Cybercrime and Strain Theory: An Examination of Online Crime and Gender

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Abstract: *Purpose*: Historically, cybercrime has been seen as a near exclusively male activity. We were interested to learn whether the relationship between strain and crime holds for both males and females.

Methods: We utilized an online survey instrument to collect data from a national sample of individuals (n=2,121) representing the US population by age, gender, race and ethnicity. We asked offending related questions regarding various cybercrimes. In the current study, we use data from 390 individuals who reported a cybercrime activity within the past 12 months.

Results: We find strong support for prior strains correlating with both specific (e.g., illegal uploading) and general cyber-offending. We further examine whether gender interacts with strain. While general strain theory (GST) correlates with cyber-offending for both males and females, we did find a few important differences. Except for lack of trust in others and receiving unsatisfactory evaluation at school or work, there are different variables responsible for online offending for men and women. Parents' divorcing, anonymity, and online video gaming increase cybercrime offending in women, whereas falling victim to a crime, breaking up with a significant other, and darkweb activity are correlated with cyber-offending for men.

Conclusion: Although GST functions differently by gender when it comes to engaging in cyber-offending, the theory is indeed gender-specific, as different strain variables are responsible for engaging in cyber-offending in women and men. Components of general strain responsible for cyber-offending need to be further studied concerning gender. According to our results, GST is gender-specific, and these variables need to be further studied.

Keywords: Strain, general strain theory, gender, women, cybercrime, cyber offending.

INTRODUCTION

The world is becoming increasingly connected by technology, with more devices connected to the internet every day (Barnett *et al*., 2018). Accompanying this increase in technology is the crime committed online. These new connections are creating opportunities for crimes such as hacking, online fraud, identity theft, spamming, and cyberbullying (Ngo and Jaishankar, 2017). Crimes committed online, often referred to as cybercrime can be classified in two ways. Crimes that existed prior to the internet but the online space has provided a new medium (e.g., illegal drug trafficking) or new crimes that were not possible before the internet (e.g., spreading malware) (Wall, 2010). Given the expansion in crimes committed online it becomes increasingly important to consider the motivations and patterns of online offenders and victims.

Criminologists are now examining whether traditional crime theory is applicable in explaining cybercrime. Studies have examined a myriad of theories and computer crimes. The most frequently discussed are routine activities (Bossler and Holt, 2009; Holt and Bossler, 2009; Reyns, 2013) and self-control (Donner *et al*., 2014; Reyns *et al*., 2019). Yet a call has been made to examine other theories that may explain cybercrime (Holt and Bossler, 2014). This call is beginning to be answered with other theories being considered, including social learning theory (Hawdon *et al*., 2019; Holt *et al*., 2010) and general strain theory (GST) (Patchin and Hinduja, 2011).

Cybercrime prevention largely includes cybersecurity measures, including better firewalls and intrusion protection (Bondoc and Malawit, 2020, p. 16). This is consistent with policy recommendations from theories such as routine activities, where a motivated offender is omnipresent. However, this approach to cybercrime prevention oversimplifies cybercrime by only focusing on making it difficult for offenders, neglecting the varied patterns and motivations behind cyber-attacks revealed by decades of criminology research. A more effective strategy requires a nuanced understanding of cyber offenders for comprehensive cybercrime reduction. This includes a better understanding of the situations and contexts that lead to cybercrime. Our paper begins to address this issue by examining whether strain predicts a series of cybercrimes.

Current research on GST and cybercrime largely examines strain and cyberbullying (e.g., Hay *et al.,*

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E-ISSN: 1929-4409/24

2010; Lianos and McGrath, 2018; Patchin and Hinduja, 2011), especially among juveniles. A broad examination of the impacts of strain on a variety of cybercrime is needed to see the applicability of GST on cybercrime generally. This study seeks to examine strain using a sample of adults using various cybercrimes. In addition, consistent with future recommendations on strain research (Robbers, 2004) we examine gender separately to see the differential impact of strain on crime.

Our study continues this call by considering the applicability of GST to cybercrimes. We include a variety of self-reported cyber-offending behaviors. To further explore this relationship, we also consider gender differences in cyber-offending. Our research aims to examine whether GST generally explains cybercrime and how gender differentially impacts this relationship. Our results show that GST can partially explain a variety of cybercrimes. Surprisingly, certain non-violent cybercrime behaviors, such as illegal software distribution, and illegal downloading, were better explained by overall GST measures than more interpersonal cybercrimes. Further, certain specific strains and emotions (i.e., anger) better explain more interpersonal cybercrimes.

Cybercrime and General Strain Theory

The earlier strain theories suggested that crime was a result of the gap between aspirations and results (Merton, 1938). Agnew's revision, termed GST, creates a readily testable framework by considering strain to stem from three sources, failure to achieve positively valued goals, loss of positive-valued stimuli and presentation of negative stimuli. These additions broaden the number of strains considered by Merton. It is also important to note that Agnew suggested that the strains themselves did not lead directly to crime but were mediated by negative emotions such as frustration and anger (Agnew, 1992). Both full and partial mediation models have been supported empirically (e.g., Rebellion *et al*., 2012 for full mediation and Moon and Jang, 2014 for partial mediation). In many situations, a strain may lead an individual to take corrective actions or reframe the strain in a prosocial way. As such, strains do not always lead to crime (Agnew, 1992).

Empirical tests of strain have largely supported GST (Akers and Sellers, 2009; Agnew, 2006; Eitle, 2010). However, studies have failed to find the conditioning effects such as coping skills and resources, social support, self-control and social control, opportunities for legitimate coping, temperament and personality traits, and exposure to criminal subcultures, hypothesized by GST (see Paternoster and Mazerolle, 1994; Hoffman and Miller, 1998; Mazerolle and Piquero, 1998; Hoffman and Cerbone, 1999).

More recent refinements have allowed researchers to focus on strains that are more closely associated with crime. These include victimization, parental rejection, bullying, and discrimination (e.g., Agnew *et al*., 2002; Craig *et al*., 2017; Hay and Evans, 2006).

The literature on GST and cybercrime is scarce. Recent theoretical work has begun to consider the importance of this theory as it relates to cybercrime (e.g., Hay and Ray, 2020). This work suggests that more violent or interpersonal cybercrimes are more likely to relate to strains. These include cyberbullying, cyber dating abuse, cyberhate and cyberterrorism. A few studies have examined cyberbullying's relationship with general strain theory. Patchin and Hinduja (2011) argue that both bullying and cyberbullying have strong theoretical ties to GST. Juveniles who are experiencing negative emotions due to strains may try to alleviate these negative emotions by lashing out. This lashing-out behavior may be bullying, either in-person or virtual. Strains were measured by asking about negative experiences, including breaking up with boyfriend/girlfriend, receiving a bad grade, and being the victim of a crime. They found a strong relationship between GST and both bullying and cyberbullying behaviors of juveniles.

Hay and Mann (2010) examined cyberbullying victimization, GST, and gender. As males and females have different responses to anger, it may be important to consider the differential relationship between strain and crime moderated by gender. This is empirically validated as well, as male crime appears to be more explained by GST than female crime (Baron, 2004; Baron, 2007; Hay, 2003). In terms of cyberbullying victimization, differences in externalizing behaviors were found between males and females (Hay and Mann, 2010).

Gender and Strain

Broidy and Agnew (1997) tested Agnew's GST in connection with gender and crime. With respect to why male criminality exceeds female criminality, they suggested that genders experience different types of strain, and genders' reactions to similar strains can be different as well. Female criminality is mostly explained by a complexity of circumstances, with social and systemic oppression as a significant moderator of female criminality.

Other studies examined the moderating effect of social support, such as family and religion, on individuals' responses to strain, and whether these effects vary by gender. Robbers (2004) analyzed data from the National Youth Survey to test these effects and found support for GST suggesting that there are gender-based differences in the types and levels of strain experienced in late teen years. According to the findings, getting support from friends and family moderates the responses of females; when females experience certain strains, a high level of social support decreases the likelihood of delinquency. In the meantime, women's exposure to negative stimuli significantly increases the propensity to engage in delinquent acts. Negative stimuli did not increase the likelihood of delinquency in men. Feminist theory also supports that negative social stimuli, such as gender-based discrimination tend to expose women to negative societal acts (Ogle *et al.,* 1995). Examples include bias in the workplace and domestic violence.

Broidy (2006) examined the interceding role of negative emotions and noncriminal coping strategies and found that emotional responses to strain are conditioned by gender. Although the mean level of anger was similar in men and women, other negative emotions were more common among women than men. However, Broidy calls for attention to the fact that besides gender differences in the level of strain and negative emotions would not be enough to explain differences in female and male criminal activity. Instead, research into qualitative sex differences is needed to find out how negative emotions contribute to certain types of strain, and how coping mechanisms can mitigate strain.

Further examining gender, strain and criminality, Jang (2007) compared the strains and the coping mechanisms of African Americans in a national survey. This study found that women were more likely to experience strains in connection to physical health, social relationships, and gender-related expectations in the home but less likely to experience racial discrimination and work-related stress than men. Women were also more likely to exhibit auto-aggression (i.e., self-harm) as a result of strain compared to men, who were more likely to generate hetero-aggression (i.e., aggression toward others), and within that, criminal activity as coping mechanism to strain. In contrast, strain-generated auto-aggressive tendencies of women are more likely to result in non-deviant, non-criminal coping mechanisms than men's hetero-aggressive tendencies. This research shows that strains can be mitigated in several ways. Social support appears to be one mechanism for reducing the impact of strain (Robbers, 2004). If these mitigating factors are not in place, then other options including self-harm or offending can occur (Jang, 2007).

Taken together, these studies consistently show that gender differences affect the experiences and outcomes of strain. What is less clear is exactly what these differences entail. For example, some research suggests that women experience more strain in certain categories, such as physical health, social relationships, gender expectations (Jang, 2007) and gender-based discrimination (Ogle *et al.,* 1995. GST has also been examined to see if strain can explain the differences in crime rates between males and females. Although it appears that strain can still have an impact on women committing crimes, key moderators, such as social support, mitigate the relationship between strain and crime for women (Ogle *et al.,* 1995). Although more work remains to be done, the relationship between strain and crime is different for males and females.

Cybercrime and Gender

Research posits that computer crimes were historically and stereotypically gendered, with "hackers" being identified as young males (Alper, 2014; Thomas, 2022). Yet recent evidence suggests that females are also involved in online crime. Nevertheless, some studies estimate that males commit more cybercrimes than females (e.g., Barlett and Coyne, 2014; Hinduja, 2007; Toupin, 2014) but others find the opposite (Kowalski and Limber, 2007; Marcum *et al*., 2012).

Absent from much of the cybercrime work has been considered gender as a moderator of theory. The earliest media portrayals of hackers were almost exclusively male (Alper, 2014). Even today, the most famous hackers are all males. These include Kevin Mitnick, the hacker who inspired War Games, Kevin Poulsen, who hacked the Pentagon's ARPANET as a teenager, and Adrian Lamo, who leaked sensitive US documents.

One example of a crime often representing female cybercriminals is a romance or sweetheart scam, where fraudsters approach victims and develop intimate relationships online. After establishing trust, they request money to cover unexpected hospital fees, immigration documents, or travel expenses. When getting the money, scammers simply abscond and abandon the relationship. Although scammers equally likely approach and victimize males and females (Whitty and Buchanan, 2012), the offenders' gender ratio is unknown due to the vastly underreported and unsuccessfully investigated nature of the scams. However, some evidence suggests that most offenders in romance scams are male (Abubakari, 2024). Even if the offender pretended to be female, their identity remains unknown.

Perhaps one reason for their underrepresentation is that females are generally underrepresented in cybersecurity careers (Peacock and Irons, 2017). Estimates suggest that only 10-15% of cybersecurity jobs are filled by females (LeClair *et al*., 2014; Reed *et al*., 2017). Several different hypotheses have been presented for why this could be. These include the general "nerdiness" of the computer-based career (D'Hondt, 2016), the socially constructed violent language around technology (e.g., "fatal error") (Sanders, 2005) or a lack of familial encouragement (Denner, 2011). While an extensive examination of the reasons that females are underrepresented in computer careers is beyond the scope of this literature review, it is worth recognizing that both female computer skills and opportunity may be different between males and females.

In several studies examining correlates of cybercrime, gender is included. For example, Holt and Morris (2009) examined the relationship between media device ownership and digital piracy. Included in the logistic regression was a binary variable indicating male/female. This variable was not significant, and no further discussion was given. Similar non-findings were presented in another study considering hacking and self-control; here the gender variable was also not significant (Bossler and Burruss, 2011).

One cybercrime that has been studied extensively is cyberbullying. Many studies have considered the likelihood of females being the offenders. While some studies show that males are more likely to be cyberbully offenders (Calvete *et al*., 2010; Vandebosch and Van Cleemput, 2009), others show females are more likely to be the offenders (Dilmaç, 2009; Sourander *et al*., 2010). Yet another study finds no difference (Kowalski *et al*., 2012).

The Present Study

The present study investigates the applicability of GST to cyber-offending across genders. Using data from a national sample of 2,121 individuals, we focuse on 390 respondents who reported engaging in cybercrime within the past year. We investigate correlations between prior strains and various forms of cyber-offending for both males and females. We also examine gender-specific differences in the types of strain that lead to cybercrime.

Hypotheses

First, given the literature reviewed above, we hypothesize that strains will be associated with cybercrime, as explained through GST.

H_1: Strains are positively correlated with cybercriminal activity.

Thus far some work on cyberbullying supports this notion (e.g., Hay and Mann, 2010). Theoretical work supports the notion that anger is more likely to predict interpersonal or violent forms of cybercrime than non-violent forms, such as hacking (Hay and Ray, 2020). This is largely explained by anger's mediating role, which leads to our second hypothesis.

H_2: GST explains more variance in violent and interpersonal cybercrimes than in non-violent cybercrimes.

Although not specific to cybercrime, work has been undertaken to examine the applicability of GST to gender. Empirical data largely support a different experience, where males and females experience different strains and respond to strains in different ways (e.g., Moon and Morash, 2017; Isom Scott and Mikell, 2018). Theoretically, the lived experiences and expectations of males and females often differ, leading to different strains. These different strains may lead to different emotions, which are the mediating mechanisms in GST. As such, a difference in explanatory power is expected in GST. Thus, we predict that

H_3: GST has a differential impact on cybercrime based on gender.

This hypothesis suggests that the impact of strain on cyber-offending varies between males and females. Previous research findings support this hypothesis, showing that while GST is associated with crime offending in both genders, specific types of strain influence men and women differently. For example, prior research has found that strain responses for women are more likely to include depressive symptoms (Kaufman, 2009). Other research has found that while anger and depressive symptoms are more common in women's responses to strain, delinquency is less common (De Coster and Zito, 2010). Given that men and women have differing responses to strain, we hypothesize that the nature of the relationship between strain and cybercrime will differ. This hypothesis is consistent with the call for creating gender-specific models in future examinations of GST (Robbers, 2004).

METHODS

Sample

Data were collected using an online survey. We obtained the panel from Dynata in Fall 2019 and Spring 2020 (formerly SSI). Dynata uses a variety of techniques, including banner ads, random digit dialing, and other permission-based techniques to form their participant pool. We used quotas to ensure that the survey was balanced based on U.S. census data. These balancing variables included sex, ethnicity, and race. Research has generally shown that online survey sampling is like other probability-based samples (Weinberg *et al*., 2014; Simmons and Bobo, 2015; MacInnis *et al*., 2018). In addition, a few techniques help increase the validity of the surveys. First, participants who speed through questions are eliminated (Wansink, 2001; Evans and Mathur, 2005). Second, rewards are offered by Dynata and research shows that this increases validity (see Wansink 2001). Participants who sign up to online panel surveys can typically be paid between $2 and $10 for completing a survey (Craig *et al*., 2013) or receive other rewards such as donations to charities in their name, "status points" from the vendor, or other inexpensive gifts (Parti *et al.,* 2024). Our survey participants received such rewards, although the authors did not receive specified information on how much exactly.

To maintain enough numbers of offenders in both men and women, we merged samples of two consecutive surveys into one single dataset. First, we compared the samples to ensure they were not significantly different. The samples differed in average age and education but did not differ in terms of racial/ethnic composition or gender. Besides this diversity in demographics, there were no significant differences between the whole sample and the sample of the offenders in GST variables, thus, we decided to analyze the merged sample. Descriptive statistics can be found in Table **1**.

We fielded the first survey between November 24 and November 30, 2019, and the second between April 14 and April 17, 2020. Overall, 2,435 respondents began the surveys, but 139 respondents completed them in less than three minutes and were considered "speeders," hence, were removed from the sample. In

Table 1: Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation
In a typical week, how many hours do you spend: Playing online video games?	2,115	7	1	8	3.15	2.373
In a typical week, how many hours do you spend: Reading news or other articles online?	2,095	7	1	8	3.51	1.877
In a typical week, how many hours do you spend: Browsing social media?	2,106	7	1	8	3.91	2.204
In a typical week, how many hours do you spend: On a computer while working?	2,104	7	1	8	3.69	2.795
In a typical week, how many hours do you spend: Shopping online	2,108	7	1	8	3.07	1.608
In a typical week, how many hours do you spend: Other online activities	2,102	7	1	8	3.85	2.011
How many hours per week do you spend on the darkweb?	1,892	6	1	7	1.79	1.642
How familiar would you say you are with computers?	2,112	4	1	5	2.96	1.107
How much do you trust people in general?	2,119	4	1	5	3.12	1.027
GST Index	2,070	9	0	9	2.48	2.183
Sample Size	2,121	10	0	10	.72	1.989
Global Offenders	390	9	1	10	3.93	2.992

addition, 175 participants did not complete the survey and were eliminated from the analysis. In total, 2,121 respondents had usable data, out of which the cleaned databases contained 1,107 and 1,014 participants, respectively. Further, 390 of the 2,121 reported at least one cyber-offending behavior in the prior 12 months. In the merged sample, 42.8% (n=167) of the offenders were female, and 53.8% (n=210) were male. The two surveys contained identical questions, and took on average 8.3 minutes to complete. The studies were reviewed by the Institutional Review Board of the authors' university (#19-1010).

Variables

The primary *dependent variables* of interest were cyber offending behaviors. To measure cybercrime, respondents were asked if they committed different types of cybercrime in the past 12 months. Cyber offending behaviors were created based on Donner *et al*. (2014). Behaviors ranged from threatening and insulting others online, illegally downloading, illegally uploading, buying illegal drugs online, and posting nude photos of someone else without their permission (see Table **2** for the types of crimes and survey items used to measure them).

We created a summated variable of all offending behaviors (Cyber-offending). This count variable reflected the number of different offending experiences the participants engaged in in the past 12 months.

The primary *independent variables* were strains related to GST. These were derived from Hinduja and Patchin's (2007) study on cyberbullying. As the original questions related only to juveniles, we expanded certain language in the strains to make them applicable for adults. For example, "I recently got a bad grade" was changed to, "I recently got a bad grade, performance review or evaluation." Strains included: "been treated unfairly in the past 12 months," "getting into a disagreement with a family member," "having a recent death or hospitalization of a close friend or family member," "recently getting into a disagreement with a friend," "recently having to deal with money problems," "breaking up with a significant other," "having parents divorced," and "having been a victim of a crime."

Finally, we considered a number of other variables when appropriate. Consistent with our third hypothesis, we asked about gender. Due to the low number of LGTBQ+ respondents these individuals were not included in the gendered analysis.

Although cybercrime researchers can combine measures from different crime theories (Ngo and Paternoster, 2011; Dearden and Parti, 2021; Holt *et al.,* 2016), we specifically included measures such as darkweb activity, and an ordinal scale of self-reported computer knowledge from routine activity theory in the current study. Routine activity theory is one of the most widely tested crime theories in cybercrime (e.g., Holt and Bossler, 2008; Gainey *et al.,* 2023; Leukfeldt and

Table 2: Cyber-Offending Behaviors

Types of Offending Behavior	Respondents Who Reported Engaging in Past 12 Months		
	Count	% of Total Sample (n=2,121)	% of Total Self-Reported Offenders (n=390*)
Posted Hurtful Information about Someone on the Internet (n=2,117)	195	9.19%	50.00%
Threatened or insulated others through email or instant messaging (n=2,114)	165	7.78%	42.31%
Excluded someone from an online community (n=2,115)	205	9.67%	52.56%
Hacked into an unauthorized area of the internet (n=2,116)	124	5.85%	31.79%
Distributed malicious software (n=2,113)	124	5.85%	31.79%
Illegally downloaded copyrighted files or programs (n=2,111)	177	8.35%	45.38%
Illegally uploaded copyrighted files or programs (n=2,113)	130	6.13%	33.33%
Used someone else's personal information on the internet without their permission (n=2,115)	135	6.36%	34.62%
Bought prescriptions (without a prescription) or other drugs on online pharmacies or websites (n=2,113)	152	7.17%	38.97%
Posted nude photos of someone else without his/her permission (n=2,111)	124	5.85%	31.79%

*add up to more than 100% as each offender can commit more than one offense.

Yar, 2017; Reyns, 2013; 2017). In addition to RAT measures, we also included measures from differential associations and social learning theories such as trust and delinquent peers (both online and offline). These additional measures could help explain the situational and conditioning factors that facilitate the involvement in criminal activities. By examining gender differences through using these additional measures we hoped to better understand how daily activities, access to technology, and anonymity and risky lifestyles such as darkweb engagement (Hawdon *et al.,* 2020) influence the opportunities for cybercrime.

Finally, common demographics included education, race, household income, and age.

Analytical Plan

To test H_1 (strains are positively correlated with cybercriminal activity), we create a correlation analysis using Spearman's rank correlation to measure the association between strain variables and the count of cyber offending behaviors (see Appendix for complete initial correlations). We apply negative binomial regression to model the count of cyber offending behaviors as a function of strain variables, accounting for the overdispersion in the data. To test H_2 (GST explains more variance in violent and interpersonal cybercrimes than in non-violent cybercrimes), we perform separate logistic regressions for the different cyber-offenses, to see how much variance is explained by GST for each offense. We use Nagelkerke's R^2 to quantify how much variance in each type of offense is explained. To test the effect of anger, we conduct linear logistic regressions using anger as an independent variable within GST to measure its specific effect on violent vs. non-violent cybercrimes. We compare effect sizes across different offense types. To test H_3 (GST has a differential impact on cybercrime based on gender), Mann-Whitney U tests are used to compare male and female cyber-offenders on strain-related variables like anonymity, trust, and darkweb usage. To examine the effect of gender on the relationship between strain and cyber-offending, separate negative binomial regressions are run for male and female offenders to compare the explanatory power of GST variables for each gender. Finaly, we run post-hoc tests to explore specific gender-based differences in strain responses.

RESULTS

To examine the first hypothesis, we investigate the rates of cyber-offending. Some of the GST variables show significance with cyber-offending, these are: (GST_2) receiving a bad grade, performance, or evaluation, (GST_7) breaking up with a significant other, (GST_8) parents' divorce, and (GST_9) having been a victim of a crime. For the model summary, we used stepwise regression where an automatic procedure was utilized to carry out the choice of predictive variables. In each step of the stepwise regression, a variable is considered for addition to or subtraction from the set of explanatory variables based on some prespecified criteria. The model summary explains 36.3% of the sample, R^2 of <.05 (F=54,040). Because our data was overdispersed, and negative binomial regression showed better goodness of fit results than Poisson regression, we also applied negative binomial regression. All the variables maintained significance with high incidence rate ratios between 2.7 (GST_7) and 4.4 (GST_9). As such, our first hypothesis is supported. Strain variables GST_2, GST_7, GST_8, and GST_9, are associated with cybercrime activity (Table **3**).

To further consider GST we created a GST scale by summating all strains into one scale. A negative binomial regression using cyber-offending as the DV and the GST scale as the IV showed significance (p<.001) with 8% of the pseudo R^2 variance explained.

Table 3: Negative Binomial Coefficients per GST Variables

Model: χ^2= 393.9, p<.001	Coefficients			z	Sig.
	IRR	*SE*	*B*		
(Constant)	.179	.078	-1.723	-22.12	.000
GST_2: Bad grade, performance evaluation	3.389	.151	1.221	8.11	.000
GST_8: Parents' divorce	3.310	.154	1.197	7.79	.000
GST_9: Victim of a crime	4.372	.191	1.475	7.73	.000
GST_7: Breaking up with partner	2.716	.163	0.999	6.13	.000

Sample size: n=379.
Notes: X^2: Likelihood Ratio Chi^2; IRR: Exp(B); SE: Std. Error.

In the next step, we examined which variables other than strain explain cyber-offending. For this, we used Spearman rank correlation, as the variables' measurement level was ordinal (Dancey and Reidy, 2004). We utilized the Mann-Whitney U test, for testing the differences between two groups on a single, ordinal variable with no specific distribution (Mann and Whitney, 1947). The Mann-Whitney U analysis tests whether there were gender differences along with variables of anonymity, trust, and darkweb activity. The average offender prefers spending time on the darkweb (rs=0.443**), anonymity (rs=-0.337**), and does not trust others (rs=-0.495**). The Mann-Whitney test was used to test whether there were gender differences when anonymity, trust, and drakweb use calculated in. The Mann-Whitney test is significant for gender for anonymity (p<.000) and trust (p<.001). That means, there is no significant difference per gender in darkweb preferences, but anonymity and trust, in that male offenders prefer anonymity more, and trust others less than females do (anonymity and trust scales are coded inversely).

To examine our second hypothesis, first we applied logistic regression to see how much variance of each cybercrime is explained. Among the offenders in our sample (n=390), posting other people's nude images without their permission (Nagelkerke's R^2: 0.180), malicious software distribution (0.180), and illegal uploading of copyrighted files (0.167) have the highest explained variance, but overall linear logistic regression explains low variance levels among all cybercrimes. For a cross-check, we applied stepwise multiple linear regression to see how much each offending behavior derives from general strain (R^2 : 0.253, F=23.826***). Surprisingly, GST showed a greater effect on less violent cybercrime behaviors, such as software distribution (Beta=0.215***), illegal download (Beta=0.168***), posting other's nude images (Beta=139**), excluding someone from the community (Beta=0.109**), and hacking (Beta=0.115**). To measure the effect of anger most responsible for interpersonal or violent cybercrimes according to the literature, we examined how much variance of each cybercrime behavior is explained by *anger* as a single independent variable within GST. There are statistically significant relations between anger and cybercrime behaviors, except for illegally downloading copyrighted material, as shown in Table **4**. Table **4** also ranks cybercrime offending behavior per effect size according to which, besides hacking (*η^2: 9.5*), interpersonal and violent offending behaviors – such as threatening someone online (*η^2: 11.9*), posting hurtful information (*η^2: 8.6*), and using someone's personal information without authorization (*η^2: 6.4*) – came out with the greatest significant effect sizes. This partly supports our second hypothesis, as GST showed a greater effect on less violent cybercrime behaviors. However, anger, an independent variable within GST, explained more variance in violent and interpersonal cybercrimes than in non-violent cybercrimes with the exception of hacking, which was among the variables with greater effect sizes.

To test our third hypothesis, we ranked all variables showing significant relations to gender, per regression Betas. Table **5** shows how much each variable explains the global offending scale for female and male offenders. GST explains 59% of the variance for male offenders (R^2: 0.592, F=42,530; p<0.01), and 47% for

Table 4: Impact of Anger on Offending

Offending	Sample Size	(Pearson) X^2	*η*	*η2*
Threatened online	387	45.943***	0.345	11.9
Hacked into unauthorized area of internet	389	37.191***	0.309	9.5
Posted hurtful information	388	33.370***	0.293	8.6
Posted nude photos of someone else	388	31.754**	0.286	8.2
Used someone else's personal information	389	21.499***	0.253	6.4
Distributed malicious software	387	23.544***	0.247	5.9
Illegally uploaded copyrighted files	386	15.953***	0.203	4.1
Excluded someone from online community	389	12.263**	0.178	3.2
Bought prescriptions or drugs online	386	7.065**	0.135	1.8
Illegally downloaded copyrighted files	384	N.S.	0.065	0.4

Note: *p<0.1; ** p<0.05; ***p<0.01.

Table 5: Male and Female Linear Regressions Predicting Cyber-Offending Index

Variables	Female Offenders				
	B	*SE(B)*	*Beta*	*t*	*p*
Lack of trust	-0.730	0.176	-0.308	-4.154	***
GST_2: Bad grade, performance, evaluation	1.827	0.406	0.307	4.503	***
GST_8: Parents' divorce	1.491	0.460	0.227	3.239	***
Anonymity	-0.277	0.117	-0.168	-2.362	**
Online video games	0.196	0.093	0.141	2.107	**
Constant	4.654	0.723		6.439	***
R^2: 0.470, ANOVA F: 21.595					
Sample size: n=164					
Variables	**Male Offenders**				
	B	*SE(B)*	*Beta*	*t*	*p*
Lack of trust	-0.820	0.145	-0.316	-5.640	***
GST_9: Victim of a crime	1.614	0.344	0.259	4.688	***
GST_2: Bad grade, performance, evaluation	1.221	0.331	0.197	3.685	***
Darkweb	0.294	0.081	0.207	3.640	***
GST_7: Breaking up with partner	0.992	0.342	0.161	2.899	***
Computer while working	-0.140	0.063	-0.114	-2.232	**
Constant	4.344	0.609		7.130	**
R^2: 0.592, ANOVA F: 42.530					
Sample size: n=210					

Notes: *p<0.1; ** p<0.05; ***p<0.01.

female offenders (R^2: 0.592, F=42,530; p<0.01). Female offending, therefore, is slightly less explained by GST variables. As we found that GST and cybercrime have differential impact on males and females, the third hypothesis is supported.

DISCUSSION

According to the stepwise method we applied to check which variables of GST is significant in the linear regression model, we found no difference between the whole sample (n=2,121) and the offender sample (n=390) in that the following GST variables were significant: received a bad grade, performance review or evaluation; broke up with a significant other; parents divorced; and been victim of a crime. This suggests that offending is related to strain, whether it is only for the offender or included with non-offenders: strains can affect behavior and hence can be a contributing factor to cyber-offending, independent of gender. On the other hand, reduced strain can protect people from becoming cyber-offenders. Thus, our first hypothesis, *H_1: Strains are positively correlated with cybercriminal activity*, was supported. Overall significant predictors included recently receiving a bad grade, performance review or evaluation, recently breaking up with a significant other, parents divorcing, and having been the victim of a crime. As the most appropriate model for analysis was a negative binomial regression, pseudo-R^2 explained 11% of the variance. We also considered a summated scale for GST behaviors. This also was significant and explained 8% of the variance in a single negative binomial regression.

Our second hypothesis, according to which *H_2: GST variables explain more variance in violent and interpersonal cybercrimes than in non-violent cybercrime,* is partly supported. GST showed a greater effect on non-violent cybercrime behaviors, such as software distribution, and illegal download. However, posting others' nude images, excluding someone from the community followed in the rank. When we had a closer look, anger, an independent variable within GST explained more variance in violent and interpersonal cybercrimes than in non-violent cybercrimes with the exception of hacking. There are statistically significant relations between anger and cybercrime behaviors.

Interpersonal and violent offending behaviors, such as threatening someone online, posting hurtful information, and using someone's personal information without authorization resulted in the largest effect sizes. This partly supports our second hypothesis, as GST showed a greater effect on less violent cybercrime behaviors.

To test our third hypothesis, H_3*: GST has a differential impact on cybercrime based on gender*, we ranked all variables showing significant relations to gender, in a multiple linear regression model. We investigated whether gender affected offending differently when controlling for strain. We have found no interaction effect for gender. Next, we created models for male and female offenders separately and examined the effect of variables per gender. We built two regression models for male and female offenders, using the same variables, applying stepwise method. These models contain the GST variables significant with offending, online activity (except for online shopping and social media use), darkweb, anonymity, and trust. Male offending is more explained (59%) than female offending (47%) with these variables, supporting our third hypothesis. We can conclude, that while strain theory works for offenders independent of gender, there is a difference in how each strain variable affects females and males and how much of female and male offender behavior can be explained by the theory.

There are different variables responsible for offending per gender. While female offending is explained (from the greatest to the weakest explaining effect in mean rank) by lack of trust, bad school or work performance or evaluation, parental divorce, anonymity, and online gaming, male offending is explained (from the greatest to the weakest explaining effect in mean rank) by lack of trust, having been victimized by a crime, bad school or work performance or evaluation, darkweb activity, breaking up with a significant other, and using computer while at work.

Although different variables are responsible for male and female online criminality, two variables – lack of trust and bad school or work performance or evaluation – seem to be strongly correlated for both genders in offending. These variables also differ in effect sizes for the two genders. Although a low level of trust is the single most deterministic in male and female offending, it has a stronger effect in male offending. On the contrary, bad work or school performance evaluation is a stronger determinant for females who offend. Female offending is further influenced by parental divorce, anonymity, and online video games. In contrast, male cyber-offenders are affected more by past victimization, darkweb activity, breaking up with a significant other, and computer use by working – with the last one being a protective factor for potential male cyber-offending. It is worth emphasizing that computer usage while working shows a negative effect only on male offending. A probable explanation is that work hours leave less time and opportunities for males to offend, while working with a computer does not protect females from engaging in online delinquent activities, as they probably would not use computers for offending as much as males anyhow. There is one exception: women who like online gaming are more prone to commit online crime as well. Darkweb activity similarly affects males, who are more likely to offend when using the darkweb. Seeking anonymity is another significant correlate of female cyber offending which does not appear to have any effect on male offending.

In online environments, societal norms and gender expectations significantly shape the experiences of men and women. Gender roles, historically defined by societal expectations, extend into online spaces, impacting interactions, self-presentation, and behavior. These norms dictate the types of activities men and women engage in and the responses they receive from others in digital platforms. As found in our analysis, variables affect male and female online criminality differently, and societal gender norms and expectations may be responsible for that. For instance, societal norms influence who is expected to participate in certain online activities, like gaming. Online gaming is often seen as a male-dominated space, and women who engage in it are sometimes viewed as outliers (Shaw, 2014; Schmitz, 2018; Mears, 2021; Jagayat and Choma, 2021). The findings indicate that women who enjoy gaming are more prone to committing online crimes, a behavior potentially tied to the pressures and marginalization they face in such spaces. Another variable, anonymity, correlates with strain that pushes women into criminal avenues online, while it has no such effect on men. This suggests that anonymity functions differently along with societal expectations for women and men. Research already shows that women may seek anonymity more in online spaces as a way to protect themselves from being victimized (e.g., by harassment), which is a direct response to societal pressures and the expectation of being targeted online (Sobieraj, 2020). In contrast, men engage more in darkweb activities, where anonymity is also key, but often for different reasons tied to being interested in engaging in risky or criminal behavior (Cole *et al*., 2021) due to societal and economic strains (Hawdon *et al*., 2022). Our analysis did not investigate the reasons as to why these factors play different roles in determining online offending differently for genders, but future research is recommended to explore the roles of gender-specific pressures and societal expectations in gender-specific strain and cyber-offending.

Our paper adds to the cybercrime literature by considering various types of cybercrime and whether GST can explain them. By examining different types of strain and cybercrimes, we show that the types of strain are differentially correlated with different cybercrimes. In addition, we examined the unique effects of gender on GST. Overall, GST has more explanatory power for males than females. Our work not only adds to the literature on GST, but also helps develop new perspectives on cybercrime. With the primary focus of cybersecurity being on protective strategies, GST and other social theories allow for a more nuanced view of cybercrime. Specifically, we highlight that people's negative experiences in local environments potentially lead to online crime. Historically, strain often focused on interpersonal and local crime. With the advent of the internet GST has moved online, allowing for new avenues of managing and dealing with the strains people experience.

Our study supports preliminary research on which genders experience different types and levels of strain (Broidy and Agnew, 1997). We found evidence that both females and males are affected by strain, and they are affected differently. Furthermore, our data supports (Ogle *et al*., 1995) that negative social stimuli, such as bad workplace performance or evaluation might expose women more than men to negative outcomes, such as criminal activities and it works in cyberspace similarly to traditional spaces. We also showed that men are more responsive than women to the loss of positively valued stimuli, such as breaking up with a significant other (Robbers, 2004; Agnew and Brezina, 1997), which applies to deviant cyber activities. Our data further justified the differential effect of positive social support on females, as parental divorce affected female cyber offending more than male cyber offending. In fact, instead of parental divorce, males are more receptive to former crime victimization experiences as negative stimuli than anything else, which makes them less trustful, and more prone to offending in cyberspace. Despite these results supporting former correlations of crime, strain, and gender, we could not examine whether and how the level of social support affects cyber offending in women.

LIMITATIONS

This study identified a gendered dimension of Agnew's general strain theory (Agnew, 1997); however, did not look at the quality of strain. According to Agnew's 2001 theory reformulation, strain particularly leads to crime if (1) strains are seen as unjust, (2) strains are high in magnitude, (3) strains are combined with low social control, and (4) strains create incentives for criminal coping (Agnew, 2001). Our survey had a limited length, thus, asking questions measuring refined components of strain was impossible. Thus, the study did not include the measure of self-control, which may moderate effects on strain (Agnew *et al*., 2002). Future analysis on the moderating effect of self-control (anger, pursuit of danger, risk-taking, impulsivity) and social learning (effect of delinquent peers in cybercrime offending) should be arranged to refine Agnew's 2001 theory in a gender-specific way. Future tests should also examine qualitative sex differences in types of strain, negative emotions, and coping mechanisms, as gender differences in the level and in the experiences of strain and negative emotions are not sufficient to explain deviant coping mechanisms (Broidy, 2006). It is worth noting that strain level and negative emotions were scarcely tested in connection with cybercrime and deviant coping; hence, it needs further examination.

The survey method includes several limitations. First, it limited our ability to detect causal relationships. Second, we used the merged data of participants from two consecutive surveys nationally representing gender, race, and age. Experimental or quasi-experimental design examining gender and crime correlations, with the mediating effect of strain should be considered. Longitudinal surveys could also be designed to consider changes over time. Third, even if we controlled for various measures, regression analysis provides no information about causality (Neter *et al*., 1996). However, our analysis sheds light on the possible connections between variables and effect sizes.

In addition, the second survey conducted during the first phase of the pandemic faces certain limitations due to the extraordinary context in which it was fielded. The significant impact of the pandemic, including widespread uncertainty and disruption to daily life, likely influenced participants' responses. This period of heightened stress and anxiety could have affected how individuals perceived their experiences, potentially leading to biased responses. Additionally, the pandemic may have altered the usual dynamics of the factors being studied, such as various strains and mental health issues, which could impact the generalizability of the findings to non-pandemic contexts. As a result, caution should be exercised when interpreting the results.

Lastly, while the merged samples included over 2,120 participants, we used the small group of 390 offenders in our analysis, because our focus was on cyber-offending, and the number of female offenders would have been very low if using only one sample. The population of cyber-offenders is intrinsically difficult to target, especially that of females, who represent a significantly lower number of offenders.

CONCLUSION

Gender roles in cybercriminal activity are vastly understudied. This paper adds to the existing literature by highlighting the importance of searching for more connections between gender, strain, and cybercrime. In a nationally representative sample of adult Americans, we found that strains are positively associated with cybercriminal activity. Our analysis resulted in a mixed effect of strain variables on various crime types, as it showed greater effect on non-violent (software distribution, illegal download) than interpersonal (posting nude photos of others, and cyber exclusion) cybercrimes; however anger, a single variable of strain explained more variance in interpersonal cybercrimes. Finally, GST has differential impact on cybercrime based on gender, therefore, the theory is indeed gender-specific, as different strain variables are responsible for engaging in cyber-offending in women and men, and female cyber-offending can be overall less explained by the theory. Consequently, components of general strain responsible for cyber-offending need to be further studied concerning gender.

LIST OF ABBREVIATION

GST = General Strain Theory

FUNDING

This research was funded by the Center for Peace Studies and Violence Prevention at Virginia Tech (Grant number 025-19), The Institute for Society Culture and Environment at Virginia Tech, and The Integrated Security Destination Area at Virginia Tech.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

APPENDIX: CORRELATION OF GST ITEMS

		GST1	GST2	GST3	GST4	GST5	GST6	GST7	GST8	GST9	GST Index	Global Offending	Gender
GST1	Pearson Correlation	1	.320**	.379**	.203**	.369**	.333**	.283**	.191**	.294**	.675**	.236**	-.070**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.002
	N	2095	2090	2092	2092	2090	2092	2090	2089	2088	2070	2095	2064
GST2	Pearson Correlation	.320**	1	.194**	.193**	.267**	.223**	.387**	.362**	.300**	.581**	.436**	.001
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000	.964
	N	2090	2099	2096	2097	2094	2096	2095	2093	2093	2070	2099	2068
GST3	Pearson Correlation	.379**	.194**	1	.206**	.404**	.334**	.197**	.105**	.161**	.621**	.106**	-.055*
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000	.012
	N	2092	2096	2101	2099	2096	2099	2096	2096	2095	2070	2101	2070
GST4	Pearson Correlation	.203**	.193**	.206**	1	.192**	.152**	.155**	.171**	.155**	.484**	.148**	-.051*
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000	.021
	N	2092	2097	2099	2101	2096	2099	2096	2096	2095	2070	2101	2070
GST5	Pearson Correlation	.369**	.267**	.404**	.192**	1	.261**	.314**	.163**	.261**	.650**	.218**	.021
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000	.343
	N	2090	2094	2096	2096	2099	2096	2094	2094	2093	2070	2099	2068

GST6	Pearson Correlation	.333**	.223**	.334**	.152**	.261**	1	.210**	.179**	.227**	.593**	.164**	-.156**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000
	N	2092	2096	2099	2099	2096	2101	2097	2097	2096	2070	2101	2070
GST7	Pearson Correlation	.283**	.387**	.197**	.155**	.314**	.210**	1	.340**	.381**	.577**	.423**	-.012
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000	.591
	N	2090	2095	2096	2096	2094	2097	2099	2094	2094	2070	2099	2068
GST8	Pearson Correlation	.191**	.362**	.105**	.171**	.163**	.179**	.340**	1	.365**	.469**	.504**	.053*
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000	.016
	N	2089	2093	2096	2096	2094	2097	2094	2098	2094	2070	2098	2067
GST9	Pearson Correlation	.294**	.300**	.161**	.155**	.261**	.227**	.381**	.365**	1	.548**	.419**	.016
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.481
	N	2088	2093	2095	2095	2093	2096	2094	2094	2097	2070	2097	2066
GST Index	Pearson Correlation	.675**	.581**	.621**	.484**	.650**	.593**	.577**	.469**	.548**	1	.453**	-.066**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000	.003
	N	2070	2070	2070	2070	2070	2070	2070	2070	2070	2070	2070	2039
Global Offending	Pearson Correlation	.236**	.436**	.106**	.148**	.218**	.164**	.423**	.504**	.419**	.453**	1	.074**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.001
	N	2095	2099	2101	2101	2099	2101	2099	2098	2097	2070	2121	2089
Gender	Pearson Correlation	-.070**	.001	-.055*	-.051*	.021	-.156**	-.012	.053*	.016	-.066**	.074**	1
	Sig. (2-tailed)	.002	.964	.012	.021	.343	.000	.591	.016	.481	.003	.001	
	N	2064	2068	2070	2070	2068	2070	2068	2067	2066	2039	2089	2089

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

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Received on 21-07-2024 Accepted on 17-08-2024 Published on 11-09-2024

https://doi.org/10.6000/1929-4409.2024.13.19