



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

Katalin Parti¹ and Thomas Dearden²

¹Associate Professor of Sociology, Department of Sociology (0137), Virginia Tech., 225 Stanger St, Blacksburg, 24061, Virginia, USA. E-mail: kparti@vt.edu; ORCID: 0000-0002-8484-3237

²Associate Professor of Sociology, Department of Sociology (0137), Virginia Tech., 225 Stanger St, Blacksburg, 24061, Virginia, USA. ORCID: 0000-0003-0549-927X

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Abstract: In this paper, we examine self-reported cyber-offending activities and their relation to life strains. 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. 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. 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. According to our results, GST is gender-specific, and these variables need to be further studied.

Keywords: strain, general strain theory, gender, cybercrime, cyber offending

Literature Review

The world is becoming increasingly connected by technology, with more devices being 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 & 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 & Holt, 2009; Holt & Bossler, 2009; Reyns, 2013) and self-control (Donner et al., 2014; Reyns et al., 2019). Yet a call has been made to start examining other theories that may explain aspects of cybercrime (Holt & 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 & Hinduja, 2011).

Our study continues this call, by considering the applicability of GST's relation to cybercrimes. We consider a variety of self-reported cyber-offending behaviors. To further explore this relationship, we consider the differences of gender in cyber-offending as well.

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 & 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. 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 & 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 & 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 & 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 through 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 response to anger, it may be important to consider the differential relationship between strain and crime moderated by gender. This is somewhat 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 & 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' reaction 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 responses of females; when females experience certain strains, high level of social support decreases the likelihood of delinquency. In the meantime, women's exposure of negative stimuli significantly increases the propensity of engaging in delinquent acts. Negative stimuli did not increase 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, Maier-Katkin & Bernard, 1995), such as bias in the workplace, and domestic violence.

Research further revealed that the loss of positively valued stimuli, such as the loss of a significant other, did not significantly increase the likelihood of female offending, but it did for males (Robbers, 2004). Nevertheless, Agnew and Brezina (1997) found that men can also be affected by strain through interpersonal relationships.

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. Contrastingly, 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.

Cybercrime and Gender

Research posits (Alper, 2014; Thomas, 2022) that computer crimes were historically and stereotypically gendered, with "hackers" being identified as young males. 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 & Coyne, 2014; Hinduja, 2007; Toupin, 2014) but others find the opposite (Kowalski & 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. Yet not all cybercrimes have been characteristically male-only.

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 costs of 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 & Buchanan, 2012), offenders' gender ratio is unknown, due to the vastly underreported and unsuccessfully investigated nature of the scams. Even if the offender pretended to have been female, their actual identity remains unknown.

Perhaps one reason for their underrepresentation is that females are also underrepresented in cybersecurity careers generally (Peacock & Irons, 2017). Estimates suggest that only between 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 & 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 a cyberbully offender (Calvete et al., 2010; Vandebosch & Van Cleemput, 2009), others show females are more likely to be the offender (Dilmaç, 2009; Sourander et al., 2010). Yet another study finds no difference (Kowalski et al., 2012).

Hypotheses

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

H₁: Strains will be positively associated with cybercriminal activity.

Thus far some work on cyberbullying supports this notion (e.g., Hay & 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 & Ray, 2020). This is largely explained through the mediating role of anger. This leads to our second hypothesis.

H₂: GST will explain 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 & Morash, 2017; Isom Scott & Mikell, 2018). Theoretically, the lived experiences and expectations of males and females are often different, leading to different strains themselves. 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

H₃: Gender will moderate the relationship between GST and cybercrime.

Methods

Sample

Data were collected using an online survey. The panel was obtained 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, Freese, & McElhattan 2014; Simmons & 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 & Mathur, 2005). Second, rewards are offered by Dynata and research shows that this increases validity (see Wansink 2001).

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. Sample demographics can be found in Table 1. 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.

The first survey was fielded between November 24 and November 30, 2019, and the second was fielded 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 addition, 125 participants did not complete the survey and were eliminated from the analysis. In total, 2,130 respondents had usable data. Further, 390 of the 2,130 reported at least one cyberoffending 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.

Table 1: Demographics

Gender	Male	Female	LGBTQ/ Non-Binary				
	1043 (49%)	1046 (49%)	32 (2%)				
Education	Less than High School	High School	Some College	College Degree	MA/ Professional/ PhD		
	60 (3%)	393 (19%)	478 (23%)	781 (37%)	407 (19%)		
Race	White	Black	American Indian	Asian	Pacific Islander / Hawaiian	Other/Prefer not to Answer	
	1518 (72%)	314 (15 %)	22 (1%)	128 (6%)	15 (1%)	124 (6%)	
Household Income	< \$25k	\$25k-\$50k	\$50k-\$75k	\$75k-\$100k	\$100k-\$150k	\$150k-\$250k	>\$250k
	348 (16%)	465 (22%)	341 (16%)	320 (15%)	329 (16%)	166 (8%)	52 (3%)
Age	Mean	Median	SD	Min	Max		
	44.50	44	13.68	18	86		
Time Spent on Dark Web (h. per week)	0	<1	1-2	2-4	4-6	7-9	10 or more
	1437 (68%)	95 (5%)	90 (4%)	71 (3%)	71 (3%)	52 (3%)	76 (4%)
Computer Knowledge	Un- comfortable	Surf Net	Software to Fix Computer	Fix & Use Multiple OS	Able to Write Code		
	166 (8%)	616 (29%)	698 (33%)	406 (19%)	226 (11%)		

How Much Do You	A Great Deal	A Lot	A Moderate Amount	A little	None at All		
Trust People in General	166 (8%)	328 (16%)	897 (42%)	547 (26%)	181 (9%)		
Online anonymity	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
	292 (14%)	368(17%)	295 (14%)	530 (25%)	137 (7%)	164 (8%)	316 (15%)
Offenders	Male	Female	Missing	Total			
	210 (10%)	167 (8%)	13 (1%)	390 (18%)			

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).

Table 2: Cyber-offending Behaviors

<i>Types of Offending Behavior</i>	<i>Respondents Who Reported Engaging in Past 12 Months</i>		
	<i>Count</i>	<i>% of Total Sample (n=2,121)</i>	<i>% of Total Self-Reported Offenders (n=390*)</i>
Posted Hurtful Information about Someone on the Internet (n=2,117)	195	9.19%	50.00%
Threatened or insulted 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.

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 & 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 LGBTQ+ respondents these individuals were not included in the gendered analysis. Questions related to routine activities were included as this is a common theory considered in cybercrime. These questions included time spent on the darkweb per week and an ordinal scale of self-reported computer knowledge. We also included questions on trust, online anonymity, and delinquent peers (both online and offline). Finally, common demographics were considered including education, race, household income, and age (Table 1).

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 being 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 OLS regressions are often inappropriate for count data, we also analyzed the same regression using a negative binomial regression. All the variables maintained significance with high incidence rate ratios between 2.7 (GST_9) and 4.4 (GST_8). 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).

Table 3: Negative Binomial Coefficients per GST Variables

<i>Model: $\chi^2= 393.9, p<.001$</i>		<i>Coefficients</i>			<i>z</i>	<i>Sig.</i>
		<i>IRR</i>	<i>SE</i>	<i>B</i>		
	(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

To further consider GST we created a GST scale by summing 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.

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 & 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 & 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 ($r_s=0.443^{**}$), anonymity ($r_s=-0.337^{**}$), and does not trust others ($r_s=-0.495^{**}$). The Mann-Whitney test was used to test whether there were gender differences and anonymity and trust were significantly different. The Mann-Whitney test is significant for gender for anonymity ($p<.000$) and trust ($p<.001$). 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 (f^2 : 9.5), interpersonal and violent offending behaviors – such as threatening someone online (f^2 : 11.9), posting hurtful information (f^2 : 8.6), and using someone’s personal information without authorization (f^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.

Table 4: Impact of Anger on Offending

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

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

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 female offenders (R^2 : 0.592, $F=42,530$; $p < 0.01$). Female offending, therefore, is slightly less explained by GST variables. As gender moderates the relationship between GST and cybercrime, the third hypothesis is supported.

Table 5: Multiple 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					
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					

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

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 offending is related to strain whether it is only 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, the lack of strain can protect people from becoming cyber-offenders. Thus, our first hypothesis, H_1 : *Strains are positively associated 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 R² 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 : *gender moderates the difference between GST and cybercrime*, we ranked all variables showing significant relations to gender, in a multiple linear regressions model. We investigated whether gender had a different effect on offending 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 variable of strain 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 low level of trust is the single most deterministic

in male and female offending, it has a stronger effect in male offending. Contrarily, bad work or school performance evaluation is a stronger determinant for females in offending. 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 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 though, women who like online gaming, are more prone to commit online crime as well. Darkweb activity has a similar effect on males, who are provided with more chances 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.

Future Perspectives and Limitations

Our study supports preliminary research according to which genders experience different types and levels of strain (Broidy & 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 & Brezina, 1997), and this applies to deviant cyber activities. Our data further justified the moderating 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 experience as negative stimuli than anything else, which makes them less trustful, and more prone to offending in cyberspace. Despite all 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.

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, pursue of danger, risk-taking, impulsivity) and social learning (effect of delinquent peers in cybercrime offending) should be arranged in order to refine Agnew's 2001 theory in a gender-specific way. Future tests also should 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; and hence, it needs to be further examined.

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, age, and household income. 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.

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, representing significantly lower number in offending.

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, although GST functions as a moderator of cyber-offending, 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 with regard to gender.

References

- Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology*, 30(1), 47–87. <https://doi.org/10.1111/j.1745-9125.1992.tb01093.x>
- Agnew, R. (2001). Building on the foundation of general strain theory: Specifying the types of strain most likely to lead to crime and delinquency, *Journal of Research in Crime and Delinquency*, 38(4): 319–361. <https://doi.org/10.1177/0022427801038004001>
- Agnew, R. & Brezina, T. (1997). Relational problems with peers: Gender and delinquency, *Youth and Society*, 29(1): 84–111. <https://doi.org/10.1177/0044118X97029001004>
- Agnew, R., Brezina, T., Wright, J. P., & Cullen, F. T. (2002). Strain, personality traits, and delinquency: Extending general strain theory. *Criminology*, 40(1), 43–72. <https://doi.org/10.1111/j.1745-9125.2002.tb00949.x>
- Alper, M. (2014). “Can our kids hack it with computers?” Constructing youth hackers in family computing magazines (1983-1987). *International Journal of Communication*, 8(1), 673–698. <https://www.hackingculture.org/sites/default/files/articles/alper--can-our-kids-hack-it-with-computers.pdf>
- Barlett, C., & Coyne, S. M. (2014). A meta-analysis of sex differences in cyber-bullying behavior: The moderating role of age. *Aggressive Behavior*, 40(5), 474–488. DOI: 10.1002/ab.21555; <https://pubmed.ncbi.nlm.nih.gov/25098968/>
- Baron, S. W. (2004). General strain, street youth and crime: A test of Agnew’s revised theory. *Criminology*, 42(2), 457–483. <https://doi.org/10.1111/j.1745-9125.2004.tb00526.x>
- Baron, S.W. (2007). Street Youth, Gender, Financial Strain, and Crime: Exploring Broidy and Agnew’s Extension to General Strain Theory, *Deviant Behavior*, 28(3): 273–302. <https://doi.org/10.1080/01639620701233217>
- Bossler, A., & Holt, T. (2009). On-Line Activities, Guardianship, and Malware Infection: An Examination of Routine Activities Theory. *International Journal of Cyber Criminology*, 3(1), 400–420. <http://www.cybercrimejournal.com/bosslerholtjan2009.htm>
- Bossler, A. M., & Burruss, G. W. (2011). The general theory of crime and computer hacking: Low self-control hackers? In T. J. Holt & B. H. Schell (Eds.), *Corporate Hacking and*

Technology-Driven Crime: Social Dynamics and Implications (pp. 38–67). Hershey, PA: IGI Global.

- Broidy, L. & Agnew, R. (1997). Gender and crime: A general strain theory perspective. *Journal of Research in Crime and Delinquency*, 34(3), 275–306. <https://doi.org/10.1177/0022427897034003001>
- Broidy, L. (2006). A test of general strain theory, *Criminology*, 39(1): 9–36. <https://doi.org/10.1111/j.1745-9125.2001.tb00915.x>
- Calvete, E., Orue, I., Estévez, A., Villardón, L., & Padilla, P. (2010). Cyberbullying in adolescents: Modalities and aggressors' profile. *Computers in Human Behavior*, 26(5), 1128–1135. <https://doi.org/10.1016/j.chb.2010.03.017>
- Barnett, T. Jr., Jain, S., Andra, U. & Khurana, T. (2018). Cisco Visual Networking Index: Forecast and Trends, 2017–2022 White Paper, *APJC Cisco Knowledge Network (CKN) Presentation*, https://www.cisco.com/c/dam/m/en_us/network-intelligence/service-provider/digital-transformation/knowledge-network-webinars/pdfs/1213-business-services-ckn.pdf
- Craig, J. M., Cardwell, S. M., & Piquero, A. R. (2017). The effects of criminal propensity and strain on later offending. *Crime and Delinquency*, 63(13), 1655–1681. <https://doi.org/10.1177/0011128716665334>
- Dancey, C. & Reidy, J. (2004). *Statistics without Math for Psychology: Using SPSS for Windows*. London: Prentice Hall
- Denner, J. (2011). What Predicts Middle School Girls' Interest in Computing? *International Journal of Gender, Science and Technology*, 3(1), 53–69. <http://genderandset.open.ac.uk/index.php/genderandset/article/view/106/245>
- D'Hondt, K. (2016). Women in Cybersecurity. *Harvard Kennedy School of Government*, https://wapp.hks.harvard.edu/files/wapp/files/dhondt_pae.pdf
- Dilmaç, B. (2009). Psychological needs as a predictor of cyber bullying: A preliminary report on college students. *Kuram ve Uygulamada Egitim Bilimleri*, 9(3), 1307–1325. <https://eric.ed.gov/?id=EJ858926>
- Donner, C. M., Marcum, C. D., Jennings, W. G., Higgins, G. E., & Banfield, J. (2014). Low self-control and cybercrime: Exploring the utility of the general theory of crime beyond digital piracy. *Computers in Human Behavior*, 34, 165–172. <https://doi.org/10.1016/j.chb.2014.01.040>
- Evans, J. & Manthur, A. (2005). The value of online surveys. *Internet Research*, 15(2), 195–219. <https://doi.org/10.1108/10662240510590360>
- Hawdon, J., Bernatzky, C., & Costello, M. (2019). Cyber-Routines, Political Attitudes, and Exposure to Violence-Advocating Online Extremism. *Social Forces*, 98(1), 329–354. <https://doi.org/10.1093/sf/soy115>

- Hay, C. (2003). Family strain, gender, and delinquency. *Sociological Perspectives*, 46, 107—135. DOI: 10.1525/sop.2003.46.1.107; <https://www.jstor.org/stable/10.1525/sop.2003.46.1.107>
- Hay, C., & Ray, K. (2020). General Strain Theory and Cybercrime. In *The Palgrave Handbook of International Cybercrime and Cyberdeviance* (pp. 583–600). https://doi.org/10.1007/978-3-319-78440-3_21
- Hay, C., & Evans, M. (2006). Violent victimization and involvement in delinquency: Examining predictions from general strain theory. *Journal of Criminal Justice*, 34(3), 261–274. <https://doi.org/10.1016/j.jcrimjus.2006.03.005>
- Hinduja, S. (2007). Neutralization theory and online software piracy: An empirical analysis. *Ethics and Information Technology*, 9(3), 187–204. <https://doi.org/10.1007/s10676-007-9143-5>
- Hinduja, S. & Patchin, J.W. (2007). Offline consequences of online victimization: School violence and delinquency. *Journal of school violence*, 6(3), 89—112. https://doi.org/10.1300/J202v06n03_06
- Holt, T. J., & Morris, R. G. (2009). An exploration of the relationship between MP3 player ownership and digital piracy. *Criminal Justice Studies*, 22(4), 381–392. <https://doi.org/10.1080/14786010903358109>
- Holt, T. J., & Bossler, A. D. (2014). An assessment of the current state of cybercrime scholarship. *Deviant Behavior*, 35(1), 20–40. <https://doi.org/10.1080/01639625.2013.822209>
- Holt, T. J., Burruss, G. W., & Bossler, A. M. (2010). Social learning and cyber-deviance: Examining the importance of a full social learning model in the virtual world. *Journal of Crime and Justice*, 33(2), 31–61. <https://doi.org/10.1080/0735648X.2010.9721287>
- Holt, T. J., & Bossler, A. M. (2009). Examining the applicability of lifestyle-routine activities theory for cybercrime victimization. *Deviant Behavior*, 30(1), 1–25. <https://doi.org/10.1080/01639620701876577>
- Isom Scott, D. A., & Mikell, T. (2019). ‘Gender’ and general strain theory: investigating the impact of gender socialization on young women’s criminal outcomes. *Journal of Crime and Justice*, 42(4), 393—413. <https://doi.org/10.1080/0735648X.2018.1559754>
- Jang, S.J. (2007). Gender Differences in Strain, Negative Emotions, and Coping Behaviors: A General Strain Theory Approach, *Justice Quarterly*, 24(3): 523—553. <https://doi.org/10.1080/07418820701485486>
- Kowalski, R. M., Giumetti, G. W., Schroeder, A. W., & Reese, H. H. (2012). Cyber bullying among college students: Evidence domains of college life. In C. Wankel & L. Wankel (Eds.), *Misbehavior online in higher education* (pp. 293-321). Bingley, UK: Emerald Publishing Group.

- Kowalski, R. M., & Limber, S. P. (2007). Electronic bullying among middle school students. *Journal of Adolescent Health, 41*(6), S22–S30. <https://doi.org/10.1016/j.jadohealth.2007.08.017>
- LeClair, J., Shih, L. & Abraham, S. (2014). Women in STEM and Cyber Security Fields, *Proceedings of the 2014 Conference for Industry and Education Collaboration, American Society for Engineering Education, Savannah (GA) 2014, February 5–7.*
- Mann, H. B. & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *Annals of Mathematical Statistics, 18*(1), 50–60. <https://doi.org/10.1214/aoms/1177730491>
- Marcum, C. D., Higgins, G. E., Freiburger, T. L., & Ricketts, M. L. (2012). Battle of the sexes: An examination of male and female cyber bullying. *International Journal of Cyber Criminology, 6*(1), 904–911. https://libres.uncg.edu/ir/asu/f/Marcum_CD_2012_Battle_of_the_Sexes.pdf
- MacInnis, B., Krosnick, J. A., Ho, A. S., & Cho, M. J. (2018). The accuracy of measurements with probability and nonprobability survey samples: Replication and extension. *Public Opinion Quarterly, 82*(4), 707–744. <https://tinyurl.com/y3j742u7>
- Merton, R. K. (1938). Social structure and anomie. *American Sociological Review, 3*(5), 672–682. DOI: 10.2307/2084686; <https://www.jstor.org/stable/2084686>
- Moon, B. & Jang, S. J. (2014). A general strain approach to psychological and physical bullying: A study of interpersonal aggression at school. *Journal of Interpersonal Violence, 29*(12), 2147–2171. <https://doi.org/10.1177/0886260513516863>
- Moon, B. & Morash, M. (2017). Gender and general strain theory: A comparison of strains, mediating, and moderating effects explaining three types of delinquency. *Youth & Society, 49*(4), 484–504. <https://doi.org/10.1177/0044118X14541877>
- Ngo, F., & Jaishankar, K. (2017). Commemorating a decade in existence of the international journal of cyber criminology: A research agenda to advance the scholarship on cybercrime. *International Journal of Cyber Criminology, 11*(1), 1–9. DOI: 10.5281/zenodo.495762; <https://pdfs.semanticscholar.org/f4c0/4b10cb59534b1d0b98c6ea19cb9da5557be6.pdf>
- Neter, J., Kutner, M.H., Nachtsheim, C.J., & Wasserman, W. (1996). *Applied Linear Regression Models* (3rd ed.) Chicago: Irwin
- Patchin, J. W., & Hinduja, S. (2011). Traditional and nontraditional bullying among youth: A test of general strain theory. *Youth & Society, 43*(2), 727–751. <https://doi.org/10.1177/0044118X10366951>
- Peacock, D. & Irons, A. (2017). Gender Inequalities in Cybersecurity: Exploring the Gender Gap in Opportunities and Progression. *International Journal of Gender, Science and Technology, 9*(1), 25–44. <http://genderandset.open.ac.uk/index.php/genderandset/article/viewFile/449/824>

- Rebellon, C. J., Manasse, M. E., Van Gundy, K. T., & Cohn, E. S. (2012). Perceived injustice and delinquency: A test of general strain theory. *Journal of Criminal Justice*, 40(3), 230–237. <https://doi.org/10.1016/j.jcrimjus.2012.02.001>
- Reed, J., Zhong, Y., Terwoerds, L., & Brocaglia, J. (2017). 2017 Global Information Security Workforce Study: Women in Cybersecurity. *The Center for Cyber Safety and Education and the Executive Women's Forum on Information Security, Risk Management & Privacy*, <https://tinyurl.com/yym5td6>
- Reyns, B. W. (2013). Online Routines and Identity Theft Victimization: Further Expanding Routine Activity Theory beyond Direct-Contact Offenses. *Journal of Research in Crime and Delinquency*, 50(2), 216–238. <https://doi.org/10.1177/0022427811425539>
- Reyns, B. W., Fisher, B. S., Bossler, A. M. & Holt, T. J. (2019). Opportunity and Self-Control: Do they Predict Multiple Forms of Online Victimization? *American Journal of Criminal Justice*, 44(1), 63–82. DOI 10.1007/s12103-018-9447-5; <https://link.springer.com/article/10.1007/s12103-018-9447-5>
- Robbers, M.L.P. (2004). Revisiting the moderating effect of social support on strain: A gendered test, *Sociological Inquiry*, 74(4): 546–569. <https://doi.org/10.1111/j.1475-682X.2004.00104.x>
- Sanders, J. (2005). Gender and technology in education: A research review. <http://www.josanders.com/pdf/gendertech0705.pdf>
- Simmons, A. D., & Bobo, L. D. (2015). Can non-full-probability internet surveys yield useful data? A comparison with full-probability face-to-face surveys in the domain of race and social inequality attitudes. *Sociological Methodology*, 45(1), 357–387. <https://doi.org/10.1177/0081175015570096>
- Sourander, A., Klomek, A. B., Ikonen, M., Lindroos, J., Luntamo, T., Koskelainen, M., Ristkari, T., & Helenius, H. (2010). Psychosocial risk factors associated with cyberbullying among adolescents: A population-based study. *Archives of General Psychiatry*, 67(7), 720–728. DOI: 10.1001/archgenpsychiatry.2010.79; <https://pubmed.ncbi.nlm.nih.gov/20603453/>
- Thomas, D. (2002). *Hacker culture*. Minnesota: University of Minnesota Press
- Toupin, S. (2014). Feminist hackerspaces: The synthesis of feminist and hacker cultures. *Journal of Peer Production*, 5(2014), 1–11. <https://tinyurl.com/y4nk79oh>
- Vandebosch, H. & Van Cleemput, K. (2009). Cyberbullying among youngsters: profiles of bullies and victims. *New Media & Society*, 11(8), 1349–1371. <https://doi.org/10.1177/1461444809341263>
- Wall, D. S. (2010). The Internet as a conduit for criminal activity. In A. Pattavina (Ed.), *Information technology and the criminal justice system* (pp. 77–98). Thousand Oaks, CA: Sage

- Wansink, B. (2001). Editorial: The Power of Panels. *Journal of Database Marketing & Customer Strategy Management*, 8(3), 190—194. <https://link.springer.com/content/pdf/10.1057%2Fpalgrave.jdm.3240034.pdf>
- Weinberg, J. D., Freese, J., & McElhattan, D. (2014). Comparing data characteristics and results of an online factorial survey between a population-based and a crowdsorce-recruited sample. *Sociological Science*, 1, 292—310. DOI 10.15195/v1.a19; <https://sociologicalscience.com/articles-vol1-19-292/>
- Whitty, M. T. & Buchanan, T. (2012). The online romance scam: A serious cybercrime. *Cyberpsychology, Behavior, and Social Networking*, 15(3), 181–183. <https://doi.org/10.1089/cyber.2011.0352>