tech self-efficacy	−0.19	−0.24	−0.14	0.03	−.17***

Note. Tech = information and communication technology; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.
Predictor variables are uncentered, race/ethnicity dummy coded with White as reference group, gender dummy coded with man as reference group, Tech use difference = techuse during COVID-19– tech use before COVID-19.
***p < .001

Hierarchical Regressions Predicting CARS

In the first set of hierarchical regressions using RAT to predict CARS, in a subset of participants who had a romantic partner since COVID-19, all four models were significant, see Table 5. Similar to COPV results, Model 4 significantly explained more variance (about 2%) than Model 3, $\Delta R^2 = .02$, $p < .001$. As such, Model 4 which regressed CARS onto race, gender, age, ICT use since COVID-19, sexual orientation, ICT change in use since COVID-19, and ICT self-efficacy was concluded to be the best model. This model successfully explained about 13% of the variance in CARS, $R^2 = .13$, $p < .001$. The strongest predictor of COPV was ICT use since COVID-19, $\beta = .28$, $p < .001$, followed by age, $\beta = -.17$, $p < .001$. ICT self-efficacy and difference in use before during the pandemic both predicted COPV, $\beta = -.17$, $p < .001$ and $\beta = -.12$, $p < .001$, respectively. Race significantly predicted COPV only for Asian participants, $\beta = -.11$, $p < .001$.

Table 6. Regression Model Comparisons Using Types of Technology Use to Predict Cyber Aggression in Relationships in a Sample of U.S. Adults With Partners During and Since COVID-19.

Model comparisons

	R^2	ΔR^2
Model 1	.12***	
Model 2	.29***	.17***
Model 3	.63***	.34***
Model 4	.64***	.02***

Parameters for best model (Model 4)

		B	95%CI [LL,UL]		SE B	β
Step 1	Intercept	4.70	1.42	7.98	1.71	
	Black	−0.004	0.72	3.37	0.69	.001
	Latino/a	0.05	−0.88	1.26	0.56	.002
	Asian	−1.87	−3.09	−0.47	0.68	−.04**
	Native	0.41	0.75	3.19	0.64	.01
	Other	2.32	1.18	6.06	1.28	.03
	Age	−0.06	−0.09	−0.04	0.01	−.07***
	Gender	0.28	−0.96	0.54	0.39	.01
	Sexual orientation	0.89	−0.72	1.72	0.64	.02
	Tech use since COVID-19	0.05	0.07	0.13	0.02	.05**
	Tech self-efficacy	−0.06	−0.09	−0.03	0.02	−.06***
Step 2	Psychological IPV	0.10	−0.17	−0.01	0.04	.04*
Step 3	Physical IPV	1.38	1.10	1.30	0.05	.61***
Step 4	Sexual IPV	0.95	0.69	1.08	0.10	.19***

Note. IPV = intimate partner violence; CI = confidence interval; *LL* = lower limit; *UL* = upper limit. Predictor variables are uncentered, race/ethnicity dummy coded with White as reference group, gender dummy coded with man as reference group.
****p* < .001
***p* < .01
**p* < .05

In the second set of analyses, previous experiences of IPV were assessed in a subset of participants who had a partner at some point before the start of COVID-19 *and* since COVID-19 ($n = 1,667$), see Table 6. The fourth model which included all three types of IPV was retained as it explained significantly more variance than Model 3, $\Delta R^2 = .02$, $p < .001$. This model explained the largest amount of variance, over 60%, in CARS, $R^2 = .64$, $p < .001$. When controlling for known predictors (i.e., age, race, gender, sexual orientation, ICT use during COVID-19, and ICT self-efficacy), the physical assault subscale of CTS-2 was the strongest predictor, $\beta = .61$, $p < .001$; followed by sexual coercion, $\beta = .19$, $p < .001$, and lastly psychological aggression, $\beta = .04$, $p < .001$.

Discussion

The purpose of this study was to utilize RAT to investigate predictors of technology-facilitated violence, specifically cyber pursuit and aggression, among U.S. adults during the COVID-19 pandemic. We predicted that technology-facilitated violence victimization would be impacted by target attractiveness, operationalized as one's gender, race/ethnicity, age, and sexual orientation based on previous research on cyber harassment and IPV (Burke Winkelman et al., 2015; Hayes et al., 2021; Mahoney et al., 2022; Näsi et al., 2017). Additionally, we expected victimization by IPV prior to COVID-19 would increase a target's attractiveness.

In terms of exposure to offenders, two aspects of internet communication use were investigated as predictors of a target's online presence: technology use and self-efficacy. Based on previous research, we predicted that greater use of technology would lead to more victimization by increasing exposure to potential perpetrators (Obada-Obieh et al., 2022; Vakhitova et al., 2016). We also considered the effect of feeling capable of safely utilizing online technologies as a protective factor against target exposure. We outline our findings and their implications in terms of RAT dimensions in the following sections.

Results replicated previous findings in terms of target attractiveness, such that individuals who were women (compared to men), younger, and of racial/ethnic minority background were more likely to be victims of online abuse. Specifically, this study expanded the understanding of race as a target attractiveness component that differentially impacts certain racial and ethnic minorities (Mahoney et al., 2022). Interestingly, this study suggests that a target's race as an attractiveness factor depends on whether the abuse is perpetrated within the context of an intimate relationship. Black, Asian, and Native American participants were all more likely than non-Hispanic White participants to experience any technology-facilitated violence, as described in the COPV scale, during COVID-19, but not violence perpetrated by an intimate partner in terms of the CARS scale. However, Asian participants compared to White participants were less likely to have been victimized online in any way during COVID-19. While the research on Asian American's experience of IPV off- and online is limited, these results replicate previous findings on Asian American prevalence of IPV which tends to be lower than the general population (Chang et al., 2009). As such, this finding may suggest that Asian Americans are at a lower risk of experiencing cyber abuse.

Our findings related to racial and ethnic minority status as a target suitability factor for general cyber violence may suggest that the violence experienced specifically by Black and Native American victims online is motivated by racial prejudice. During the COVID-19 pandemic, many racial and ethnic minorities reported heightened experiences of discrimination—including increased police brutality experienced by Black people in the United States (Chae et al., 2021). Racial tensions have continued to rise in recent years, with an increase in racially motivated hate crimes between 2021 and 2022 (U.S. Department of Justice, 2023). Cyber racism is thus an important issue in the online sphere which may benefit from further exploration using RAT predictors (Bliuc et al., 2018). Specifically, racial and ethnic identities have complex effects on target attractiveness, with perpetrators strategically targeting certain minorities. Interventions aimed at reducing cyber violence in the United States motivated by racist ideology should pay particular attention to Black and Native American victimization.

Similar findings emerged for sexual orientation, suggesting that a potential victim's sexual orientation is an important aspect of target attractiveness. While individuals who do not identify as heterosexual are more likely to be victims of general technology-facilitated abuse, this was not the case in terms of technology-facilitated IPV in our study. This finding may suggest that general cyber violence toward queer victims may be motivated by homophobic sentiments. Previous research on technology-facilitated has demonstrated that LGBTQ+ individuals are often subject to hate online on the basis of their sexual and gender identity (Dunn, 2020). When accounting for previous experience of IPV, sexual orientation was not a significant predictor of any type of cyber violence. To this effect, the results of this study suggest a nuanced role of sexual orientation as a target attractiveness factor which should be investigated further. Future studies should study how different types of technology violence, for instance, online hate crimes compared to online sexual abuse, are predicted by RAT.

It is important to acknowledge that models which included only demographic information such as sexual orientation and race/ethnicity as target attractiveness predictors explained a marginal amount of variance in our two cyber aggression outcomes. However, models which included in-person violence experiences as a component of target attractiveness were able to explain nearly two-thirds of the variance in both intimate and nonintimate forms of cyber abuse. Specifically, previous IPV victimization was found to increase target risk of both intimate and nonintimate cyber abuse. Physical IPV was the strongest predictor of cyber violence when accounting for other known predictors, followed by sexual IPV. The effect of psychological IPV as a predictor of both measures of technology-facilitated abuse was much smaller. It is important to note that the analyses which included IPV experiences before COVID-19 as predictors explained a much larger amount of the variance in technology-facilitated abuse victimization outcomes (58% for COPV and 64% for CAR) than models that did not. These findings suggest that individuals who have previously experienced physical and/or sexual abuse by an intimate partner are at greater risk of becoming victims of abuse in the online sphere.

This finding underlies the concept of polyvictimization such that individuals in our study who previously experienced IPV may be more likely to be subject to violence again in their lives (Kuijpers et al., 2012). Previous research has demonstrated that experiencing in-person IPV predicts technology-facilitated IPV (Duerksen & Woodin, 2019) and sextortion (Eaton et al, 2023). Interestingly, our findings suggest that previous experiences of IPV not only make victims suitable to intimate partners perpetrating technology-facilitated violence, but all perpetrators at large. This replicates previous findings on cyber psychological abuse which was predicted by physical IPV for severe cyber abuse and emotional IPV for less severed cyber abuse (Mahoney et al., 2022). These results have implications for interventions, as prevention of cyberfacilitated abuse should focus on identifying IPV victims as a vulnerable group. Secondly, these findings continue to build upon the framework of polyvictimization by highlighting the complex nature of having experienced IPV and its repercussions on future victimization. As such, cyber victimization prevention efforts should be mindful of the co-occurrence of violence that is sexual *and* violence that is nonsexual in nature to better understand cyber victimization experiences.

In accordance with previous research, greater use of technology was a significant predictor of technology-facilitated violence victimization above and beyond demographic predictors (Vakhitova et al., 2016; Wick et al., 2017). Self-efficacy related to using technology also was found to significantly protect individuals from victimization when accounting for technology use. In other words, no matter the extent to which someone spends time online, feeling capable of protecting one's information online reduces exposure to offenders. While cyber safety interventions have been created to ensure children's and teen's safe use of the internet, less interventions focus on adult population (Mishna et al., 2011). These results provide an avenue for intervention, as increasing individuals' knowledge related to increasing privacy and utilizing protective practices online may be an important factor in preventing victimization.

Limitations and Future Directions

There are some noteworthy limitations of this study. First, this research utilized self-reports of people's behaviors and experiences at a singular time point. The cross-sectional design of this study is an important limitation which reduces our ability to interpret what predicts cyber victimization. Future studies should investigate online violence using a longitudinal design to better understand what behaviors and characteristics influence victimization. Nevertheless, this study provides an updated picture of the ways in which identity characteristics, previous experience of IPV, and technology use predict technology-facilitated violence during the COVID-19 pandemic. Secondly, while the sample of this study was large and diverse, we were compelled to remove participants who were not cisgender due to the small number of participants ($n = 33$) who identified as transgender and gender nonbinary. Future studies should further investigate how diverse gender identities impact target attractiveness by oversampling gender minorities.

This study assesses constructs of RAT in complex ways, with implications for interventions aimed at preventing cyber abuse. Our findings suggest that a person's use of different types of technology, previous experiences of IPV, and self-efficacy impact their victimization. To this effect, interventions can focus on targeting individuals who are most at risk of victimization in the online sphere. Furthermore, studies have not utilized RAT to assess predictors of technology-facilitated violence perpetrated by *anyone* compared to *intimate partners*. We have revealed here how different types of perpetrators view targets as suitable for their crimes, which impacts prevention methods. Programs should ensure differentiation of types of abuse *and* types of perpetrators, as protecting individuals against unknown perpetrators of cyber violence, compared to intimate partners, may require unique intervention methods. Lastly, our findings related to technology self-efficacy demonstrate that feeling confident in one's ability to protect themselves online suggests potential protective factors against cyber violence. However, our study only investigated self-efficacy related to technology privacy rather than actual privacy behaviors. While previous research has found technology self-efficacy to be related to actual privacy behaviors (Boerman et al., 2021), future research should further investigate the effects of actual privacy behaviors and self-efficacy as components of exposure to offenders of cyber violence.

Conclusion

The RAT components of target attractiveness and target exposure as predictors of crime are useful in the understanding of technology-facilitated abuse, including during periods of higher online use. Specifically, target attractiveness can be understood in terms of demographics as well as previous experiences that make individuals online more likely to be victimized. Women, younger people, Black individuals, and Native American individuals are all at greater risk of being targets of technology-facilitated violence. On the other hand, Asian individuals may be less likely to become victims of any type of cyber violence. Sexual minorities also face a greater risk of cyber abuse, but only the crime is not perpetrated by an intimate partner. The most impactful predictor that makes targets attractive to potential offenders is related to previous experience of IPV. In-person physical and sexual abuse predict victimization by both unknown and known offenders. These results suggest that one way to identify potential victims of technology-facilitated abuse is to target interventions toward survivors of IPV, with consideration to intersectional identities related to race/ethnicity, age, gender, and sexual orientation. One potential prevention technique to equip potential victims with is to improve self-efficacy related to technology use. When accounting for a person's actual use of technology, the degree to which they feel able to protect themselves remains a protective factor against victimization. In sum, RAT helps us understand how individuals become at greater risk of experiencing technology-facilitated violence, which can in turn inform ways to prevent these types of cybercrimes from occurring.

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References

Atske, S. (2021). *The state of online harassment*. Internet, Science & Technology, Pew Research Center. https://www.pewresearch.org/internet/2021/01/13/the-state-of-online-harassment/

Bliuc, A.-M., Faulkner, N., Jakubowicz, A., & McGarty, C. (2018). Online networks of racial hate: A systematic review of 10 years of research on cyber-racism. *Computers in Human Behavior*, *87*, 75–86. https://doi.org/10.1016/j.chb.2018.05.026

Boerman, S. C., Kruikemeier, S., & Zuiderveen Borgesius, F. J. (2021). Exploring motivations for online privacy protection behavior: Insights from panel data. *Communication Research*, *48*(7), 953–977. https://doi.org/10.1177/0093650218800915

Burke Winkelman, S., Oomen-Early, J., Walker, A., Chu, L., & Yick-Flanagan, A. (2015). Exploring cyber harassment among women who use social media. *Universal Journal of Public Health*, *3*(5), 194–201. https://doi.org/10.13189/ujph.2015.030504

Chae, D. H., Yip, T., Martz, C. D., Chung, K., Richeson, J. A., Hajat, A., Curtis, D. S., Rogers, L. O., & LaVeist, T. A. (2021). Vicarious racism and vigilance during the COVID-19 pandemic: Mental health implications among Asian and Black Americans. *Public Health Reports*, *136*(4), 508–517. https://doi.org/10.1177/00333549211018675

Chang, D. F., Shen, B.-J., & Takeuchi, D. T. (2009). Prevalence and demographic correlates of intimate partner violence in Asian Americans. *International Journal of Law and Psychiatry*, *32*(3), 167–175. https://doi.org/10.1016/j.ijlp.2009.02.004

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, *44*(4), 588–608. https://doi.org/10.2307/2094589

De', R., Pandey, N., & Pal, A. (2020). Impact of digital surge during Covid-19 pandemic: A viewpoint on research and practice. *International Journal of Information Management*, *55*(102171), 1–5. https://doi.org/10.1016/j.ijinfomgt.2020.102171

Duerksen, K. N., & Woodin, E. M. (2019). Technological intimate partner violence: Exploring technology-related perpetration factors and overlap with in-person intimate partner violence. *Computers in Human Behavior*, *98*, 223–231. https://doi.org/10.1016/j.chb.2019.05.001

Dunn, S. (2020). *Technology-facilitated gender-based violence: An overview*. SSRN. https://papers.ssrn.com/abstract=3772042

Eaton, A. A., Ramjee, D., & Saunders, J. F. (2023). The relationship between sextortion during COVID-19 and pre-pandemic intimate partner violence: A large study of victimization among diverse U.S men and women. *Victims & Offenders*, *18*(2), 338–355. https://doi.org/10.1080/15564886.2021.2022057

Finn, J. (2004). A survey of online harassment at a university campus. *Journal of Interpersonal Violence*, *19*(4), 468–483. https://doi.org/10.1177/0886260503262083

Fox, J., & Ralston, R. (2016). Queer identity online: Informal learning and teaching experiences of LGBTQ individuals on social media. *Computers in Human Behavior*, *65*, 635–642. https://doi.org/10.1016/j.chb.2016.06.009

Hamby, S., Smith, A., Mitchell, K., & Turner, H. (2016). Poly-victimization and resilience portfolios: Trends in violence research that can enhance the understanding and prevention of elder abuse. *Journal of Elder Abuse & Neglect*, *28*(4–5), 217–234. https://doi.org/10.1080/08946566.2016.1232182

Hayes, B. E., O'Neal, E. N., & Hernandez, C. N. (2021). The sexual victimization of college students: A test of routine activity theory. *Crime & Delinquency*, *67*(12), 2043–2068. https://doi.org/10.1177/0011128720954347

Henry, N., Flynn, A., & Powell, A. (2020). Technology-facilitated domestic and sexual violence: A review. *Violence Against Women*, *26*(15–16), 1828–1854. https://doi.org/10.1177/1077801219875821

Johnson, S. D., & Nikolovska, M. (2022). The effect of COVID-19 restrictions on routine activities and online crime. *Journal of Quantitative Criminology*, *40*, 131–150. https://doi.org/10.1007/s10940-022-09564-7

Krebs, C., Breiding, M. J., Browne, A., & Warner, T. (2011). The association between different types of intimate partner violence experienced by women. *Journal of Family Violence*, *26*(6), 487–500. https://doi.org/10.1007/s10896-011-9383-3

Kuijpers, K. F., van der Knaap, L. M., & Winkel, F. W. (2012). Risk of revictimization of intimate partner violence: The role of attachment, anger and violent behavior of the victim. *Journal of Family Violence*, *27*(1), 33–44. https://doi.org/10.1007/s10896-011-9399-8

Lallie, H. S., Shepherd, L. A., Nurse, J. R. C., Erola, A., Epiphaniou, G., Maple, C., & Bellekens, X. (2021). Cyber security in the age of COVID-19: A timeline and analysis of cyber-crime and cyber-attacks during the pandemic. *Computers & Security*, *105*, Article 102248. https://doi.org/10.1016/j.cose.2021.102248

Mahoney, J. C., Farrell, D. M., & Murphy, C. M. (2022). Prevalence and predictors of cyber psychological abuse among adults. *Journal of Family Violence*, *37*(1), 151–163. https://doi.org/10.1007/s10896-021-00317-x

Mannon, J. M. (1997). Domestic and intimate violence: An application of routine activities theory. *Aggression and Violent Behavior*, *2*(1), 9–24. https://doi.org/10.1016/S1359-1789(96)00023-7

McClain, C., Vogels, E. A., Perrin, A., Sechopoulos, S, & Rainie, L. (2021). *The internet and the pandemic*. Internet & Technology, Pew Research Center. https://www.pewresearch.org/internet/2021/09/01/the-internet-and-the-pandemic/

Melander, L., & Hughes, V. (2018). College partner violence in the digital age: Explaining cyber aggression using routine activities theory. *Partner Abuse*, *9*(2), 158–180. https://doi.org/10.1891/1946-6560.9.2.158

Mishna, F., Cook, C., Saini, M., Wu, M.-J., & MacFadden, R. (2011). Interventions to prevent and reduce cyber abuse of youth: A systematic review. *Research on Social Work Practice*, *21*(1), 5–14. https://doi.org/10.1177/1049731509351988

Mohler, G., Bertozzi, A. L., Carter, J., Short, M. B., Sledge, D., Tita, G. E., Uchida, C. D., & Brantingham, P. J. (2020). Impact of social distancing during COVID-19 pandemic on crime in Los Angeles and Indianapolis. *Journal of Criminal Justice*, *68*, Article 101692. https://doi.org/10.1016/j.jcrimjus.2020.101692

Musharraf, S., Bauman, S., Anis-ul-Haque, M., & Malik, J. A. (2018). Development and validation of ICT self-efficacy scale: Exploring the relationship with cyberbullying and victimization. *International Journal of Environmental Research and Public Health*, *15*(12), Article 12.1–13. https://doi.org/10.3390/ijerph15122867

Näsi, M., Räsänen, P., Kaakinen, M., Keipi, T., & Oksanen, A. (2017). Do routine activities help predict young adults' online harassment: A multi-nation study. *Criminology & Criminal Justice*, *17*(4), 418–432. https://doi.org/10.1177/1748895816679866

Obada-Obieh, B., Huang, Y., Spagnolo, L., & Beznosov, K. (2022). Sok: The dual nature of technology in sexual abuse [Paper presentation]. 2022 IEEE Symposium on Security and Privacy (SP), San Francisco, CA, United States, May 22–26, 2022 (pp. 2320–2343). https://doi.org/10.1109/SP46214.2022.9833663

Pew Research Center. (2021). *Internet/broadband fact sheet*. Internet, Science & Technology, Pew Research Center. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/

Robertson, C. A., & Knight, R. A. (2014). Relating sexual sadism and psychopathy to one another, non-sexual violence, and sexual crime behaviors. *Aggressive Behavior*, *40*(1), 12–23. https://doi.org/10.1002/ab.21505

Rosen, L. D., Whaling, K., Carrier, L. M., Cheever, N. A., & Rokkum, J. (2013). The media and technology usage and attitudes scale: An empirical investigation. *Computers in Human Behavior*, *29*(6), 2501–2511. https://doi.org/10.1016/j.chb.2013.06.006

Snyder, J. A., Scherer, H. L., & Fisher, B. S. (2021). Poly-victimization among female college students: Are the risk factors the same as those who experience one type of victimization? *Violence Against Women*, *27*(10), 1716–1735. https://doi.org/10.1177/1077801220952176

Spitzberg, B. H., & Hoobler, G. (2002). Cyberstalking and the technologies of interpersonal terrorism. *New Media & Society*, *4*(1), 71–92. https://doi.org/10.1177/14614440222226271

Stevens, F., Nurse, J. R. C., & Arief, B. (2021). Cyber stalking, cyber harassment, and adult mental health: A systematic review. *Cyberpsychology, Behavior, and Social Networking*, *24*(6), 367–376. https://doi.org/10.1089/cyber.2020.0253

Straus, M. A., Hamby, S. L., BONEY-McCOY, S., & Sugarman, D. B. (1996). The revised conflict tactics scales (CTS2): Development and preliminary psychometric data. *Journal of Family Issues*, *17*(3), 283–316. https://doi.org/10.1177/019251396017003001

Strawhun, J., Adams, N., & Huss, M. T. (2013). The assessment of cyberstalking: An expanded examination including social networking, attachment, jealousy, and anger in relation to violence and abuse. *Violence and Victims*, *28*(4), 715–730. https://doi.org/10.1891/0886-6708.11-00145

U.S. Department of Justice. (2023). 2022 *FBI hate crimes statistics*. https://www.justice.gov/crs/highlights/2022-hate-crime-statistics

Vakhitova, Z. I., Reynald, D. M., & Townsley, M. (2016). Toward the adaptation of routine activity and lifestyle exposure theories to account for cyber abuse victimization. *Journal of Contemporary Criminal Justice*, *32*(2), 169–188. https://doi.org/10.1177/1043986215621379

Vargo, D., Zhu, L., Benwell, B., & Yan, Z. (2021). Digital technology use during COVID-19 pandemic: A rapid review. *Human Behavior and Emerging Technologies*, *3*(1), 13–24. https://doi.org/10.1002/hbe2.242

Vogler, S., Kappel, R., & Mumford, E. (2023). Experiences of technology-facilitated abuse among sexual and gender minorities. *Journal of Interpersonal Violence*, *38*(19–20), 11290–11313. https://doi.org/10.1177/08862605231179724

Walker, H. E., Freud, J. S., Ellis, R. A., Fraine, S. M., & Wilson, L. C. (2019). The prevalence of sexual revictimization: A meta-analytic review. *Trauma, Violence & Abuse*, *20*(1), 67–80. https://doi.org/10.1177/1524838017692364

Watkins, L. E., Maldonado, R. C., & DiLillo, D. (2018). The cyber aggression in relationships scale: A new multidimensional measure of technology-based intimate partner aggression. *Assessment*, *25*(5), 608–626. https://doi.org/10.1177/1073191116665696

Wick, S. E., Nagoshi, C., Basham, R., Jordan, C., Kim, Y. K., Nguyen, A. P., & Lehmann, P. (2017). *Patterns of cyber harassment and perpetration among college students in the United States: A test of routine activities theory*. https://doi.org/10.5281/ZENODO.495770

Wolfe, D. A. (2018). Why polyvictimization matters. *Journal of Interpersonal Violence*, *33*(5), 832–837. https://doi.org/10.1177/0886260517752215

Yar, M. (2005). The novelty of ‘cybercrime’: An assessment in light of routine activity theory. *European Journal of Criminology*, *2*(4), 407–427. https://doi.org/10.1177/147737080556056

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