PREDICTING ONLINE SEXUAL VICTIMIZATION AMONG COLLEGE STUDENTS: SEXTING, SOLICITATIONS, AND OTHER RISKY ONLINE BEHAVIORS

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APPROVAL SHEET

PREDICTING ONLINE SEXUAL VICTIMIZATION AMONG COLLEGE STUDENTS:

SEXTING, SOLICITATIONS, AND OTHER RISKY ONLINE BEHAVIORS

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Dedication

To my parents, Robert and Lillie Knight, who always believed in me.

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ABSTRACT

With the high prevalence rates of internet usage and smartphone ownership, risky online behaviors have become more and more widespread. These behaviors include sexting, online sexual solicitations, and online sexual interactions. Research indicates that these risky behaviors are related to online sexual victimization (OSV). OSV has been associated with poorer mental health, loneliness, lower life satisfaction, and other negative outcomes. Another phenomenon linked to OSV and sexting is sexual exploitation, but no study has yet analyzed the predictive ability of beliefs and awareness about sexual exploitation and human trafficking on OSV. Optimism bias, or the tendency to think that one's chances of experiencing a negative event are less than the average person's chances, is a bias that is related to one's own risky behaviors, but no research has looked at its connection with OSV and sexting. The purpose of this study was to analyze the ability of sexting, online sexual solicitations, online sexual interactions, optimism bias, attitudes about human trafficking, social media, and the amount of time one spends on their cell phone and the internet to predict OSV.

This project analyzed self-reported levels of OSV, sexting, online sexual solicitations, online sexual interactions, optimism bias, human trafficking myth acceptance, number of social media platforms, time spent on the internet, and cell phone screen time among a sample of undergraduate university students ($N = 458$). Independent samples *t*-tests were conducted to compare males and females. A multiple linear regression was conducted using the eight variables as predictors of OSV, and then a regression with a reduced model was conducted with only five predictors. Males reported higher levels of sexting than females, and females reported spending more time online than males. The regression analysis revealed that the model explained 60% of the variance in OSV scores. Based on the β weights, squared structure coefficients (r_s^2), and *p* values, sexting and solicitations were the strongest predictors of OSV. The reduced model, which excluded cell phone screen time, internet time, and optimism bias, also explained 60% of the variance in OSV scores. Findings indicate strong predictive abilities of sexting and solicitations on OSV experience, expanding the current understanding of OSV and its predictors. Future research should aim to further analyze the individual predictors as well as determining the direction of these relationships.

Keywords: Online sexual victimization, Sexting, Online sexual solicitations, Online sexual interactions, Risky online behaviors, Sexual exploitation

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure **Page**

Chapter 1: Introduction

With the high prevalence rates of internet usage and smartphone ownership, risky online behaviors have become more and more widespread. Sexting prevalence rates have varied throughout the years due to different measurement methods and operational definitions of *sexting*, but it is not rare by any means, with some studies finding sexting prevalence to be as high as 38% among 18- to 24-year-olds (Reyns et al., 2011). Sexting is linked to a number of risky behaviors, but one of the most concerning outcomes is online sexual victimization (OSV), which is defined as the experience of unwanted sexual exchanges online and/or receives threats of disseminating private sexual content (Gámez-Gaudix et al., 2015). OSV has been associated with poorer psychosocial well-being, specifically regarding loneliness, depression, anxiety, and life satisfaction (Festl et al., 2019). The research has shown that sexting linearly increases risk for OSV, positioning itself to be a dangerous predictor of this type of victimization (Gámez-Gaudix et al., 2015).

Another phenomenon that is linked to sexting and online sexual victimization is sexual exploitation and sex trafficking. Specifically, this is often accomplished through sextortion on the internet, which can be defined as coercing someone into providing something (sex, sexual images, money, etc.) by threatening to disseminate private information, such as photos received via sexting (Kunstle, 2020). No study has yet analyzed the impact of beliefs and awareness about human trafficking and exploitation on experiencing OSV.

Additionally, optimism bias, which is the tendency to think that one's chances of experiencing a negative event are less than the average person's chances, directly influences behaviors and decisions in risky situations, so understanding what one thinks about their chances of falling victim to negative events like OSV and sextortion is critical to understanding this victimization (Weinstein, 1980). Although sexting is a phenomenon that is linked to OSV, no study has looked at the relationship between optimism bias and sexting.

The aim of this project is to analyze the ability of risky online behaviors, optimism bias, attitudes about human trafficking, social media, and the amount of time one spends on their cell phone and the internet to predict OSV. This will broaden the scientific community's understanding of the relationships between these variables and online sexual victimization. Findings could suggest ideal targets for OSV preventions and interventions, contributing to fewer negative outcomes associated with OSV.

Chapter 2: Literature Review

Internet and Smartphone Use

In recent years, the widespread usage of technology has become extremely prevalent, and most homes are connected to the internet. A 2019 study conducted by the Pew Research Center revealed that approximately 81% of American adults use the internet daily, 28% were online "almost constantly," 45% went online several times a day, and 9% went online only once a day (Perrin & Kumar, 2019). Only 10% of adults reported no use of the internet at all, and some demographic variables related to internet non-adoption are older age (>65 years old), lower educational attainment (less than a high school diploma), lower income (<$30,000 per year), rural location, and race (Blacks and Hispanics; Anderson et al., 2019). The rise in technology use is especially apparent in young people. A shocking 48% of young adults (18- to 29-year-olds) reported using the internet almost constantly, which is nine percentage points higher than the results from the previous year (Perrin & Kumar, 2019). These increases in internet use have produced radical changes in how society communicates, forms relationships, shares and acquires information, and lives life daily.

Widespread use and ownership of smartphones and other portable devices have made this cultural shift even more pronounced. In the United States, 96% of adults own some type of cellphone, and 81% own a smartphone (Pew Research Center, 2019). When looking at specific age groups, 99% of young adults between 18 and 29 years old own some type of cellphone, and 96% own a smartphone (Pew Research Center, 2019). Additionally, there has been a sudden surge in smartphone use and ownership among children. By 11 years old, 53% of children have their own smartphone, and 69% do by 12 years old (Common Sense Media, 2019). Additionally, one-in-five eight-year-olds own a smart phone (Common Sense Media, 2019). The percentage of children with smartphones has risen consistently, with 24% of 8- to 12-years old owning a smartphone in 2015 and 41% in 2019 and 67% of 13- to 18-year-olds having one in 2015 and 84% in 2019 (Common Sense Media, 2019). This same report also found that 8- to 12-year-olds spend an average of four hours and forty-four minutes on entertainment screen time per *day,* and teens have an average screen time of seven hours twenty-two minutes per day (Common Sense Media, 2019). As high as these statistics may seem, it is a recognition of establishing new standards for cell phone ownership and use as technology continues to inundate society, especially in the United States.

COVID-19 Impact on Internet Use

Internet use has increased greatly recently, due to the global COVID-19 pandemic that caused governments to decree strict lockdowns. Because of these lockdowns, many adults have established home offices, and most students have transitioned from in-person schooling to internet-learning. Teachers of all grades have been required to employ their teaching techniques from the webcam of a laptop, instead of face-to-face teacher-student interactions. Many normal activities that were once in-person were either cancelled or suddenly transitioned to being online. A recent study by Lee et al. (2020) revealed that levels of loneliness have increased significantly from pre-pandemic to during the pandemic, and this increase was especially demonstrated in females. It is unlikely a coincidence that increases in internet use have spiked simultaneously with increases in loneliness. Some internet providers have seen increases in internet usage from 40% to 100% (De' et al., 2020). Additionally, online video communication services have seen a 10x rise in usage (De' et al., 2020). With the overall increase in internet usage, pornography use has increased during the COVID-19 pandemic, as well. The world's most popular pornography website, Pornhub, reported over an 11% increase in traffic globally from the end of February 2020 to the middle March 2020 (Mestre-Bach et al., 2020). Some countries had increases in pornography use up to 24% in that same time frame (Mestre-Bach et al., 2020). This data on pornography is only coming from a single website, so it can be theorized that the increase is much larger in pornography use due to the COVID-19 pandemic.

Problematic Internet Use

With the recent surge in the usage of the web comes an increase in problematic internet use (PIU). PIU can be broadly defined as the inability to control one's internet usage, leading to significant negative outcomes in one's life (Spada, 2014). Social isolation and distancing can contribute to the development of PIU. Recent research shows that there has not only been an increase in problematic pornography use but also in online gaming since the onset of the pandemic (Mestre-Bach et al., 2020; King et al., 2020). A large study (N = 6,416) that took place in China from March 24, 2020 to March 31, 2020 revealed that more than 46% of respondents reported increased dependency on the internet and over 16% reported longer time spent on the internet, as determined by the Internet Addiction Test (Sun et al., 2020). The prevalence of severe internet addiction in this sample was 4.3%, which is 23% higher than it was before the onset of the pandemic in October 2019 (Sun et al., 2020).

Risks and Negative Outcomes of Internet Use

The rise in internet usage has resulted in increased risks and negative consequences. In a prospective longitudinal study on social media use and psychosocial well-being, Vannucci and Ohannessian (2019) found that adolescents who had the highest levels of social media use also had the most negative outcomes. These negative outcomes included higher levels of depressive symptoms, panic disorder symptoms, family conflict, and delinquent behaviors. Complementing this, the adolescents who fell within the low social media use category, defined as those who reported using social media less than once a day, had the lowest levels of delinquent behaviors and anxiety at the six-month follow up assessment (Vannucci & Ohannessian, 2019). They also found that females used social media more often and through more platforms compared to male adolescents, highlighting the importance of looking at social media and internet use in females (Vannucci & Ohannessian, 2019).

It is important to note that the internet impacts neural and behavioral outcomes in adolescents, as well as psychosocial outcomes. Peer influence is extremely impactful to adolescents, and a study by Sherman et al. (2018) revealed that viewing photos with differing amounts of Instagram Likes influenced the activation of the nucleus accumbens (NAcc), with the photos with the most Likes receiving the most NAcc activation. The NAcc is a brain region associated with reward processing, so the differing activation of the NAcc based on Instagram Likes suggests that this type of social stimuli is processed as reward in the brain. This contributes to the heightened use of social media and technology by adolescents and young adults.

Adolescence and young adulthood are periods marked by identity formation and autonomy, and the increased use of social media in the past year as noted will further influence identity development.

In addition to negative mental health outcomes and delinquent behaviors, increased use of the internet presents another risk as well: online sexual solicitations. The vast majority of research on this topic has focused on minors; therefore, the following definitions reflect this demographic. De Santisteban and Gámez-Gaudix (2018) define online sexual solicitations as "requests by an adult to obtain personal sexual information or engage in sexual talk or sexual activities" (p. 939). Online sexual interactions is defined as sexual interactions which occur via information and communications technology, including "cybersex [and] meeting in person for sexual contact" (de Santisteban & Gámez-Gaudix, 2018, p. 939). While online sexual interactions require a response from the solicited, online sexual solicitations simply refer to person requesting sexual content from someone else. Online sexual solicitations and online sexual interactions will be explored in more detail in the context of risks correlated with sexting and OSV.

Sexting

Use of social media and the internet provides opportunities for connection and information. However, this access raises risks for potentially harmful behaviors. One risky behavior that is commonly associated with internet use in adolescents is sexting, which was first coined by the Daily Telegraph in 2005 and is a combination of the words "sex" and "texting" to denote the online exchange of sexual content between communicators (Gassó et al., 2019; Forbes, 2011). For the purpose of this thesis, sexting can be defined as the "creation and delivery of text messages, photos, or videos, with personal sexual content via the Internet or mobile devices" (Gámez-Gaudix, 2017, 29). Some studies have defined sexting as a behavior that is completely voluntary, while other studies suggest that it is impossible to tell if sexting is truly voluntary or in reality coercively manipulated by the individual receiving the sexual content (Gámez-Gaudix, 2017; de Santisteban, 2018).

Prevalence

There have been mixed findings regarding the prevalence of sexting. In one study, the researchers analyzed the prevalence of sexting among 10- to 17-year-olds who had used the internet at least once per month (Mitchell et al., 2012). They found that within the past year, 9.6% of respondents reported creating or appearing in sexual images sent via technology and receiving sexts of the same nature (Mitchell et al., 2012). Out of the youths who reported creating sexual images, 61% were female, and 72% were 16 – 17 years old (Mitchell et al., 2012). Out of the youths who reported receiving sexual images, 56% were female, and 55% were 16-17 years old, highlighting differences between the youths who created sexual images and received sexual images (Mitchell et al., 2012). The findings from this study show that female youths are more often appearing in sexts than male youths and that younger youths are receiving sexual images more often than they are creating sexual images (Mitchell et al., 2012). It is important to note that in this particular study, sexting refers to sending sexual images and does not necessarily include any type of sexual content, such as sexual text conversations. Additionally, the data collection phase of this study took place in 2010 and 2011 and the inclusion criteria was that the youth used the internet at least one time in the past month, potentially explaining the low prevalence of sexting they found.

Reyns et al. (2011) measured lifetime sexting based on sending sexually explicit images online or via text. They sampled 974 college students with a mean age of 20.4 years and found

38% of respondents reported having sent or received sexual images through technology. Regarding males, 39% reported receiving sexts, and 18% reported sending sexts (Reyns et al., 2011). On the other hand, 35% of females had received sexts, and 21% had sent sexts (Reyns et al., 2011). As a general rule, there were no significant differences between genders in participating in sexting (Reyns et al., 2011). The researchers found significant differences between whites and non-whites; 54% of non-white respondents reported receiving sexts, while only 20% of white respondents reported receiving sexts (Reyns et al., 2011).

One factor that potentially confounds these estimates of prevalence is social desirability bias. Because sexting is a personal topic that many people may feel uncomfortable disclosing, it is highly likely that these prevalence rates vastly underestimate the reality of sexting. This could especially be true for females, as social norms suggest that females might tend to deny sexual encounters, while males are more open to discussing their sexual behaviors (de Santisteban & Gámez-Gaudix, 2018). Considering this information in combination with the current estimates of sexting and the recent increases in internet use, one can predict that sexting is much more common than most prevalence studies suggest.

Sexting and Social Media

By definition, it makes sense that individuals who use the internet or smartphones more are more likely to participate in sexting. In a study of 179 adolescents, 93.8% reported spending at least one hour on social media per day, and 27.4% reported having sent sexually explicit messages (Vente et al., 2020). Specifically for adolescents who used four or more different social media platforms, the relative risk for sexting was 1.96 (Vente et al., 2020). Time spent online is also linked to both online sexual solicitations and interactions. Specifically, some researchers have found that solicitations and interactions are related to time spent online on a weekday (de

Santisteban & Gámez-Gaudix, 2018). Although it seems odd that time spent online on specifically weekdays was related to sexual solicitations and interactions, de Santisteban and Gámez-Gaudix (2018) suggested that this could be because of decreased parental supervision when the internet is used on a weekday, as many parents would think that their children are doing homework instead. Because of this, it is likely that there would be more parental supervision on weekends, potentially explaining the apparent asymmetry of this finding. Considering the public health implications of behaviors like sexting, these findings are very important. There appears to be a connection between high social media use and certain risky behaviors such as sexting. The recent increase in internet use due to the COVID-19 pandemic makes this especially concerning.

Risky Correlates of Sexting

Sexting is tightly linked to other types of risky behaviors as well. One study looking at sexting among 18- to 25-year-olds found that individuals who participated in sexting were more likely to also report recently using illicit substances, including alcohol, cocaine, marijuana, and ecstasy (Benotsch et al., 2012). Individuals who participated in sexting also had higher rates of risky sexual behaviors. Compared to those who did not sext, individuals who sexted were more likely to have unprotected sex, sex after alcohol or drug use, and a higher number of past three-months and lifetime sexual partners (Benotsch et al., 2012). Individuals who sexted were also more likely to have had a sexually transmitted infection at some point in their lives (Benotsch et al., 2012). As this study is approximately 10 years old, it could be hypothesized that there has continued to be an increase in these risky behaviors and its relationship with sexting.

There is an emotional impact of sexting as well. A prevalence study by Mitchell et al. (2012) found that 21% of respondents who reported sexting experienced intense feelings of embarrassment and fear as a result of sexting. Additionally, only 28% of respondents who received sexts and/or created and sent sexts reported these incidents to authority figures, highlighting the fact that people who need to know about these risky behaviors are oftentimes unaware of the types of messages their children are sending (Mitchell et al., 2012).

Online Sexual Solicitations and Online Sexual Victimization

Not only is sexting related to offline risks, but it is also related to unique types of online risks. A study by Gámez-Gaudix and Mateos-Pérez (2019) found that sexting significantly predicted receiving sexual solicitations online one year later. Similarly, they found that receiving online sexual solicitations predicted sexting behaviors one year later. (Gámez-Gaudix & Mateos-Pérez, 2019). Other covariates related to online sexual solicitations include being female, age (older adolescents experienced more solicitations compared to younger adolescents), cyberbullying, IMing, video chat, chat, strangers on friend list, amount of web time on weekdays, and depression (de Santisteban & Gámez-Gaudix, 2018). In a study analyzing a sample of Spanish adults, Gámez-Gaudix et al. (2015) found that even after controlling for age, sex, and sexual orientation, each one-point increase in the sexting scale was related to a 2.16 increase in odds for online sexual victimization (OSV), which is a facet of online sexual interactions that encompasses unwanted sexual exchanges and threats of disseminating sexual content. Although sexting was significantly associated with OSV across all recipients (e.g. stranger, friend, partner, etc.), sexting someone who was known only through online platforms was most strongly related to OSV (Gámez-Gaudix et al., 2015). Sexting increased the odds ratios most for insistence, non-consensual dissemination, and threats, respectively (Gámez-Gaudix et al., 2015). Other covariates related to online sexual interactions include age, cyberbullying, amount of web time on weekdays, online games, chat, strangers on friend list, and depression (de

Santisteban & Gámez-Gaudix, 2018). Considering these studies, sexting is a predictor of OSV, as OSV requires the response of the victim and the interaction between the victim and perpetrator. On the other hand, sexting is not necessarily a predictor of sexual solicitations, although the work by Gámez-Gaudix and Mateos-Pérez (2019) suggests that the two have a bidirectional relationship. Conceptually, there cannot be OSV without some sort of sexual solicitation, or request from the perpetrator. Reyns et al. (2011) found that sexting increases odds of cybervictimization by 2.2 times compared to a non-sexter, with cybervictimization being conceptualized as online threats and sexual harassment. The odds of cybervictimization for sexters compared to non-sexters increased even more when different types of cybervictimization were delineated (e.g., contact after asking them to stop, harassment, unwanted sexual content, threats of violence; Reyns et al., 2011). In fact, odds increased 5.77 times for any combination of two types of cybervictimization, and for any combination of three or more types of cybervictimization, odds increased by more than 11 times (Reyns et al., 2011). Although sexting is an important factor to consider in the discussion of online sexual solicitations and OSV, there has yet to be research on whether sexting predicts OSV more accurately than other associated phenomena. There is a distinct relationship between sexting and OSV, as many types of OSV required an exchange of sexually explicit images and content.

Negative Outcomes of Online Sexual Victimization. The prevalence of sexting and the potential for OSV has led to heightened attention of the potential negative outcomes. Festl et al. (2019) analyzed a number of variables, including willingness to sext, OSV, and different psychosocial outcomes. In addition to a significant association between willingness to participate in sexting and OSV, they also found that OSV was positively associated with loneliness, depression and anxiety, and lower satisfaction with life (Festl et al., 2019). “Sexy” selfpresentation online was also associated with higher levels of OSV, suggesting that willingness to sext and portrayals of the self on the internet influence the extent to which one may experience OSV. On top of that, the more one experiences OSV, the worse their psychosocial well-being is predicted to be. Dahlqvist and Gadin (2018) similarly found that among female Swedish students, unwanted sexual solicitation victimization, which similar to OSV, is associated with being twice as likely to report depressive symptoms. OSV is a negative experience that appears to be influenced by risky behaviors such as sexting.

Sexting and Age

The age and sex of the individual are key variables in much of the research. Gámez-Gaudix et al. (2015) found that sexting showed to be most common among young adults aged 19 – 24 (70.5%) and adults aged 25-34 (75.8%). It was much less common among adults older than 45 years (33%). Similarly, OSV was most common among young adults (39%) and adults (43.1%) rather than older adults (21.4%; Gámez-Gaudix et al., 2015). In adolescents aged 12 – 15 years, the researchers found that both online sexual solicitations and interactions gradually increased as age increased (de Santisteban & Gámez-Gaudix, 2018). Among the 12-year-olds in the study, 3.8% experienced sexual solicitations, but 21.1% of 15-year-olds experienced them, with a significantly higher prevalence in girls than boys (de Santisteban & Gámez-Gaudix, 2018). For sexual interactions, only 2% of 12-year-olds reported experiencing them, while 15.4% of 15-year-olds reported interacting online sexually (de Santisteban & Gámez-Gaudix, 2018). For interactions, there were no gender differences (de Santisteban & Gámez-Gaudix, 2018). Similarly, in a longitudinal study, Gámez-Gaudix and Meteos-Pérez (2019) found a consistent increase among 12- to 14-year-olds in rates of sexting as age increased. Specifically, there was a 7.6% prevalence rate of sexting at the first assessment and a 17.5% prevalence rate one year later

(Gámez-Gaudix & Meteos-Pérez, 2019). This same study also looked at online sexual solicitations and discovered that the rates of unwanted online solicitations also consistently increased with age, with a prevalence rate of 7% at the first assessment and 15% one year later (Gámez-Gaudix & Meteos-Pérez, 2019).

These studies indicate that older adolescence might be a peak for risk of sexting and OSV. This time period occurs when most adolescents are being granted more autonomy and freedom over their own lives, leading to less parental supervision and more independent decision-making. Many adolescents in this age group are also leaving home for the first time, whether that is moving out or leaving for college. Either way, this continued exposure to freedom and independence coupled with peer influence appears to be a logical reason for the peak in sexting and OSV. These behaviors increase through younger adolescence beginning at age 12, peak between the ages of 18 to around 26, and then taper off into older adulthood (Gámez-Gaudix et al., 2015). Reyns et al. (2011) describe college students as being the ideal population to study for these topics, as they are theoretically at-risk for these phenomena. Considering this, research on sexting and OSV in the context of college students will be of benefit to understanding the correlates of OSV.

Negative Outcomes of Sexting

Depression

Aside from the connection between sexting and online sexual solicitations and victimization, sexting is also associated with other negative outcomes. A striking majority of studies analyzing sexting and depression have found a strong positive relationship between participating in sexting and depressive symptomology (Gassó et al., 2019). In a sample of 1,760 teenagers, Chaudhary et al. (2017) found that those who reported sexting were significantly more likely to report experiencing depressive and anxiety symptoms, and 20% – 27% of teenagers who reported sexting also reported depressive symptoms. When delineating between consensual and non-consensual sexting, researchers have found varying results regarding depressive symptoms. Frankel et al. (2018) found that while consensual sexting was positively associated with depression and past suicide attempts, nonconsensual sexting was positively associated with severe depression, suicide attempts, and self-harm. In general, male and female teenagers who sext are more likely to report suicidal thoughts compared to those who do not sext (Medrano et al., 2018). A potential explanation for this relationship is the fact that exchanging private photos online and via text message increases one's risk of OSV, not only by the individual who originally received the content but also anyone who might come across it, leaving the sender in a very risky, dangerous situation. Nonconsensual sexting is exploitative and similar to online sexual exploitation, which will be described further later.

Anxiety

The vast majority of studies on sexting have also found an association between sexting and symptoms of anxiety (Gassó et al., 2019). Chaudhary et al. (2017) found that among adolescents who participated in sexting, 57% – 61% also reported anxiety symptoms. Similarly, Klettke et al. (2019) found that among older teenagers, being coerced into exchanging online sexual content was associated with anxiety, depression, low self-esteem, and overall poor mental health. In their review on sexting victimization, Cooper et al. (2016) found that victimization of this type was correlated with not only anger and sadness but also clinical anxiety disorders and suicide.

Psychosocial Health

Less specifically, sexting has been shown to be related to overall worse psychosocial health. Research on sexting and psychosocial problems has found that sexting is negatively associated with self-esteem and positively associated with emotional problems (Ybarra & Mitchell, 2014; Ahern & Mechling, 2013). Emotional problems might be both a predictor and outcome of sexting behaviors (Ahern & Mechling, 2013). A willingness to engage in sexting is indirectly associated with loneliness, depression and anxiety, and lower life satisfaction (Festl et al., 2019). Regarding personality disorders, Brinkley et al. (2017) noticed that sexting at age 16 was related to borderline personality symptomology at age 18, highlighting the longitudinal contribution of sexting to this specific personality feature. Generally, sexting is significantly related to psychological distress and emotional difficulties. Based on the research that shows the link between sexting and a number of negative outcomes, it is imperative to gather a deep understanding of sexting and its related factors. As well, with the increased risk of sexting and OSV comes the increased risk of sex trafficking and online sexual exploitation.

Human Trafficking

According to the Department of Homeland Security (n.d.), human trafficking can be defined as the use of “force, fraud, or coercion to obtain some type of labor or commercial sex act.” Human trafficking is a gross violation of human rights, in which a human being is sold for financial gain. The International Labour Organization (ILO) suggests that an estimated 40.3 million people are victims of human trafficking (ILO, 2017). Out of those victims, 71% of are females, and one in four victims are children (ILO, 2017). To differentiate between labor and sex trafficking, 97% of sex trafficking victims are female, but 65% of labor trafficking victims are male (United Nations Office on Drugs and Crime [UNODC], 2015). In 2019 alone, over 22,000 human trafficking victims were identified in the United States via the human trafficking hotline, with 14,597 sex trafficking victims, 4,934 labor trafficking victims, 1,048 sex and labor trafficking victims, and 1,747 unspecified (UNODC, 2015). It is understood that this is an underestimation of the number of victims in the US, due to the hidden nature of the industry and the fact that those numbers come from only one hotline. Human trafficking is a unique type of trauma that is associated with extreme psychological distress. Some of the psychological diagnoses that are linked with human trafficking are PTSD, complex-PTSD, anxiety, and depression (Tsutsumi et al., 2008; Choi et al., 2020).

Online Sexual Exploitation

Online sexual exploitation is one component of human trafficking and has been shown to be linked with sexting. Most research on online sexual exploitation centers on children (online sexual exploitation of children, OSEC). OSEC can include numerous different activities and crimes but most commonly include grooming, live streaming, and coercing children for sexual material (ECPAT, n.d.). In 2020 alone, the National Center for Missing and Exploited Children (NCMEC) received over 37,800 reports of online enticement. Enticement is defined as an individual communicating with a child online for the purpose of sexual exploitation (NCMEC, 2021). Online abuse can be particularly traumatic, especially when child abuse material or sensitive photos are leaked onto the internet. It is very difficult to get things like that taken down, and the spread of such material can be instantaneous. A child’s sexual abuse material can be seen by thousands upon thousands, for the profit of the person who released the material. While the physical abuse may not currently be present, the online material is continuous, hence the continued psychological negative ramifications. Research shows that there are unique psychological consequences for victims of online sexual exploitation in addition to what would be expected in victims of in-person sexual exploitation. Some of these outcomes include depression, posttraumatic stress disorder (PTSD), and intense feelings of shame and humility (Say et al., 2015; ECPAT, 2020).

A more recent impact on OSEC is the COVID-19 pandemic. As more people remained home due to government lockdowns and employment closures, internet usage increased as previously indicated. A 2020 INTERPOL report on the impact of COVID-19 on OSEC showed a decrease in the activities of transnational child sex offenders since the global pandemic began, yet there has been an increase in online child sexual exploitation and abuse material (CSEAM) and an increase in the sharing of CSEAM over peer-to-peer networks (INTERPOL, 2020). The NCMEC CyberTipline for child sexual exploitation saw a 97.5% increase in online enticement reports for 2020 (37,872) compared to 2019 (19,174; NCMEC, 2021). This data would seem to indicate a shift from physical activity to online activity of OSEC, thus challenging the ability to clearly identify perpetrators and victims.

Sexting and Human Trafficking

While sexting is not always an indicator for human trafficking, the two phenomena share similar concepts. In sexting, the individual sending the content provides sensitive images and material for the pleasure of the person receiving the sexts. The receiving individual sexually objectifies the person in the sext and can potentially use the images against them in blackmail and coercion. In human trafficking, specifically sex trafficking, the perpetrator takes advantage of a victim and coerces them into doing sexual acts with others. Sexting and sex trafficking are both centered on the vulnerability of the sender/victim. In sexting, the vulnerability is established through the acquisition of sensitive images and can be framed as a need to privacy of the victim. In sex trafficking, the vulnerability can be any number of things that can be framed as a need, such as drugs, finances, protection for themselves and their family, and seeking love and affirmation, among other vulnerabilities. While sexting takes place online, sex trafficking is an in-person event, making it exceptionally dangerous and harmful both physically and mentally. Online sexual exploitation can also be extremely traumatizing to the victim, as online material is nearly impossible to take down and one's sexual abuse or private sexual content can be online and re-lived for years.

Sextortion

Sextortion is one of the ways through which sexting can lead into being sexually trafficked. *Sextortion* can be defined as coercing someone into providing something (sex, sexual images, money, etc.) by threatening to disseminate private information, such as photos received via sexting (Kunstle, 2020). In sextortion, there is a sudden imbalance in power. The perpetrator has fundamentally all the power in the situation, leaving the victim helpless and hopeless (Kunstle, 2020). Through sextortion, the perpetrator forces the victim to keep sending sexual pictures, solicits the victim to have sex with them, and eventually to have sex with others (Kunstle, 2020). The victim does not need to be in captivity for this to happen. Considering that 99% of young adults have access to the internet and messaging, the likelihood of an increase in prevalence of sexting and subsequent sextortion is high (Pew Research Center, 2019).

Wolak et al. (2018) conducted a revealing study on the characteristics of sextortion of minors among a sample of 18- to 25-year-olds. Ninety-one percent of the sample (n = 1,628) who reported sextortion experience as a minor were females (Wolak et al., 2018). Three out of five sextortion victims knew the perpetrator in person. The perpetrators were most often a current or former sexual/romantic partner, a friend or acquaintance, or someone from work or school (Wolak et al., 2018). Two out of five who were victimized through sextortion claimed that they never met the perpetrator in person; they only interacted online (Wolak et al., 2018).

The initial communication oftentimes occurred on messaging platforms (34%) and social media websites (32%; Wolak et al., 2018). Voluntarily providing sexual images (three quarters) and being pressured to sext (two thirds) were both common among respondents (Wolak et al., 2018). Additionally, some perpetrators even recorded sexual images without the respondents' consent (22%; Wolak et al., 2018). Most of the threats given by perpetrators were sending the sexual images to friends and family and posting the images online, but some threatened the victims with offline harm, including stalking, beating, and raping them (Wolak et al., 2018). Almost half of the time, perpetrators carried through with their threats, and a notable percentage of respondents who experienced the threatened acts lost relationships with family and friends, changed or left school, sought mental health services, or moved to a new community (Wolak et al., 2018). This study demonstrates that sextortion is a cruel phenomenon that is detrimental to the biological, psychological, and sociological well-being of its victims.

Sexting and Offline Exploitation and Abuse

Other studies show a correlation between sexting and topics associated with human trafficking. However, it is important to keep in mind that because of the criminal, underground nature of human trafficking, it is extremely difficult to research. Therefore, the prevalence of topics of this nature is likely underestimated. One study looking at sexting and exploitation among adolescents in impoverished communities found that among girls, there was a significant association between sexting and intimate partner violence victimization and sexual abuse (Titchen et al., 2019). On the other hand, sexting was associated with sexual abuse and intimate partner violence perpetration among boys (Titchen et al., 2019). Sexual abuse and intimate partner violence are two phenomena similar to sex trafficking and which can both easily evolve into sex trafficking.

Choi et al. (2016) investigated whether online sexting behaviors were associated with offline sexual coercion. They defined offline sexual coercion as giving in to sex or sexual activity because of overwhelming pressure from someone else. The researchers found that even after controlling for a number of important demographic variables (e.g., age, education level, race, length of relationship, etc.), being sexually coerced offline was still significantly associated with sending a sext, being asked for a sext, and receiving a sext without consent (Choi et al., 2016). The findings of this study indicate that sexting might be conceptualized as a predictor of offline sexual coercion. Considering the researchers' definition of offline sexual coercion in this study, human trafficking is not very different from offline sexual coercion.

Myth Acceptance

Beliefs and attitudes can directly translate into observable behaviors and decisions. A common way that attitudes about certain topics has been measured is through myth acceptance, or the level to which someone holds false beliefs about something. One type of myth acceptance that has been thoroughly researched is rape myth acceptance. Rape myth acceptance is defined as "a complex set of cultural beliefs thought to support and perpetuate male sexual violence against women" (Payne et al., 1999, 27). Numerous studies have found practical implications of rape myth acceptance. The more rape myth acceptance an individual demonstrates, the more likely they are to blame the victim for the rape (Frese et al., 2004). One study by Krahe et al. (2008) found that jury members who had higher rape myth acceptance were more likely to find the perpetrator of the rape not guilty than jury members with lower levels of rape myth acceptance. Beliefs and attitudes play a major role in decisions about the self and others. They are also important in behaviors and actions. For example, a recent meta-analysis on rape myth acceptance and sexual coercion perpetration found a significant relationship between higher rape myth acceptance and increased sexual coercion, suggesting that myth acceptance could potentially lead to observable actions like sexual coercion perpetration (Trottier et al., 2021).

Because of the importance of myth acceptance in behaviors, measuring human trafficking myth acceptance will be critical in understanding one's risk for OSV. There are numerous myths regarding human trafficking. Some common human trafficking myths are believing that all human trafficking victims are young children, human trafficking does not happen in the United States, and human trafficking victims are always physically constrained and forced to work (Cunningham & Cromer, 2016). Cunningham and Cromer (2016) developed the *Human Trafficking Myth Scale* to measure attitudes towards human trafficking. It measures 16 beliefs about human trafficking that may have an impact on behaviors and decision-making about topics related to human trafficking (Cunningham & Cromer, 2016). Cunningham and Cromer (2016) found that belief in human trafficking myths helped explain the variance in whether respondents attributed blame to human trafficking victim.

Optimism Bias

People tend to think that their chances of experiencing a negative event are less than the average person's chances. The individual may consider this perspective as being more positive; however, it is a reflection of optimism bias (Weinstein, 1980). Optimism bias is a systematic error in judgement, with the majority of people assuming their risk of negative events to be lower than the average person's risk (Weinstein, 1980). Optimism bias applies to a number of different events, including getting a divorce, giving up on something, and getting caught if a crime was committed, among other things (Lapsley & Hill, 2010). Optimism bias can be reflected in the incorrect estimations of experiencing OSV, making this type of thinking an important potential predictor to assess.

Optimism Bias and Risk of Sexual Victimization

Much research has been conducted looking at the role of optimism bias in assessing one's own risk for being a victim of a sexual crime. One study looking at college students, a group at high risk for sexual victimization, found that women were less likely to rate a vignette situation as "high risk" when the individual in the vignette was themselves compared to when the individual was another person (Rinehart et al., 2018). Technically speaking, when the women were shown vignettes of other individuals, they were more likely to demonstrate a lower decisional threshold, meaning that a lower amount of risk was required for a situation to be deemed as risky (Rinehart et al., 2018). When the women viewed vignettes that included themselves as the individual in the situation, the vignettes had to be objectively riskier to be labeled risky than when it was someone besides the self in the vignette. Relevant information regarding if the situation was risky or not was typically used more so by women in the "others" condition (Rinehart et al., 2018). Some relevant risk information included location, relationship with the man, and pressure to engage in sexual behaviors (Rinehart et al., 2018). In other words, when the woman in the situation was someone else, respondents relied more so on objective information to deem the situation as risky, compared to when the woman in the situation was the "self" (Rinehart et al., 2018). This study demonstrated that women who exhibit optimism bias in regard to risk for a sexual crime may be more likely to stay in sexually risky situations, heightening their risk of being victimized, compared to those who rely on relevant risk information.

Yeater et al. (2020) conducted a longitudinal prospective study on optimism bias regarding sexual victimization and found some evidence suggesting a causal timeline of risk perceptions on actual sexual victimization. They found that women who rated fewer vignettes as high risk were less likely to make effective decisions in lowering risk of sexual victimization (Yeater et al., 2020). Interestingly, risk threshold had an impact on decision making, which influenced real-life sexual victimization at a six-month follow-up (Yeater et al., 2020). Similarly, the more risk-relevant information the women utilized in rating situations as risky, the better decision making they demonstrated and the less sexual victimization they experienced at follow-up. This study emphasizes the importance of optimism bias in real life situations, including both offline and online activities.

Neural Correlates of Optimism Bias

Higher optimism bias is linked to more sexually risky behaviors, and the aforementioned studies show that it is also linked to actual sexual victimization (Chapin, 2001). Not only is optimism bias a psychological phenomenon, but it can be directly translated into neural correlates as well. Optimism bias is associated with enhanced activation in both the amygdala and rostral anterior cingulate cortex (ACC), regions of the brain which relate to emotional salience (Sharot et al., 2007). The rostral ACC is also associated with trait optimism. Therefore, optimism bias might be a phenomenon grounded within the brain, raising questions as to if these individuals are more likely to be high risk for sexual victimization and OSV.

Optimism Bias and Human Trafficking and Exploitation

People who demonstrate optimism bias tend to compare themselves to a stereotypical victim of whatever negative event is being considered. This can be especially harmful in regard to human trafficking because there is no one stereotypical victim profile. In this way, optimism bias about human trafficking and sexual exploitation goes hand-in-hand with levels of human trafficking myth acceptance. If an individual has a high level of human trafficking myth acceptance, then they likely have false beliefs about stereotypical human trafficking victims. In reality, human trafficking victims are not always innocent children. Instead, fundamentally anyone is capable of becoming a victim of sex trafficking and sexual exploitation.

Sexting and online sexual risky behaviors can act as a gateway into exploitation and sex trafficking. As ownership and use of smartphones increases to nearly all of the younger generation, vulnerability to exploitation through sextortion of private images has become widespread. Currently, there has been no research about whether optimism bias plays a role in OSV. Optimism bias is a factor that needs to be measured along with sexting and online sexual victimization, because thinking that one is at less risk for online victimization than the average person will potentially put them at more risk for experiencing that event.

The Current Study

Gaps in the Literature

Although internet use, sexting, and other online activities have become very common among the younger generation, there is a gap in the literature about the roles of optimism bias, human trafficking myth acceptance, sexting, online sexual solicitations, online sexual interactions, daily internet use, daily cell phone screen time, and number of social media platforms on OSV. Which of these variables most accurately predict OSV? Both optimism bias and human trafficking myth acceptance interact with thought patterns and beliefs of risk for exploitation and OSV, so consequently, the more optimism bias and the more human trafficking myth acceptance one displays, the more likely it will be that they will report experiencing OSV.

Rationale and Innovation

With internet use and smartphone continually increasing – especially in light of the recent pandemic impact – sexting, is increasing as well. Because of the close relationship between sexting and OSV, an understanding of what factors impact the likelihood of sexting would guide research in preventing OSV from occurring. Additionally, since we will be analyzing college students, which is a group that is high-risk for OSV and risky online behaviors, this study will provide important implications that can be used to help lower rates of some of the negative outcomes associated with OSV. This study is innovative because it will be the first to analyze the predictive ability of this collection of predictors on OSV levels.

Specific Aims

Aim 1: Analyze the prevalence of OSV and sexting among a sample of college students.

Hypothesis 1: Females will report more sexting and OSV compared to males.

Aim 2: Test the prediction that a multiple regression model including sexting, online sexual solicitations, online sexual interactions, optimism bias, human trafficking myth acceptance, number of social media platforms, daily average cell phone screen time, and time spent on the internet daily will predict OSV. *Hypothesis 2:* The proposed model will statistically significantly predict levels of OSV.

Aim 3: Test the prediction that sexting will most accurately predict OSV. *Hypothesis 3:* Sexting will be the best predictor of OSV.

Chapter 3: Methodology

Participants and Recruitment

The full sample size consisted of 458 college students between the ages of 18 and 26. After deleting responses due to excessive missing data, the final sample size was 413 and 78% of the final sample were female (see *Data Screening* section). Eligibility criteria for participation were 1) being currently enrolled in a class at Liberty University and 2) being between the ages of 18-26. The sampling method for this study was snowball sampling. This convenience sample was recruited by 1) pitching the current study in psychology classes at Liberty University and inviting students in participate, 2) posting the recruitment on social media, and 3) telling eligible friends to participate and encourage their friends to participate. Participants were compensated with either an activity credit for psychology classes or entering a raffle for one of ten $10 gift cards. The survey was an online survey, made and distributed via Qualtrics™. It was completely anonymous and took respondents between 10-15 minutes to complete. All respondents had the option of exiting the survey at any point.

Measures

Online Sexual Victimization

The Online Sexual Victimization (OSV) Scale is a 10-item questionnaire developed by Gámez-Guadix et al. (2015) and measures two levels of OSV: threats and insistence. This includes threatening and insisting to obtain personal sexual photos and videos, disclose private sexual information, make someone do a sexual act over the internet, or make someone have sexual relations in person. Responses were Likert-style and captured the number of times an individual has experienced OSV in their lifetime, with responses ranging from *0 = never* to *4 = 7 or more times* (Chronbach's $\alpha = 0.81$).

Sexting

This 6-item instrument was developed by Gámez-Guadix et al. (2015). It measures lifetime occurrence of being involved in sexting. This scale measures two types of content: pictures/videos and written sexual content. The response scale was Likert-style, with responses ranging from *0 = never* to *4 = 7 or more times* (Chronbach's $\alpha = 0.78$).

Questionnaire for Online Sexual Solicitations and Interactions with Adults (QOSSIA)

The QOSSIA was developed in 2017 by Gámez-Guadix et al. It has 10 items and measures how many times an individual has had an online sexual solicitation or interaction with someone 18 years or older. The online sexual solicitations subscale consisted of the first five items, and the online sexual interactions subscale consisted of the latter five items. The measure was originally designed for minors; however, I used this measure in a sample of college students aged 18-26. The questions are framed in a way that applies to both minors and adults (e.g., "I talked about sexual things with an adult on the Internet."). The responses range from *0 = never* to *3 = 6 or more times.* Chronbach's alpha coefficient was .87 for solicitations and .69 for interactions.

Optimism Bias

This measure was developed by Lapsley and Hill in 2010. Respondents rate their chances of experiencing certain events compared to the average student of the university being studied. The items reflect a wide variety of scenarios (e.g., "Getting a divorce if I were married."). The first 19 items were negative-valence items (Chronbach's $\alpha = 0.85$), and the remaining three items were reverse-coded positive-valence items (Chronbach's $\alpha = 0.76$). Responses range from *-3 = much below average* to *3 = much above average.* Lower scores on this measure reflect more optimism bias.

Human Trafficking Myth Scale

The Human Trafficking Myth Scale was developed by Cunningham and Cromer in 2016. It measures belief in myths about human trafficking. The lower one's summed score is, the less they believe myths, meaning that they have a more accurate understanding of human trafficking. The scale consists of 17 human trafficking myth statements, to which respondents must indicate the level to which they think the statements are true or false. One of the items is reverse coded.

Most of the items reflect human trafficking as a whole, and two reflect sex trafficking specifically. Responses range from *1 = definitely false* to *6 = definitely true* (Chronbach's α = 0.81). Higher scores on this measure reflect more human trafficking myth acceptance.

Social Media, Cell Phone Screen Time, and Internet Time

Respondents answered one item each to measure how many social media platforms they owned and used regularly, their daily average cell phone screen time, and their daily average number of hours spent on the internet. Participants responded using whole numbers, rounding if needed (e.g., "3").

Data Screening

Responses were deleted based on the amount of missing data. If a respondent did not finish the first measure (OSV) and hence following measures, their response was deleted. Missing data was filled in using either the mean or median, based on the skew of the variable. If the variable was normally distributed, the mean was used to fill in missing data points. If the data was skewed at a score of 1.00 or higher, the median was used to fill in missing data points. In the case of skewness, the median was used because it better represented the variable than the mean, since means are not robust against skewed distributions. Responses to each item were summed to capture the respondents' scores for a measure, and each measure was analyzed as one variable.

Data Analyses

Statistical analyses were conducted using SPSS Statistics 24. After gathering descriptive statistics, independent samples *t*-tests were conducted to compare males and females on all nine variables. A multiple regression analysis was conducted to analyze the predictive ability of the eight predictors of OSV. A second multiple regression analysis was conducted for a reduced model with only five predictors. For the regression analyses, Pearson correlations were calculated for all of the variables as well as the predicted values. This was done to compute the squared structure coefficients (r_s^2). For exploratory purposes, a third multiple regression was conducted in which all cases with an OSV score of 0 were excluded. This was done to see the influence of the floor effect on the R^2 and to see how different the skewness of OSV would be.

Chapter 4: Results

Descriptive statistics were analyzed for OSV (*M* = 6.242, *SD* = 8.235), sexting (*M* = 4.276, *SD* = 5.495), online sexual solicitations (*M* = 3.189, *SD* = 4.669), online sexual interactions (*M* = 2.099, *SD* = 3.759), optimism bias (*M* = -8.794, *SD* = 15.624), human trafficking myth acceptance (*M* = 35.680, *SD* = 12.030), number of social media platforms (*M* = 3.170, *SD* = 1.482), cell phone screen time (*M* = 4.590, *SD* = 1.963), and time spent on the internet (*M* = 5.940, *SD* = 2.823). Among the sample, 62% of respondents reported having ever experience some form of OSV. OSV was statistically significantly related all the predictor variables except time spent on the internet (see Table 1).

The data was screened for homoscedasticity by examining the scatterplot of the predicted and residual values, and the assumption was adequately met, given the inherent skewness of the variable (see Figure 1). There was a slight floor effect (skewness = 1.543, kurtosis = 1.806), but that is because many respondents reported experiencing no OSV. This is a natural consequence of measuring something not everyone experiences. Either many respondents truly have not experienced OSV, or they did not report it because of social desirability bias.

Table 1

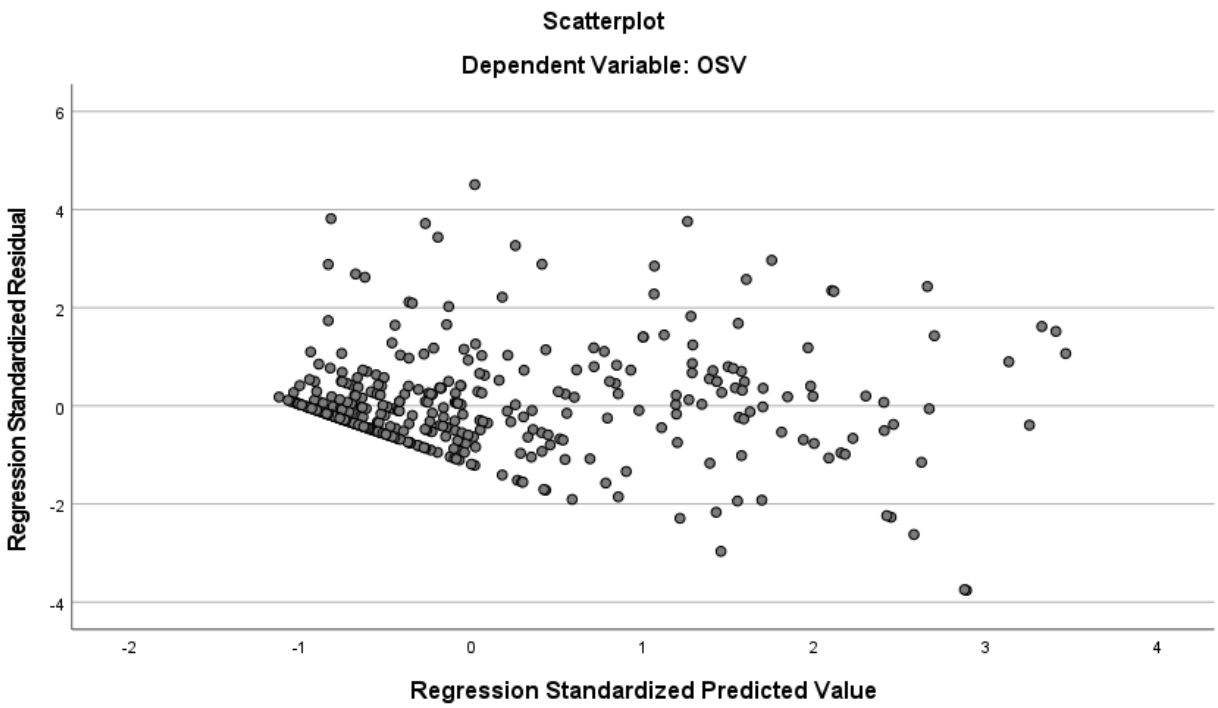
Pearson Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9
1. OSV	-								
2. Sexting	.628***	-							
3. OSS	.719***	.574***	-						
4. OSI	.622***	.597***	.722***	-					
5. OB	.171***	.171***	.222***	.212***	-				
6. HTMA	.274***	.208***	.250***	.429***	.157***	-			
7. SM	.201***	.133**	.156***	.064	.092*	-.062	-		
8. ST	.145**	.069	.156***	.114**	.159***	.250***	.173***	-	
9. IT	.029	.012	-.009	-.022	.056	-.064	.119**	.300***	-

Note. * indicates p < .05. ** indicates p < .01. *** indicates <.001. OSV: online sexual victimization. OSS: online sexual solicitations. OSI: online sexual interactions. OB: optimism bias. HTMA: human trafficking myth acceptance. SM: number of social media platforms. ST: cell phone screen time. IT: time spent on the internet.

Figure 1

Homoscedasticity Scatterplot for Full Model



T-Test for Males and Females

Independent samples *t*-test were conducted to compare males and females on OSV scores and the eight predictor variables. Table 2 presents the results for the *t*-test. Males and females were statistically significantly different in sexting, with males reporting higher levels of sexting than females. There was also a significant difference in time spent on the internet, with females reporting more time spent on the internet than males. Interactions, social media, and human trafficking myth acceptance were also statistically significant, but they did not meet the assumption of equal variances according to Levene's test. However, examining the standard deviations revealed that the variances for interactions are similar for males and females. This is also the case for number of social media platforms. For OSV, equal variances were assumed, but males and females were not statistically significantly different in their reported levels of OSV.

Table 2

T-test Results and Descriptive Statistics for Males and Females

	Male	Female			
	M(SD)	*M(SD)*	*t*	*p*	*d*
Sexting	5.33(5.81)	3.98(5.37)	-2.09	.037	-.25
Solicitations	3.54(4.73)	3.09(4.66)	-.83	.409	-.10
Interactions	3.15(4.31)	1.80(3.54)	-2.76*	.007	-.36
Optimism bias	-7.76(17.13)	-9.09(15.18)	-.72	.472	-.09
HTMA	40.87(14.33)	34.19(10.86)	-4.14*	<.001	-.57
Social media	2.68(1.76)	3.31(1.36)	3.16*	<.001	.43
Screen time	4.59(2.31)	4.59(1.86)	.02	.983	.003
Internet time	5.09(2.28)	6.18(2.92)	3.29	.001	.39
OSV	5.59(7.48)	6.43(8.44)	.87	.387	.10

Note. HTMA: human trafficking myth acceptance. OSV: online sexual victimization. Equal variances assumed using Levene's test unless marked with *. *d* = *Cohen's d*. *df* = 411.

Multiple Linear Regression Results

I conducted a multiple regression to analyze the predictive ability of sexting, solicitations, interactions, optimism bias, human trafficking myth acceptance, number of social media platforms, cellphone screen time, and time spent on the internet on OSV scores. The full model explained about 60% of the variance in OSV scores (R^2 = .603, adjusted R^2 = .595. F(8,404) = 76.625, p = <.001). The adjusted R^2 is the amount of variance in OSV explained after theoretical correction for sampling error influence. An adjusted R^2 of 59.5% is a substantially large effect size with minimal shrinkage, suggesting that not much correction was needed for sampling error (Leach & Henson, 2007).

Next, the individual predictor roles were evaluated by examining β weights, squared structure coefficients (r_s^2), and p values. β weights arbitrarily assign weight to different variables when they are correlated (Yeatts et al., 2017). The r_s^2 portrays how much of the explained variance is explained by each of the predictor variables (Courville & Thompson, 2001). See table 3 for the full results for the individual predictors. Sexting, solicitations, and number of social media platforms were statistically significant predictors in the model. Human trafficking myth acceptance and online sexual interactions were noteworthy predictors as well; human trafficking myth acceptance was not statistically significant, but it explained 12.5% of the variance in the obtained effect. Additionally, online sexual interactions had a substantially large squared structure coefficient similar to that of sexting, although it did not reach statistical significance.

While sexting and online sexual solicitations had both high β weights and squared structure coefficients, online sexual interactions had a low β weight but a large squared structure coefficient. This suggests that although online sexual interactions might have a strong bivariate correlation with OSV ($r = .622$, $p <.001$), its predictive ability in the regression can also be explained by other variables, such as sexting ($r = .597$, $p <.001$) and solicitations ($r = .722$, $p <.001$), indicating some shared variance, especially with solicitations. The low β weight of interactions suggests that although the variable has a large r_s^2, its predictive ability is also being captured by other predictors in this model.

Table 3

Multiple Regression Analysis of OSV

Predictor	β	*p*	r_s^2
Sexting	.287	<.001	.654
Solicitations	.469	<.001	.860
Interactions	.081	.117	.643
Optimism bias	-.020	.537	.049
HTMA	.072	.051	.125
Social media	.087	.008	.067
Screen time	.005	.886	.035
Internet time	.025	.446	.001

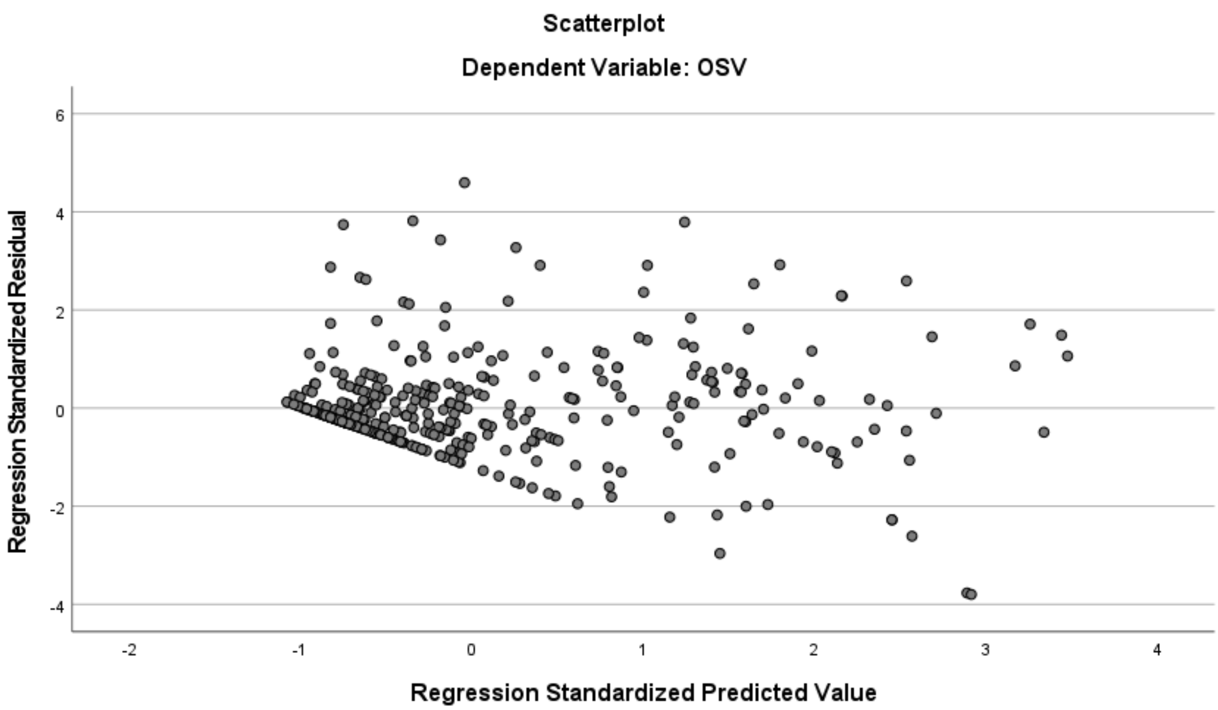
Note. HTMA: human trafficking myth acceptance. r_s^2: squared structure coefficient.

Reduced Model

Due to the strong predictive ability of some variables and the minimal effect of others, a second multiple regression was conducted with only sexting, solicitations, interactions, social media, and human trafficking myth acceptance as the predictor variables. Interactions were included in the reduced model because of the shared variance and correlation with sexting and solicitations. Because of its strong correlation with other predictors, it is quite possible that the low β weight of interactions could be due to sampling error. This is called the bouncing beta problem, in which highly correlated predictor variables in a multiple regression can have a high β weight in one sample and a low β weight in another (Vervloet et al., 2018). A slight alteration in the sample could cause one predictor to have more weight than another highly correlated predictor. It is possible that although interactions has a low β weight in the present study, a replication of this same study would produce a high β weight for interactions and a low β weight for sexting or solicitations. Similarly, although both social media and human trafficking myth acceptance have low β weights and r_s^2, they are still predictors in the model and contribute to the effect size. Social media was a statistically significant predictor in the full model, and human trafficking myth acceptance explained nearly 13% of the variance in the obtained effect. Therefore, after analyzing their β weights, r_s^2, and p values, I decided to include them in the reduced model. The assumption for homoscedasticity was adequately met again, and it had a similar floor effect to the first model for the same reasons (see Figure 2).

Figure 2

Homoscedasticity Scatterplot for Reduced Model



The reduced model also explained about 60% of the variance in OSV scores (R^2 = .602, adjusted R^2 = .597. F(5,407) = 122.977, p = <.001), with the reduced model effect size being only 0.1% smaller than the full model effect size. It should also be noted that the adjusted R^2 for both the reduced model is .597, suggesting that after theoretical correction for sampling error influence, the effect size of the reduced model is larger than that of the full model. Sexting (β = .286, p = <.001, r_s^2 = .654), solicitations (β = .466, p = <.001, r_s^2 = .859), social media (β = .089, p = .006, r_s^2 = .067), and human trafficking myth acceptance (β = .070, p = .047, r_s^2 = .125) were statistically significant predictors in the model. Interactions (β = .080, p = .122, r_s^2 = .643) was not statistically significant, but it explained 64% of the variance in the obtained effect. Sexting, solicitations, and interactions were the strongest predictors again based on r_s^2, but the medium-level contributors were also important in explaining the obtained effect.

Full Model Excluding OSV Scores of 0

To see whether the floor effect and skewness of my dependent variable impacted the multiple regression, a third multiple regression was conducted including all the predictor values; however, any case with an OSV score of 0 was excluded. This alteration made the skewness and kurtosis more normal (skewness = 1.110, kurtosis = .620) and lowered the sample size from 413 to 257. This model was also statistically significant and explained about 50% of the variance in OSV. This effect size is still substantial, and the β weights and r_s^2 were very comparable to the first model. The results from this adjusted model suggest that the floor effect of OSV did not negatively influence the full or reduced models.

Chapter 5: Discussion

The current study aimed to determine what are the variables that best predict OSV, among optimism bias, human trafficking myth acceptance, sexting, online sexual solicitations, online sexual interactions, daily internet use, daily cell phone screen time, and number of social media platforms. Specifically, I hypothesized that females would report more sexting and OSV compared to males (hypothesis 1), my proposed model would statistically significantly predict levels of OSV (hypothesis 2), and sexting would be the best predictor of OSV (hypothesis 3). I ran a multiple linear regression to assess the predictive ability of these variables on levels of OSV experience. In addition, I also conducted *t*-tests to compare males and females on the nine variables and to determine whether there were significant gender differences in any of them. This study was an exploratory and innovative study, as no research has been conducted that is similar to this, using this methodology and data analysis. This research expands the current scientific understanding of OSV and its correlates. This study contributes to previous research that proposes sexting as a predictor of OSV by revealing a number of new predictors, including solicitations, interactions, human trafficking myth acceptance, and number of social media platforms (Gámez-Gaudix et al., 2015). These predictors have not been studied in this way until now and will provide a foundation for future research on OSV correlates and prevention.

While much research has been done on the predictor variables included in this study, no study before this included all of them into a unified model designed to predict levels of OSV. Every variable had theoretical and research-based backing as to why they were included in the analyses. In addition to the overall trends of increased internet and cell phone usage, previous research on sexting behaviors shows that sexting statistically significantly increases risk for experiencing OSV (Pew Research Center, 2019; De' et al., 2020; Gámez-Gaudix et al., 2015). Similarly, previous research shows that there is a bidirectional predictive relationship between sexting and online sexual solicitations, suggesting that solicitations would also be a strong predictor of OSV (Gámez-Gaudix & Mateos-Pérez, 2019). Online sexual interactions are an extension of online sexual solicitations, with the exception that interactions require a response from the participant (de Santisteban & Gámez-Gaudix, 2018). Research on optimism bias regarding experiencing a sexual crime suggests that those who display higher levels of optimism bias might be more at risk for online victimization, specifically OSV in this study, making it an important contributor to consider for my model (Rinehart et al., 2018; Yeater et al., 2020). Furthermore, believing myths about sexual crimes is associated with sexual coercion, highlighting the role of human trafficking myth acceptance in experiencing OSV (Trottier et al., 2021; Cunningham & Cromer, 2016). The previous research on social media use also suggests that this plays a role, with past findings suggesting more social media use is associated with worse outcomes (Vannucci & Ohannessian, 2019). The drastically high and increasing rates of cell phone and internet use also make it a theoretically contributor to OSV (Perrin & Kumar, 2019; Pew Research Center, 2019).

There are research-based reasons for each of these variables to be considered and included in my regression model. However, it should be noted that this study is exploratory by nature; no study has yet to do anything similar to this. This is partially due to the fact that OSV is a relatively new phenomenon that is being studied, and the OSV scale by Gámez-Guadix et al. was developed in 2015. This scale is the first to measure OSV according to the operational definition provided earlier. Because of the relative novelty of OSV research, I gathered the predictors to include in this model from a thorough review of the literature. Aside from sexting as a predictor of OSV, I did not formulate specific hypotheses about any of the other predictors in the regression model.

Findings from the *T*-Tests

In order to determine whether there were any gender differences in OSV and its predictors, I conducted *t*-tests for males and females. Previous research suggests gender differences in social media usage, sexting, solicitations, and OSV (Vannucci & Ohannessian, 2019; Mitchell et al., 2012; de Santisteban & Gámez-Gaudix, 2018; Gámez-Gaudix et al., 2015). In the current study, I hypothesized that females would report higher sexting and OSV scores than males. Contrary to my prediction, males reported more sexting than females. Additionally, although there was a mean difference between males and females for OSV, equal variances were not assumed. Therefore, one cannot confidently say that there is a statistically significant difference between males and females in OSV. Hypothesis 1 was not supported.

The finding that males reported more sexting than females was interesting. This seems to contradict previous research that found that females are more likely to appear in sexts than males and that there are no gender differences in participating in sexting (Mitchell et al., 2012; Reyns et al., 2011). However, sexting in Mitchell et al.'s (2012) study did not include written sexual content. There are some potential explanations for this finding in the current study. One explanation could be due to the items included in the sexting scale. Half of the items measured sending sexual photos or videos to someone, while the other half measured sending sexual written information. This could be due to differences in how males and females sext. While previous research suggests gender differences in sending sexts, with males being more likely to send a sext to a friend or acquaintance than females, there has not been research on the differences in how males and females sext (e.g., written information, photos, videos, etc.; Gámez-Gaudix et al., 2015). Future research should seek to determine differences in the sexual content that is sent. Social desirability bias could also play a role in this unexpected result. Social desirability bias is the tendency for respondents to answer questions in a way to put them in the best light possible. This type of bias is present even in completely anonymous surveys, as mine was, especially when a topic as sensitive as sexting is being measured. This lines up with de Santisteban and Gámez-Gaudix (2018) claim that females have a tendency to deny sexual encounters while males are more likely to be open about them. There are ways to reduce the probability of social desirability bias being present in a study, but most of those ways require someone to be interviewing the respondent in person (Grimm, 2010). The survey for this study was completed online, so in-person strategies were not feasible. This is a limitation that should be considered when interpreting the *t*-test results for sexting.

Next, there is a mean difference of 0.84 between males and females in OSV scores, with the mean of males being 5.59 and the mean of females being 6.43. However, equal variances were not assumed. This means that the standard deviations for males and females on OSV scores were not similar enough to determine if the mean difference comes from males and females actually demonstrating a statistically significant mean difference or from the different variability in the scores. If the standard deviations are very different, there could be enough overlap in the scores to fail to meet statistical significance, even if the means are quite different. Because of this, one cannot say with confidence that males and females are different in levels of OSV, although previous research suggests that OSV is more common in women (Gámez-Gaudix et al., 2015).

Findings from the Regression Analysis

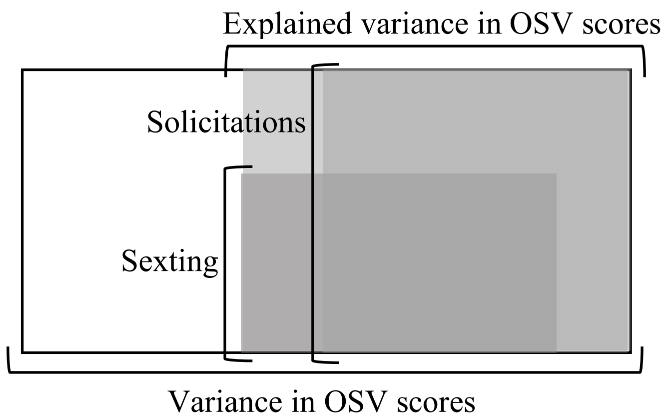
Consistent with what was expected, the regression model was statistically significant in explaining the variance in OSV scores. Therefore, hypothesis 2 is supported, and I reject the null hypothesis that the model would not predict OSV. The full model explained about 60% of the variance in OSV scores, which is a substantially large effect size. This is no surprise, as previous research suggests that the included predictors might play a role in explaining OSV levels (Gámez-Gaudix et al., 2015; Gámez-Gaudix & Mateos-Pérez, 2019; de Santisteban & Gámez-Gaudix, 2018; Rinehart et al., 2018; Yeater et al., 2020; Trottier et al., 2021; Cunningham & Cromer, 2016; Vannucci & Ohannessian, 2019). The adjusted effect size (adjusted R^2) was 59.5%, meaning that after correcting for bias and error in the sample that is not representative of the population as a whole, my effect size was still around 60% (Leach & Henson, 2007). The adjusted R^2 provides theoretical insight into the generalizability and replicability of the result; the more shrinkage there is from the standard effect size to the adjusted effect size, the more that it had to be corrected due to potential sampling error bias. The adjusted R^2 is a good estimate of what one could expect if this study were replicated with another sample (Leach & Henson, 2007).

Analysis of the Individual Predictors

Among all the predictors, online sexual solicitations and sexting were the best predictors, respectively. Online sexual solicitations explained 86% of the variance explained, and sexting explained 65% of the variance explained. In other words, out of the 60% of variance in OSV that the full model predicted, 86% of that was predicted by solicitations and 65% was predicted by sexting. The present finding about sexting supports research by Gámez-Gaudix et al. (2015), which found that increased sexting is associated with increased odds of OSV. Therefore, hypothesis 3, in which I predicted that sexting would be the best predictor of OSV, is not supported. Although it seems like solicitations and sexting alone predict over 100% of the obtained effect, this is not the case, because some of the predictive ability of each predictor overlaps with the others. In other words, although solicitations explains 86% of the obtained effect, some of the 65% that is explained by sexting must predict some of the same variance as solicitations. See figure 3 for a theoretical visual representation.

Figure 3

Visual Representation of the Variance Explained by Solicitations and Sexting



Note. This figure is theoretical, not literal.

If the full box is all the variance in OSV scores, then the entire shaded area is what is explained by the regression model. Solicitations, which explains 86% of what the model can predict, is the larger shaded area, and sexting, which explained 65% of what the model can predict, is the lower shaded rectangle. Although they both individually predict a large amount of variance, some of their variance explained overlaps with each other. This is why it is important to look at the β weights for each predictor. Solicitations has a heavier β weight than sexting, allowing me to come to the conclusion that solicitations is given more credit in explaining variance in the model and explains some of the same variance that the other variables also explain, namely sexting (Yeatts et al., 2017).

As defined earlier, online sexual solicitations are requests from another adult for personal sexual content or conversation (Gámez-Gaudix, 2018). It was unanticipated that this would be the strongest predictor of OSV in the regression model. There are a few potential reasons for solicitations to predict the most variance in the effect. Firstly, considering the definition of OSV according to the scale I used, which is 1) experiencing unwanted online sexual exchanges and/or 2) receiving threats to disseminate private sexual content and/or 3) being pressured/insisted to send private sexual content, it makes sense why solicitations would be a strong predictor of OSV (Gámez-Gaudix et al., 2015). Being pressured to send content of a sexual nature appears to be similar in concept to solicitations, which is essentially the same thing but without the insistence aspect (Gámez-Gaudix, 2018). Secondly, solicitations can by a gateway to OSV; if an individual asks for sexual content and the person on the other hand responds accordingly, that private sexual content can be taken advantage of by the perpetrator and used against the other person in ways that match the definition of OSV (e.g. "Someone has disseminated or uploaded to the Internet photos or videos of you with erotic or sexual content without your consent" (Gámez-Gaudix et al., 2015, p. 150). The dissemination items in the OSV scale are not possible without the perpetrator being in possession of private sexual content that the victim does not want to be revealed, and soliciting victims is a way through which perpetrators can receive this content. Thirdly, a reason why solicitations could have been such a strong predictor is its high multicollinearity with other variables, namely sexting and online sexual interactions. This concept will be discussed next with regard to online sexual interactions as a predictor that explained a large amount of variance in the effect and yet was given almost no weight in the regression model.

The finding that online sexual interactions explained a large amount of variance in the obtained effect (64%) and yet had a low β weight (.08) was both unexpected and interesting. In figure 3, I visually depicted how it is possible for sexting to have a high r_s^2 and a low β weight relative to the r_s^2. Based on the β weight and r_s^2 of interactions, my research-informed explanation is that a similar phenomenon happened with interactions, except the predictive ability of interactions was almost completely capture by other variables as well, most likely solicitations and sexting. This occurrence is not rare in research, and it occurs primarily when there is high multicollinearity, or bivariate correlation, between the variable at hand and other variables in the model (Kraha et al., 2012). Although this can provide some complications in interpreting multiple regression results, it is not a concerning problem in my model. My correlation matrix provided in table 1 reveals high bivariate correlations between online sexual interactions and online sexual solicitations and online sexual interactions and sexting. This suggests that these variables might explain some shared variance with each other. When this is the case, it is crucial to analyze both the β weights and r_s^2 to understand the credit given to the variable in explaining unique variance and the total area of variance that is explained by the predictor, respectively (Kraha et al., 2012). Multicollinearity lends to a phenomenon called the bouncing beta problem, which was briefly mentioned earlier (Kiers & Smilde, 2007). The bouncing beta problem helps explain what is happening when variables that share variance have high r_s^2 and low β weights. While my study found that solicitations had the highest β weight, a replication of this study with a slightly different sample might find that sexting or interactions has the highest β weight, and simultaneously the β weight for solicitations would drop. This occurs through differences in the sample, or sampling error bias. This is not necessarily a "problem," per say; looking at the r_s^2 of interactions, I can say with confidence that the predictor explained just as much variance in the effect as sexting – 64% and 65%, respectively. The lack of statistical significance simply reflects the fact that the explained variance was also encapsulated by other predictors. Hence, although online sexual interactions was given a low weight potentially due to sampling error and the high bivariate correlations with other strong predictors, it is still an important predictor of OSV levels.

Human trafficking myth acceptance and the number of social media platforms that one owns and uses regularly are also contributors in explaining variance in the model. Refer to table 2 for the β weights and r_s^2. Although both predictors had low β weights and r_s^2, they still predicted variance in the effect. That is, although they did not have a large effect, their contributions were not nothing. Considering the lack of research of human trafficking myth acceptance and OSV, it is beneficial to the scientific community to see that human trafficking myth acceptance both explains some variance in OSV and has a bivariate correlation with OSV. Although it did not meet statistical significance requirements, human trafficking myth acceptance explained 12.5% of the variance in the obtained effect. The correlation results suggest that there is not much shared variance between myth acceptance and the other predictors, but nonetheless it would be interesting to continue to research the relationship between attitudes/beliefs about human trafficking and the clear, measurable outcome of experiencing OSV. This would contribute to the growing pool of research on the behavioral outcomes of myth acceptance (Cunningham & Cromer, 2016; Trottier et al., 2021).

Similarly, although social media only explained approximately 7% of the variance in the effect, it was statistically significant. This finding goes well with Vannucci and Ohannessian's (2019) findings that lower social media use was associated with less delinquent behaviors. Again, this can be partially explained by the predictive ability being also explained by other, stronger variables, such as solicitations, sexting, which were given the most credit in the model. The small structure coefficient of social media could be attributable to the fact that OSV does not need to happen on social media. It can happen via text or email, as well. In addition, even if an individual has one social media platform that they use regularly, that is all that is needed for a perpetrator to reach out to a victim and threaten or coerce them through the ways delineated in the OSV scale. Further, the item in my survey measuring social media use did not define what is meant by “regular use”; therefore, while one respondent might interpret regular use as three or more hours a day, another respondent might interpret regular use as 15 minutes a day. This is a limitation of the study and should be considered when analyzing the predictors in my regression model.

Optimism bias, daily cell phone screen time, and daily time spent on the internet were not useful in predicting OSV scores. Since they were included in the model, these variables are still given credit in explaining variance, although it is quite close to zero. Although the optimism bias scale measured a wide variety of negative and positive events, it did not assess anything related to online victimization of any sort, whether that be cyberbullying or OSV (Lapsley & Hill, 2010). A high daily cell phone screen time and time spent on the internet are not necessarily related to OSV as well, as a perpetrator may not require the victim to spend large amounts of time on their phone/the internet. Perhaps the overall increase in technology use partially due to the COVID-19 pandemic can help explain why these variables were not predictive of OSV (De’ et al., 2020; Perrin & Kumar, 2019). If there has been an overall society-wide increase in technology use, then OSV experiences would increase as well across society. Therefore, other variables are necessary in explaining variance in OSV, as potentially increasing OSV levels are reflected in increasing technology usage.

Findings from the Reduced Model

My reduced model included only sexting, online sexual solicitations, online sexual interactions, human trafficking myth acceptance, and social media. These are the predictors that I considered to be important enough to include in the reduced model, and I determined this by analyzing *p* values, β weights, and r_s^2. The reduced model also explained about 60% of the variance in OSV scores, lending more credit to my suggestion that optimism bias, cell phone screen time, and time spent on the internet were not important predictors of OSV in my model. Interestingly, the adjusted effect size of the reduced model was larger than the adjusted effect size for the full model, suggesting that after taking sampling error into consideration, the reduced model explained more variance in OSV scores than the full model. This could partially be due to the fact that the more predictors a model has, the more likely that the sample will not be representative of the population, because with each new variable that one measures comes a higher chance of encountering error not synchronous with that of the population. Therefore, when predicting OSV, it might be more beneficial to develop smaller predictor models to make the findings as generalizable and replicable as possible. This study was exploratory by nature, so it was important to look at a sizable number of predictor variables and see which ones predict OSV levels most accurately.

Implications

The findings of the current study have implications for lowering the prevalence of OSV and preventing it from occurring. Through this, the negative outcomes associated with OSV can potentially be reduced as well, and these outcomes include depression, loneliness, anxiety, and low satisfaction with life (Fest et al., 2019). It is important to lower rates of OSV because in the current, 62% of respondents reported having ever experienced OSV, highlighting the immediate need for preventative efforts, especially with the trend of increasing technology usage (Perrin & Kumar, 2019; Pew Research Center, 2019; Common Sense Media, 2019).

Based on the model used in this study, a strategic way to reduce and prevent OSV and potentially its associated adverse outcomes would be to target its strongest predictors, namely online sexual solicitations and sexting. Research on solicitations suggests that reducing time spent online is associated with a decrease in being solicited online (de Santisteban & Gámez-Gaudix, 2018). Theoretically, it makes sense for solicitations to decrease as time spent online decreases. However, my study did not find a bivariate correlation between daily average time spent online and online sexual solicitations. This could be due to sampling error, but it should be researched further. Additionally, the question measuring daily time spent on the internet asked respondents to give their best estimate as to how much time they spend online, since one cannot fully know how long they are online each day unless they are tracking all of their digital devices. Another way to lower one's chances of experiencing online solicitations is to keep social networking accounts on a private setting. Although solicitations can occur with someone that is known, keeping one's accounts private can at least help prevent strangers from soliciting for sexual content. Decreasing time spent online and preventing strangers from accessing one's social media profiles are concrete ways to lower the likelihood that one will be solicited on the internet and, secondarily, help prevent OSV.

As for sexting, Gámez-Gaudix and Mateos-Pérez (2019) found a bidirectional relationship between sexting and online sexual solicitations, meaning that as sexting decreases, solicitations tend to decrease, and vice versa. Making effort towards reducing and preventing sexting, therefore, can consequentially contribute to decreased online sexual solicitation rates and OSV. It would be beneficial for schools to educate students on sexting, specifically what it is and why it is dangerous. Education about OSV is crucial in this as well, as an understanding of OSV and its dangers can be a motivating factor for students to not sext. Information about sexting and OSV could easily be incorporated into the standard sex education curriculum. Although schools are an important target for these education initiatives, sexting education should not be limited to schools; clubs, non-profits, community awareness initiatives are all great options in raising awareness about sexting and how it can be a gateway to experiencing OSV.

The findings of this study also have implications for human trafficking awareness. Human trafficking myth acceptance contributed a portion of the explained variance in the model, suggesting that higher myth acceptance partially predicted experiencing more OSV. Although the effect size of its predictive ability was not large, it existed, nonetheless. Therefore, human trafficking awareness initiatives are a way through which OSV prevention and reduction can occur. Teaching specifically about online sexual exploitation as well would be beneficial, as it is a concept similar in nature to OSV (Say et al., 2015; ECPAT, 2020).

Another concrete way to help reduce and prevent OSV is for individuals to avoid sexually interacting with others online. Online sexual interactions predicted a large amount of explained variance in the model, although it was not given a heavy β weight. Individuals should pay special attention to who they are interacting with online and should make an effort to only share interactions with trustworthy people. When it comes to exchanges of a sexual nature, online interactions should be avoided with anyone, because of the risks related to putting sexual content on the internet.

As mentioned previously, OSV is associated with a number of negative outcomes, including negative mental health outcomes (Festl et al., 2019). A likely consequence of efforts to prevent and reduce OSV is a decrease in its associated adverse outcomes. The prior implications mentioned will hopefully not only have an impact on OSV rates, but they might also prevent outcomes like depression and anxiety (Festl et al., 2019). However, the direction of this relationship between mental health outcomes and OSV has not been determined, so one cannot say whether lowering OSV will also lower its associated adverse outcomes.

Limitations and Future Directions

Since the current study utilized an online survey, there are limitations concerning the self-report nature of this project. First, there is always the potential for social desirability bias. Especially with topics as sensitive as OSV and sexting, it is likely that there was at least some element of this type of bias, with respondents answering the items in such a way to put them in the best light possible. Although the anonymity of my survey likely made this type of bias less extreme, people still have a tendency to want to make themselves look as good as possible, even if it is just to themselves (Grimm, 2010). It was beyond the scope of this study to measure these variables in such a way to prevent social desirability bias, but future research should aim towards taking more objective, behavior-based measurements of these phenomena. Secondly, there is the possibility that respondents had recall bias, as the items in my survey measured lifetime experience of the variables. If something happened a long period of time ago, it is possible that they could have forgotten whether something – like victimization, for example – happened twice or three times. Future research should provide a timeframe through which to answer the items, lowering the potential impact of recall bias.

While there are objective ways to measure internet usage, it was beyond the scope of the present study to use measures that were not self-report. The item measuring internet use asked participants to estimate their internet usage, and respondents could have been either dishonest or simply inaccurate when reporting their daily average time spent on the internet. This could explain why internet use in the current study was not statistically significantly correlated with any of the other variables except social media and cell phone screen time. The same limitation goes for cell phone screen time, although the item measuring screen time encourages respondents to refer to the screen time settings in their smart phones to see the actual number of hours spent on screen time each day. In addition, the item measuring internet time did not ask respondents to differentiate between being on the internet for the purposes of social media, school entertainment, etc. Since the current sample was college students, respondents could have reported high internet usage and little to no OSV due to being online for the sole purpose of doing schoolwork. Future research should utilize objective information about internet use and screen time, such as having a third party keep track of participants internet use for a short period of time. A simpler but less objective way would be to have participants keep a log of their internet use and screen time for a period of time prior to taking the survey on OSV.

Another limitation is sampling error. The current study sampled college students from one university in the southeastern region of the United States. The findings from this sample may not be generalizable to people outside of this culture. This is a problem that occurs when any one group, or university, is used for a study. This is not the only problem, however; the current sample was a convenience sample. Random selection was beyond the scope of this study, especially if I were to get a sample size large enough to have substantial statistical power. Because of this convenience sampling, the participants who chose to participate in this study might be systematically different from those who did not choose to participate in the study. Therefore, the findings may not be generalizable beyond the convenience sample. Future research should utilize random selection in order to best represent the population. This will prevent the limitations associated to convenience sampling and also provide participants from more than just one group/university.

Another limitation that was encountered during the data analysis portion of the current study was the floor effect seen in the dependent variable. An assumption of multiple linear regression is that the variables are distributed normally, or, in other words, they are assumption homoscedastic (Osborne & Waters, 2002). Normal distribution is crucial for a robust multiple linear regression, because if there is an extreme skew and/or kurtosis in the variable, then one could argue that the explanatory ability of the predictors falls only within the skewed area and is not capable of explaining the scores on the positive or negative end. In the current study, OSV was positively skewed, meaning that the majority of the OSV scores were within the lower range of the scale. When looking at the results, one could suggest that perhaps the regression model only predicts the lower OSV scores that fall within the majority of the distribution. This argument is legitimate, and if this were to be true, then the model of the current study would not be able to actually predict OSV scores. However, as mentioned earlier, another multiple regression analysis was conducted, excluding all OSV scores of zero. This reduced the skewness of the distribution. The results were quite similar to the full model, except the adjusted model explained approximately 50% of the variance in OSV scores instead of 60%. One would except the effect size to go up with the floor effect being reduced, but it is important to keep in mind that the sample size was reduced substantially when cases with OSV scores of zero were excluded. Although the finding that the full model's effect size is larger than the reduced model's effect size is positive for the sake of my study, the floor effect due to the nature of OSV is a limitation that should be addressed more in future research. Researchers should consider excluding all participants with OSV scores of zero and to reduce this limitation. This will provide more insight into the predictability ability of the independent variables of interest.

There are data transformation strategies to reduce floor effects and variable skewness. The most common ways to do this are to use the inverse, square root, or logarithm of the scores (Osborne & Waters, 2002). Using these transformations would spread the data out to a more normal distribution, making it more well-suited for a multiple regression analysis in which the purpose of the study is pure prediction. While this might be of benefit to certain studies depending on the purpose and research question, it would not have made sense for the current study to employ these strategies. The purpose of the present study was to analyze the predictor variables and determine which ones best predict OSV, not the logarithm or square root of OSV. Transforming the data may have provided a larger R^2, but it would defeat the purpose of the study. Future researchers studying OSV should keep the aims of the study in mind as they are deciding whether to transform the data. It would also be beneficial for future research to determine ways to predict OSV without the limitation of variable skewness, such as the ways mentioned just previously.

Additionally, this study only focused on sexting, online sexual solicitations, online sexual interactions, optimism bias, human trafficking myth acceptance, daily internet use, daily cell phone screen time, and number of social media platforms in regard to predicting OSV. However, these are not the only variables that may play a role in predicting victimization. Two variables of importance that this study did not analyze are pornography usage and body image. These two variables have been established in the literature as constructs that are not only related to but also tightly intertwined with OSV (Holt et al., 2016; Powell & Henry, 2019; Longobardi et al., 2021; Tamarit et al., 2021; Salazar, 2021). While including these variables in this study would have provided more insight into predicting OSV, it also would have caused numerous ethical complications that were beyond the scope of this study. Furthermore, pornography usage and body image are substantial constructs that would have drawn attention away from the other significant findings that were revealed from the present regression model. Future research should replicate this study and include pornography usage and body image as predictors.

The present study is the first to analyze the abilities of sexting, online sexual solicitations, online sexual interactions, optimism bias, human trafficking myth acceptance, daily internet use, daily cell phone screen time, and number of social media platforms to predict levels of online sexual victimization; hence, the current research design was exploratory by nature. This research fills in a gap in the scientific community's current understanding of OSV and its predictors, but there is much research to be done on predictors of OSV. Specifically, some of the present findings point to the potential for moderating and mediating variables. Future research efforts should be put towards analyzing each of the individual predictors to better understand their relationships with OSV and to determine the direction of these relationships. Doing so will contribute to implications for schools, non-profits, and other organizations to reduce and prevent OSV in their communities.

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