2020

Social Learning Theory and Digital Piracy: Explaining Uploading Behaviors of Digital Pirates

Cydney J. Lowenstein
Virginia Commonwealth University

Social Learning Theory and Digital Piracy: Explaining Uploading Behaviors of Digital Pirates

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

By

Cydney J. Lowenstein

B.S. in Criminal Justice, Virginia Commonwealth University, 2010

M.S. in Criminal Justice, Virginia Commonwealth University, 2014

Director: Nancy A. Morris, Ph.D.

L. Douglas Wilder School of Government and Public Affairs

Virginia Commonwealth University

Richmond, VA

December, 2020

Acknowledgment

First, I would like to thank my Dissertation Chair, Nancy Morris, Ph.D., whose guidance over these past few grueling years has kept me on track—I'm not sure I would have made it through the dissertation process without her. Thank you for dedicating so much of your time to helping me. Secondly, I'd like to thank the other members of my dissertation committee, Jay Albanese, Ph.D., George Burruss, Ph.D., and Jill Gordon, Ph.D., who have supported me throughout my dissertation and have generously given their time.

I'd also like to thank Blythe Balestrieri, Ph.D., without whom I likely wouldn't have considered applying for the doctoral program. Thank you for planting the idea in my head all those years ago when I was still an undergraduate student.

Finally, thank you to my family, for all of your love and support. Thank you especially to my mother, my brother Eric, and my sister Lisa who have been extremely patient throughout the years and have always cheered me on from the sidelines.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

SOCIAL LEARNING THEORY AND DIGITAL PIRACY: EXPLAINING UPLOADING BEHAVIORS OF DIGITAL PIRATES

By Cydney J. Lowenstein, Ph.D.

A dissertation submitted in partial fulfillment of the requirements for the degree Doctor of Philosophy at Virginia Commonwealth University.

Virginia Commonwealth University, 2020.

Major Director: Nancy A. Morris, Ph.D., L. Douglas Wilder School of Government and Public Affairs

Digital piracy has received significant attention in criminological research but almost no studies have explored illegal uploading and how it may differ from illegal downloading. It is important to examine what theories can explain illegal uploading behaviors and their related factors to develop more effective policies to address digital piracy. This dissertation examined whether Akers' (1998) social learning theory could explain engagement in digital piracy, both illegal downloading and uploading behavior. Additionally, this research examined the relationship between reciprocity and digital piracy. Questionnaires were administered to 398 university students and 315 visitors to several online communities using a combination of random and nonrandom sampling techniques. Confirmatory factor analysis and a series of structural equation models were used for analysis. Social learning theory was modeled as a second-order latent factor with latent factors for reciprocity and both outcomes while controlling for multiple covariates. Social learning theory was positively related to self-reported illegal downloading behavior and self-reported illegal uploading behavior. Perceptions of reciprocity had a positive direct effect on illegal uploading behavior but did not have a significant direct effect on illegal downloading behavior. Perceptions of reciprocity partially mediated the relationship between social learning and illegal uploading behavior. Self-control was not related to illegal downloading and uploading behaviors, but did have significant indirect effects through social learning. The main contributions of this dissertation were the application of social learning theory to explain illegal uploading and the empirical evidence supporting reciprocity. Possible directions for future research and policy implications are discussed.

Keywords: digital piracy, cybercrime, social learning, illegal uploading, reciprocity

CHAPTER 1: INTRODUCTION

Digital piracy refers to the unauthorized copying or distribution of copyrighted digital content such as music, films, or software without permission from or payment to the copyright holder (Hinduja, 2012; Recording Industry Association of America [RIAA], 2017). It can occur on an individual level via person-to-person interaction or on a larger scale through the Internet using peer-to-peer (P2P) technologies like BitTorrent (Morris, Johnson, & Higgins, 2009). Any copyrighted digital file can be the subject of digital piracy though some of the more common files targeted by piracy are music, movies, software, and eBooks. Acts of digital piracy can be as simple as someone sending a single music file to their friend over instant messaging or as complex as removing the copyright protections off of a software program and distributing it widespread through online P2P networks.

Despite efforts by representatives of the media industry to curb the problem, digital piracy continues to flourish around the world and has caused heavy financial losses through lost earnings, jobs, and tax revenue (Blackburn, Eisenach, & Harrison, 2019; Cenite, Wang, Peiwen, & Chan, 2009; Siwek, 2007). The U.S. economy loses an estimated $58 billion annually in revenue and other gross economic performance measures due to sound recording piracy alone (Siwek, 2007). According to the Business Software Alliance (2010), software piracy also deals a heavy toll and has led to $51 billion in lost commercial value in 2009. In a 2019 study on the effects of digital video piracy, it was estimated that global online piracy costs the U.S. economy at least $29.2 billion each year (Blackburn et al., 2019). The same study estimated that, in 2017, between 230,000 and 560,000 jobs and between $47.5 billion and $115.3 billion in GDP was lost in the U.S. due to digital video piracy. In addition to the harm caused directly by digital piracy, participation could be linked to engagement in other, possibly more serious digital crimes such as computer hacking (Morris & Higgins, 2010). Given these reasons, it is important to work towards a better understanding of why individuals engage in digital piracy to assist in the development of more effective policies aimed at reducing its prevalence.

In an attempt to curb digital piracy over the years, various organizations such as the RIAA and the British Phonographic Industry (BPI) have targeted legal action against sources responsible for uploading (Castro, Bennett, & Andes, 2009; "Hit the uploaders", 2004). Sometimes this has taken the form of lawsuits against the organizations behind websites or software that facilitates digital piracy (i.e. Napster) while in other cases it has been the individual file-sharers that are targeted for lawsuits (Cenite, Wang, Peiwen, & Chan, 2009). Oftentimes, these organizations have specifically pursued individuals who engaged in high-volume uploading as it has been estimated that a small percentage of file-sharers are responsible for the vast majority of copyrighted files shared illegally online (Cuevas, Kryczka, Cuevas, Kaune, Guerrero, & Rejaie, 2013; "Hit the uploaders", 2004).

Despite this targeting of uploaders in past legal action, most digital piracy studies have focused on downloading behavior, particularly music downloading, with little to no focus on uploading behavior. While existing research indicates downloading is far more prolific (Becker & Clement, 2006; Chiu & Chou, 2011) than illegal uploading, it is the illegal uploaders that maintain the continued survival of file-sharing networks that facilitate illegal downloading, despite fewer apparent rewards and heightened legal risk (Becker & Clement, 2006).

Although existing research on digital piracy has examined many of the predictors of illegal downloading, illegal downloading and uploading are not equivalent behaviors and these findings may not be extended to the explanation and prevention of illegal uploading behaviors. Illegal downloading and uploading differ in a variety of ways.

For example, illegal uploading requires more work and potentially higher levels of computer skill than illegal downloading. Individuals who upload copyrighted files need to first acquire these files before making them accessible in some way to downloaders (i.e. torrent files, IRC). In some cases, file-sharers need to remove copyright protections such as digital rights management (DRM) before other individuals can use them—a process that requires considerably more technical skill and time than illegally downloading copyrighted materials (Goode & Cruise, 2006). By comparison, illegal downloading is a quick and fairly simple process.

Uploading, while sharing some similarities with downloading, is qualitatively different as it requires distinct knowledge and an arguably longer time commitment while carrying different benefits and higher risks (Fleming, Watson, Patouris, Bartholomew, & Zizzo, 2017).[1] Due to these differences, theories and policies developed to address digital piracy based on illegal downloading studies may not be suitable for addressing illegal uploading behaviors. There may be different theoretical mechanisms and motivations underlying illegal uploading and downloading behaviors—for instance, the learning process for each behavior may differ. As such, in addition to illegal downloading, it is important to examine illegal uploading behaviors specifically to develop a more comprehensive explanation of engagement in digital piracy.

Nonetheless, previous research examining illegal downloading and other types of cyber-deviance have provided empirical support for a variety of mainstream criminological theories. Studies into pirating have shown varying degrees of support for the explanatory value of differential association theory (Marcum, Higgins, Wolfe, & Ricketts, 2011), self-control theory (Marcum et al., 2011), techniques of neutralization (Smallridge & Roberts, 2013), and social

[1] Further details and discussion about the process of downloading and uploading illegal content are discussed in Chapter 2.

learning theory (Burruss, Bossler, & Holt, 2012; Higgins, Fell, & Wilson, 2006; Hinduja & Ingram, 2009; Holt, Burruss, & Bossler, 2010; Morris & Higgins, 2010).

Differential association theory (Gunter, 2009; Higgins & Makin, 2004; Marcum et al., 2011) and self-control theory (Higgins, 2007; Higgins et al., 2006; Higgins & Makin, 2004; Hinduja, 2012; Marcum et al., 2011) have both garnered somewhat strong support. Association with peers that engage in or approve of digital piracy and low self-control are both associated with higher levels of self-reported digital piracy. Findings for techniques of neutralization, on the other hand, have been mixed overall with weak to moderate support (Smallridge & Roberts, 2013). Denial of injury has the most consistent support of the neutralization techniques that have been examined (Hinduja, 2007; Ingram & Hinduja, 2008; Marcum et al., 2011; Moore & McMullan, 2009; Morris & Higgins, 2009; Morris et al., 2009; Smallridge & Roberts, 2013; Steinmetz & Tunnell, 2013). Social learning theory, in particular, has found strong support in its ability to explain variations in digital piracy engagement (Burruss et al., 2012; Pratt et al., 2010). Although only two studies have included measures for all four components of social learning theory (Burruss et al., 2012; Burruss et al., 2018), there is strong support for certain theoretical components of the theory (Gunter, 2008; Higgins et al., 2012; Hinduja & Ingram, 2009). Individuals who self-report having more direct or indirect associations with others who engage in or approve of digital piracy, and those who report reinforcement for such behaviors, are more likely to engage in illegal downloading.

Another potential explanation for digital piracy, specifically for illegal uploading behaviors, is reciprocity. Studies from the computer science and communications literature (Becker & Clement, 2006; Chiu & Chou, 2011; Cenite et al, 3009) have indicated that one of the possible motivations driving illegal file sharing and uploading may be the expectation of reciprocity—the belief that when one gives something, they should receive something back in return (Beck & Clement, 2006). This “quid pro quo” is a prevalent code of conduct within the file-sharing community (Offer, 1997). Other online groups, such as the hacking community, also operate similarly—hackers trade information and are recognized for their deeds (Holt, 2007). Norms of reciprocity may be more relevant for explaining illegal uploading behavior than factors related to illegal downloading such as low self-control or immediate benefits.

Although a large body of criminological research has been dedicated to the study of factors relating to digital piracy, the vast majority of this research has been exclusively focused on the illegal downloading of copyrighted digital content. Due to the lack of attention in the criminological research literature, there is still much to be learned about illegal uploading behavior. In addition, most of the research that has examined illegal downloading has only used data collected from university study samples—few studies have included samples from the larger, general population. This is a limitation of existing research given that findings based exclusively on university samples may not be generalizable to other populations (Morris & Higgins, 2010). Furthermore, while some prior research has found that university students report high levels of engagement in digital piracy (Hinduja, 2003), it has yet to be established whether this extends to illegal uploading due to the lack of differentiation between downloading and uploading in prior research. Based on this and the evidence that a smaller proportion of individuals engage in illegal uploading compared to illegal downloading (Becker & Clement, 2006), widening the sample to include individuals from the general population may be more suitable for the study of illegal uploading behavior.

Current Dissertation

The current dissertation contributes to criminological research on digital piracy in several ways. Firstly, this dissertation examines whether existing theories previously used to explain illegal downloading are also suitable for explaining illegal uploading behavior. While there is a wealth of empirical research that has identified factors relating to illegal downloading behaviors, the same cannot be said for illegal uploading behaviors. This is problematic because it means that existing theoretical explanations for digital piracy are incomplete. Research focusing on illegal uploading may help develop more effective policies and enforcement strategies intended to deter digital piracy. Second, this dissertation utilizes primary data collected from both a university sample and a sample of respondents from multiple online communities. The use of primary data allows this dissertation to examine factors that may be more strongly related to illegal uploading behaviors, such as reciprocity. The addition of a sample of online respondents may also increase the likelihood of including participants that engage in illegal uploading behaviors. Third, this dissertation conducts a full test of social learning theory, including measurements for all four components of the theory—differential association, differential reinforcement, imitation, and definitions. Finally, building on extant qualitative studies on illegal uploading behaviors, this dissertation includes the concept of reciprocity

Using Akers' (1985; 1998) social learning theory as a theoretical framework, this dissertation examines factors relating to self-reported illegal downloading and uploading behaviors. To do so, original survey data was collected from 398 students sampled from a large southeastern university, and 315 respondents from several online communities during the spring of 2020.

Dissertation Overview

Chapter 1 introduces the dissertation's research focus and introduces the conceptual background of the major research questions. Chapter 2 defines digital piracy and discusses what constitutes digital piracy while distinguishing between two different forms of digital piracy—illegal downloading and illegal uploading. Chapter 2 also discusses the theoretical framework for this dissertation, social learning theory, as well as other relevant theories, such as a general theory of crime (Gottfredson & Hirschi, 1990) and the norm of reciprocity (Whatley, Webster, Smith, & Rhodes, 1999) and reviews existing empirical research that examines social learning theory, self-control, and reciprocity to explain illegal downloading and uploading behaviors. Chapter 3 presents the methodology for the current dissertation and discusses the hypotheses, data, and analytical framework. Chapter 4 presents and discusses the results from the measurement models, and all descriptive and multivariate analyses of illegal downloading and uploading behaviors with a focus on the effects of social learning theory, self-control, and reciprocity for explaining illegal uploading behaviors. Chapter 4 also discusses any significant similarities and differences between the university and online samples in regards to the extent of illegal downloading and uploading behaviors. Additionally, sensitivity tests are conducted to determine the robustness of this dissertation's analysis and the extent to which the results are affected by methodological changes. Finally, Chapter 5 discusses the overall conclusions of this dissertation, its limitations, and the implications of the findings for criminological theory and policy relating to digital piracy.

CHAPTER 2: LITERATURE REVIEW

Digital Piracy

Digital piracy can refer to a wide range of illicit activities that involve the unauthorized copying or distribution of copyrighted digital content (Recording Industry Association of America [RIAA], 2017). Any digital copyrighted good can be pirated but some of the more frequent types of content include music, movies, computer software, video games, and TV shows (Dey, Kim, & Lahiri, 2019). Digital piracy can also take many shapes—for instance, if an individual shares a music file with one of their friends over instant messaging software, that would be an act of digital piracy. When an individual maintains a website that hosts thousands of copyrighted movies for others to stream, that would also constitute digital piracy. Even the act of downloading a video from YouTube using a downloading tool may be digital piracy if the owner of the video did not provide permission. Digital piracy is typically a two-sided process—there is the individual who provides the pirated content, frequently through uploading the content in some way, and then there is the individual who received the pirated content, typically by downloading it from some online source.

Some common sources of pirated files include P2P networks, Internet Relay Chat (IRC), and file-hosting websites that carry pirated content (i.e. "cyberlockers" such as RapidShare or DropBox) (Lai, 2009). While P2P file-sharing networks have many legitimate legal applications, they are also frequently used for digital piracy by facilitating the exchange of copyrighted music, software, movies, and other such files without permission (Chiu & Chou, 201). The rise in popularity of P2P file-sharing is due in large part to the availability of these files (Cuevas, Kryczka, Cuevas, Kaune, Guerrero, & Rejaie, 2013). IRC and cyberlockers too have very legitimate uses but also greatly facilitate engagement in digital piracy. Internet Relay Chat (IRC) is a service that provides real-time text messaging and can be used for direct messaging between just two users or for messaging multiple users within chat rooms, or "channels" ("*What is IRC"*, n.d.). Although not used as frequently anymore due to the development of more efficient technologies, IRC is still used to discuss pirated files and to transfer them between users, possibly due to the ability to access IRC through more secure methods (i.e. Tor network) or the ability to automate file-sharing of large libraries of pirated content through IRC scripting. Cyberlockers, like DropBox, are often used to store files as a backup or to send files to others rather than using e-mail attachments (Gil, 2019). While they are useful tools for file safety and productivity, they are also very useful and popular for sharing pirated content, particularly given how difficult they are to monitor—cyberlockers typically do not have centralized search functions, so identifying potentially pirated files is more difficult than with other file-sharing methods. Cyberlockers also financially benefit from the files hosted on their service, whether legal or pirated, and therefore are not as motivated to curb the issue (Marx, 2013).

Within the literature, digital piracy is generally measured as one or more specific forms of digital piracy—these forms are music, movies, and software (Gunter, 2008; Gunter, 2009). Measurement of digital piracy is almost exclusively reliant on self-report data, whether as actual involvement or willingness to engage in digital piracy. Involvement is generally measured by asking an individual how frequently they've pirated commercial music, movie, or software files and providing ranges in Likert-type format with higher scores indicating greater digital piracy involvement (Burruss et al., 2012; Burruss et al., 2018; Gunter, 2009; Hinduja & Ingram, 2009; Skinner & Fream, 1997). For instance, Gunter (2009) provided response options with ranges of songs downloaded each month (i.e. 6-15 songs per month). Rather than measure self-reported involvement, many researchers have instead utilized vignettes to capture willingness to engage in digital piracy (Higgins & Wilson, 2006; Higgins et al., 2006; Shore, Venkatachalam, Solorzano, Burn, Hassan, & Janczewski, 2001). In such instances, individuals are offered scenarios to consider that depict illegal downloading and Likert-type responses with higher scores indicating a greater likelihood that they would engage in the specific act of digital piracy. Most digital piracy research also focuses exclusively on illegal downloading or does not differentiate between downloading and uploading behavior, despite the potential for significant differences between the two processes (Cenite et al., 2009).

To date, there are very few studies that have specifically examined uploading in the digital piracy literature and, on the rare occasion that they are mentioned, they are combined with downloading to represent measure general digital piracy. While illegal uploading and downloading may have similarities to each other, several differences make the two behaviors qualitatively different (Fleming et al., 2017). Illegal uploading and downloading differ in potential risks, potential benefits, and the skill and time required to commit each action.

The potential risks of digital piracy, both as an uploader and as a downloader, vary based on a variety of factors. One such factor is the country in which an individual resides—for instance, downloading copyrighted files is legal in some countries while uploading is illegal (Fleming et al., 2017). For instance, while EU copyright law prohibits the downloading of pirated content, Poland has yet to amend their national laws and so the legal status of downloading is unclear (Quintais, 2018). Poland has largely pushed back against enacting the legal changes on a national level (Liptak, 2019). In countries where this is the case, the risks are more significant for those who choose to upload illegally. Legal statutes and private initiatives from different countries also differ in how aggressively they try to stop digital piracy and the methods they use to do so. For instance, although it ended in 2017, the Copyright Alert System

(CAS) allowed media companies to monitor the internet traffic of users of participating U.S. internet service providers (i.e. Verizon and Comcast) for potential copyright infringement and—if wrongdoing was suspected—allowed the user's internet service to be restricted (Nazer, 2013). This particular measure, though now defunct, was targeted at anyone engaged in digital piracy, whether as a downloader or uploader.

Anti-piracy enforcement measures fall under either those that punish the illegal use of pirated content (demand-side) or those that try to restrict the availability of pirated content (supply-side) (Dey, Kim, & Lahiri, 2019). There are some notable cases of legal action against individuals, such as the graduate student at Boston University who was fined $675,000 after illegally downloading just 30 songs. While individual downloaders have been and remain a target (Dey et al., 2019), organizations like the RIAA and the BPI have heavily focused their legal efforts on targeting the websites and services that facilitate digital piracy (i.e. Napster) and individuals identified as high-volume uploaders (Cenite et al., 2009; Cuevas et al., 2013; "Hit the uploaders", 2004). Internet security companies have even developed tools specifically targeted to illegal uploaders (Kipnis, 20005). For instance, the company BayTSP developed a tool called FirstSource which can be utilized to identify the initial uploader of copyrighted digital material so that legal action can be taken against them. Governments have also started to scan for websites that illegally share or facilitate the illegal sharing of copyright-protected content (Dey et al., 2019).

Illegal downloading carries the obvious benefit of receiving copyrighted content without having to pay for it, but the benefits of illegal uploading are less clear (Cenite et al., 2009). Although empirical research into the motivations of uploaders is lacking, some research has examined their motivations. Cenite and colleagues (2009) conducted interviews with file-sharers regarding their motivations for downloading and uploading—uploaders reported that one important motivator for their file uploading was a norm of reciprocity. Becker and Clement (2006) also identified reciprocity as a significant factor among uploaders.

Reciprocity involves the expectation by file-sharers that if they share their files, then other users will reciprocate by providing their files (Becker & Clement, 2006). Similarly, if a user downloads files, reciprocity involves the feeling of obligation to share their files. Although reciprocity has not been heavily studied in digital piracy literature, some evidence shows it to be a significant motivator for illegal uploading. Becker and Clement (2006) found that users who expected reciprocal acts from other P2P users were more willing to share their files, though the effects of reciprocity varied depending upon a user's experience level with P2P networks—more experienced users were less influenced by reciprocity. The findings of Cenite et al. (2009) also supported reciprocity as a significant motivator for illegal uploading. Approximately a third of their sample of 40 file-sharing interviewees described motivations for uploading that fall under a norm of reciprocity.

Unlike the immediate benefits of downloading, reciprocity implies that the benefits to the uploader may not be immediate or even guaranteed (Whatley et al., 1999). Cuevas et al. (2013) found that many content publishers on BitTorrent are at least partially motivated by financial benefits. Many publishers included advertisements for their websites in the files they uploaded. While not all uploaders maintain their own websites, those that do can generate ad revenue from visitors (Dey et al., 2019). The benefits of illegal uploading may be significant, but they appear to be less guaranteed and more long-term than downloading.

Finally, illegal uploading typically requires more skill and a greater time commitment. To download, an individual may need the skills to use P2P software or IRC—at the minimum, they must know where to access pirated files. In addition to these skills, uploaders must also know how to distribute these files, whether they do so by creating torrent files, sharing them via IRC, uploading them to file-hosting websites like cyberlockers, or some other method.

Peer-to-peer network technologies, such as the popular protocol BitTorrent, are designed to allow for fast data transfers of files between users without the need for a centralized server (Chiu & Chou, 2011). Rather than a client-server structure, P2P file-sharing technology provides the means through which an individual, or a peer, can perform the roles of both a “client” and a “server” at the same time. Each peer allows others to access particular files on their computer while simultaneously downloading files from other peers.

The P2P software known as BitTorrent functions by allowing individuals to create torrent files, which are essentially instructions to tell another user’s BitTorrent software how to access the other peers connected to the same torrent network, commonly referred to as a “swarm” (Fung & Lakhani, 2013). These torrent files are distributed online through a variety of ways including torrent trackers and index websites (i.e. The Pirate Bay, isoHunt) (Chiu & Chou, 2011). Typically, each peer is both downloading from and uploading to other peers within the swarm (Chiu & Chou, 2011; Fung & Lakhani, 2013).

Any individual who intends to upload also must first source a copyrighted file. Depending on the type of copyrighted content (music or software) that the individual intends to share, a variety of tools, skills, and effort may also be required to prepare the content before it can be used by others. For instance, despite its questionable effectiveness and significant consumer complaints, digital rights management (DRM) is a fairly common tool used by content creators and publishers to protect digital content from piracy (Sun, Easley, & Kim, 2015). Though in some cases companies have moved away from DRM—particularly with music—some types of content continue to be restricted. The initial acquisition of pirated digital content, particularly software files, requires more effort and skill to remove piracy protections before uploading. For instance, software often requires valid license codes to install and activate online (Holm, 2014). All of these protections must first be removed by someone using either an existing tool or they must find a way to bypass the DRM protections on their own through the process of "cracking". While some proportion of uploaders may just be distributing copyrighted files that they've illegally downloaded from someone else, at least some segment of uploaders will need to acquire the files themselves.

The minimum skills needed for downloading are fairly simplistic—websites hosting illegally uploaded files can commonly be found on most popular search engines. Even the more complicated methods of downloading pirated files such as using BitTorrent or IRC—which requires individuals to install software, understand how to use it, and then locate the files they want to download—do not require much skill or time commitment. Moreover, the information necessary to use those methods is easily discoverable. Illegally uploaded files are so prolific that it is likely that an individual will encounter such files available for download without even intending to.

For all of these reasons, research into digital piracy should separately measure uploading and downloading behaviors as they are qualitatively different—to date only a limited number of studies have done so and none within the criminology literature.

Theoretical Explanations for Digital Piracy

Many research studies have examined the applicability of various criminological theories to explain different forms of digital piracy (Burruss et al., 2012; Gunter, 2009). Some criminological theories that have been tested for explaining digital piracy include social learning theory (Holt et al., 2010; Morris & Higgins, 2010), differential association theory (Marcum et al., 2011), self-control theory (Hinduja, 2012; Marcum et al., 2011), and techniques of neutralization (Smallridge & Roberts, 2013; Steinmetz & Tunnell, 2013). Overall, social learning theory—which is the theory of focus within the current study—has garnered the strongest empirical support for explaining digital piracy (Morris & Higgins, 2010).

Social Learning Theory

Sutherland (1947) was one of the first to theorize that criminality is a learned behavior through social interaction and he articulated nine elements of differential association theory. The main arguments within differential association theory are that criminal behavior is learned by interacting with others, primarily within intimate personal groups. The theory also posits that this learning includes both the techniques for committing the crime and the direction of motives, attitudes, drives, and rationalizations concerning the crime. The direction of these motives is learned from "definitions" of laws as either favorable or unfavorable and, Sutherland argues, an individual engages in deviance when definitions favorable to committing crime exceed those that are unfavorable. Associations with criminal behavior, or "differential associations," can also vary across several dimensions (frequency, duration, priority, and intensity), and learning criminality through these associations is possible through any learning mechanism. Finally, Sutherland argues that criminality is not explained by needs and values because non-criminal behavior is also an expression of the same needs and values.

Burgess and Akers (1966) drew upon Sutherland's (1947) differential association theory, particularly the concepts of differential association and definitions, but reformulated them in such a way to define the learning process explicitly using modern behavioral theory. One of the major concepts that they added based on behavioral theory is differential reinforcement whereby behavior is conditioned through rewards and punishments (Burgess & Akers, 1966). Other areas that they expounded on were the differential influence of reinforcements based on their frequency, amount, and probability along with the redefining of “intimate personal groups” as the source of learning criminality to “groups which comprise the individual’s major source of reinforcement” (Burgess & Akers, 1966, p. 146).

This study will be utilizing Akers’ (1985, 1998) social learning theory, which was a further refinement on Sutherland’s (1947) differential association theory and Burgess and Akers’ (1966) differential association-reinforcement theory. Akers (1985, 1998) articulated social learning theory to be composed of four mechanisms: (1) differential association, (2) differential reinforcement, (3) imitation, and (4) definitions. Social learning theory posits that individuals differentially associate with peers, family, and other individuals who expose them to deviant behavior or attitudes about deviance. These differential associations can be either direct or indirect and include both verbal and nonverbal communications, interactions, and identifications with others. Additionally, the strength of these associations—based on frequency, intensity, duration, and priority—influences the exposure to norms, attitudes, and rewards/punishments.

The second element of social learning theory is differential reinforcement, which refers to the balance of punishment and rewards that an individual experiences or anticipates experiencing as the result of their deviance. According to the theory, an individual’s decisions regarding whether or not to commit criminal acts is dependent on the frequency, amount, and probability of rewards and punishments associated with the behavior. Reinforcements can be either non-social or social—the former including effects of physical and physiological stimuli while the latter encompasses both direct reactions of others and rewards valued in society or its subgroups. For instance, an individual’s piracy could carry with it the positive reinforcement of gaining files that hold monetary value while also leading to negative reinforcement in the form of reproach from a family member upon discovery of their deviance.

Those with whom individuals associate also provide a source for imitation of deviant behavior. Imitation is the mechanism through which an individual observes a form of behavior and its associated consequences and copies it. In the context of digital piracy, an individual may observe illegal downloading and uploading behaviors from online peers or online communities, and this may provide them with the attitudes and the means to learn how to pirate themselves.

Finally, through differential associations, individuals can also espouse definitions that are either favorable or unfavorable to criminality. According to the theories (Akers, 1985; Akers, 1998; Burgess & Akers, 1966; Sutherland, 1947), these definitions include any beliefs, rationalizations, or attitudes surrounding a particular behavior. For instance, an individual might believe that downloading copyrighted files is a victimless offense—this would constitute a justification that is favorable to engaging in digital piracy.

Social learning theory has undergone significant empirical testing in the research literature for general crime as well as a wide variety of specific criminal behaviors and has remained one of the primary criminological theories for decades (Pratt, Cullen, Sellers, Winfree, Madensen, Daigle, Fearn, & Gau, 2010). In a 2010 meta-analysis on the empirical status of social learning theory, Pratt and colleagues found that empirical support for social learning theory was comparable or, in some cases, stronger than other major criminological paradigms. When examining mean effect sizes, they found that differential association and definitions were comparable to self-control and larger than rational choice/deterrence theory.

Notably, some elements of social learning theory have undergone more extensive testing than others—differential association and definitions, in particular, have received significantly more attention in the research literature (Pratt et al., 2010). Differential association and definitions measures commonly appear not only in research into social learning theory but also heavily feature in studies focusing on other criminological theories as control variables. In addition to being included more frequently, differential association and definitions have received stronger empirical support within the literature than the remaining components of social learning theory. Differential reinforcement and imitation have fared worse empirically and are generally found to have a weak effect or, occasionally, were not found statistically significant.

Within each component of social learning theory, mean effect sizes also differed depending on how they were measured (Pratt et al., 2010). For instance, for differential association, behaviors of peers, parents, and others rated more strongly than attitudes of these same groups. Also, in both differential association and differential reinforcement, peer behaviors, attitudes, and reactions had higher mean effect sizes than those with parents and others. Based on the results of their meta-analysis, Pratt and colleagues (2010) concluded that how components of social learning theory were measured—in addition to other aspects of research design (i.e. sampling)—bore a significant influence on the effect strength of social learning theory predictors.

A General Theory of Crime

A general theory of crime, developed by Gottfredson and Hirschi (1990), argues self-control is a relatively time stable individual trait that influences the likelihood of an individual engaging in criminal acts throughout their entire life. Individuals with low self-control are described as "impulsive, insensitive, physical (as opposed to mental), risk-taking, short-sighted, and nonverbal" (Gottfredson & Hirschi, 1990, p. 90). Although low self-control increases the propensity for crime, there must still be sufficient opportunity for a crime to be committed

(Akers & Sellers, 2004). Low self-control is not only limited to criminal behavior—noncriminal acts such as smoking and alcohol use are also prescribed to low self-control.

Individuals with low self-control may be more likely to engage in illegal downloading behaviors because of the immediate gratification of receiving pirated digital content for free. As mentioned earlier, while illegal downloading requires some technical skills and knowledge to engage in, those skills are fairly easy to learn—a quick internet search on "torrenting" will give multiple guides showing what software to use for illegal downloading and the basics of how to use it. On the other hand, individuals with low self-control may not be as likely to engage in illegal uploading. Illegal uploading requires higher skills and a greater time commitment than downloading without an immediate benefit—these traits likely would not appeal to individuals with low self-control.

A general theory of crime has been heavily tested with both criminal and noncriminal behaviors (i.e. alcohol use) and has found considerable empirical support (Pratt & Cullen, 2000). According to a meta-analysis by Pratt and Cullen (2000), the effect size for low self-control would rank it as one of the strongest known correlates of criminal behavior, even when controlling for other theories and using different measurement techniques. Despite this, self-control had less support in longitudinal studies—an important distinction considering self-control is argued to be stable over the life course.

Empirical Studies of Digital Piracy

Overall, Akers' (1985, 1998) social learning theory has garnered significant support for its ability to explain digital piracy (Burruss et al., 2012; Burruss et al., 2018; Cenite et al., 2009; Chiu & Chou, 2011; Gunter, 2008; Gunter, 2009; Higgins & Wilson, 2006; Hinduja & Ingram, 2009; Holt & Copes, 2010; Morris & Higgins, 2010). As with the larger body of research into social learning theory, each component of social learning theory has received different levels of attention and empirical support. Few studies have included measures for all four components of social learning theory—instead, as with social learning theory research as a whole, empirical studies have largely focused on differential association and definitions.

Burruss et al. (2012) provided a complete empirical test by including measures for all four elements of social learning theory. Using a model linking low self-control and social learning theory, they examined both the indirect effect of low self-control through the social learning process and its direct effect on software piracy using data collected with self-report surveys from a sample of 574 university students. Software piracy was measured using an item asking about software piracy committed within the past year rather than the vignettes capturing willingness to pirate, which are heavily used in extant digital piracy research. Their findings provided strong support for social learning theory while only partially supporting self-control theory. While self-control was supported without controlling for the social learning process, when these controls were included, low self-control actually corresponded with a lower likelihood of software piracy.

In another full test of social learning theory, Burruss et al. (2018) examined whether a suppression relationship exists between social learning and low self-control in relation to software piracy. Rather than using university students—as is common in digital piracy research—data was collected from 467 middle and high school students with self-report surveys. Individually, self-control and social learning were significantly related to software piracy. Additionally, a suppression relationship was found to exist between social learning and self-control—individuals with low self-control but who do not associate with pirating peers are less likely to engage in software piracy.

Unlike the prior two studies, Higgins and Wilson (2006) tested two components of social learning theory: differential association and definitions. In their study, they explored the effects of low self-control, differential association, and attitudes on software piracy using data collected from 318 university students. Digital piracy was captured as willingness to engage in software piracy using vignettes that posed a scenario and asked respondents how likely it would be for them to engage in the behavior. Their findings indicated that low self-control, differential association, and attitudes were all positively correlated with software piracy while a negative correlation exists between software piracy and moral beliefs. Social learning theory was found to have a mediating effect on low self-control and digital piracy such that individuals with low self-control were more likely to learn to pirate. Also, individuals who are more heavily associated with peers who pirate software and who have attitudes favorable to software piracy are more willing to pirate software. Finally, when individuals viewed software piracy as morally wrong, they were less likely to engage in this behavior.

Although not a complete test of social learning theory, Higgins and colleagues (2006) examined how the integration of Gottfredson and Hirschi's (1990) theory and Akers' (1985, 1998) social learning theory could be used to explain digital piracy. Rather than use a measure capturing self-reported piracy, they measured intentions for digital piracy using three vignettes modified from Shore et al. (2001). For social learning theory, they only examined differential association and definitions—differential association was measured using a 6-item composite developed by Krohn, Skinner, Massey, and Akers (1985), and definitions were measured using an 11-item scale from Rahim, Seyal, and Rahman (2001). Their data was collected using self-administered surveys distributed to 392 university students (Higgins et al., 2006). Both social learning and self-control were supported by their analysis, adding to the existing support for both theories. The results also favored a three-factor model whereby individuals with low self-control who socially learn digital piracy will have a higher likelihood of intending to pirate.

Morris and Higgins (2010) also empirically tested differential association and definitions in explaining the likelihood of performing digital piracy. Both components of social learning theory were measured using the same survey items as the previous study by Higgins et al. (2006), established by Krohn et al. (1985) and Rahim et al. (2001) respectively. The researchers used a series of 14 survey items recommended by Maruna and Copes (2005) which measure the following neutralization techniques: denial of responsibility, denial of victim, denial of injury, condemnation of the condemners, defense of necessity, and appeal to higher loyalties (Morris & Higgins, 2010). Based on the data from 585 students from two universities, differential association, definitions, and neutralizations were all found to be significant in explaining the likelihood of engaging in digital piracy.

Gunter (2008) also included measures capturing differential association along with differential reinforcement. Unlike many other digital piracy studies, they measured multiple forms of digital piracy—their questionnaires included hypothetical vignettes about engaging in music, software, and movie piracy. For each of the three vignettes, items were included to measure piracy involvement, peer involvement, parental approval, reinforcement certainty, reinforcement severity, technical ability, and belief. Based on data from 587 undergraduate students across two universities, their results revealed support for differential association—college students who reported peer involvement and parental approval were more likely to engage in digital piracy. The effects of differential association were also found to be mediated through motives, beliefs, and technical ability as predicted by the researchers. On the other hand, the effects of differential reinforcement—measured as perceptions of the certainty and severity of punishment—were found to not be statistically significant overall.[2]

Expanding on their previous study, Gunter (2009) examined the explanatory power of both differential association and general deterrence theories. Using survey data from 541 undergraduate university students. Digital piracy was measured in two ways across six variables: three variables used vignettes to measure willingness to engage in movie, music, and software piracy, and three used questions that asked respondents how often they downloaded files without paying. Overall, their findings further supported differential association—specifically measured as peer activity and parental support in this case—as a predictor of digital piracy. In regards to general deterrence, punishment severity was not statistically significant in predicting any form of digital piracy, and punishment certainty was only a significant predictor for software piracy.

Hinduja and Ingram (2009) further tested social learning theory, this time with music piracy and a focus on both offline and online peer influences. Their sample included 2,032 undergraduate students at a single public university who were purposively sampled to ensure variation across majors and class levels. Students' participation in music piracy was measured using a 13-item instrument which was combined into a single score. Both offline and online peer influences were measured—four Likert-type items were used to measure real-life peers, popular media, online peers, and online media. Through their analysis, online peers and online media sources were significant predictors of music piracy, however, real-life peers though had the strongest effect on music piracy. This signifies that, while both online and offline peers and media can provide a source of differential associations for the learning of music piracy,

---

[2] Measures of perceived certainty and severity of punishment are typically used as measures of perceptual deterrence (Klepper & Nagin, 1987; Paternoster, 1987).

associations with real-life peers have the strongest impact on the likelihood of an individual pirating music.

Similarly, Higgins, Marcum, Freiburger, and Ricketts (2012) also examined offline and virtual peer influences—in this case, alongside low self-control—to explain illegal music downloading. Based on survey data from 287 university students across four institutions, they found that both virtual and offline peer influences were significant predictors of music piracy. Low self-control was also significant, though the relationship was not as strong with music piracy as either of the peer influence measures. Despite only examining one component of social learning theory, their findings do provide further support for the differential association component of the theory.

Although not specifically testing any component of social learning theory, Chiu and Chou's (2011) study using in-depth interviews with users of P2P file-sharing software offered some support for social learning components. Using data collected from 21 university students in Taiwan within the school's department of information management, interviews covered several topics relating to software file-sharing including types of software, adoption of use, value of software, feature of software, file sharing, legal awareness, suggestions, and future development. In regards to adoption, some participants reported that they came into contact with P2P file-sharing software through reports in newspapers, magazines, and online discussion boards. Others became interested after seeing classmates or friends using it or they were introduced to P2P software by their teacher in class. According to participants, the value of P2P file-sharing software is that it allows them to watch films early, it saves them time and money, and it provides a way to retrieve old files that are not readily accessible by other means. Some individuals were aware that their actions were illegal while others were unaware or believed that using the files for personal use made their actions legal. Despite their study not specifically testing social learning theory, their findings lend some support to differential association and imitation, given that individuals reported learning piracy through their peers and teachers. Some of the values and beliefs attributed to digital piracy also seem to align with differential reinforcement and definitions under social learning theory.

Similar to the previous study, Holt and Copes (2010) provided some additional support for the explanatory value of differential association with digital piracy despite not explicitly testing social learning theory. In their study, they performed a non-participant ethnography of a piracy-related online discussion board and interviews with digital pirates to explore the role of online interactions in the social learning process of digital piracy. Nine face-to-face interviewees were recruited through a combination of online solicitation and snowball sampling. Twenty-five additional participants were recruited from posts made on two forums and two IRC channels dedicated to piracy as well as referrals from the face-to-face group. Their analysis revealed that online interaction can provide individuals with a source for learning norms and values of digital piracy. Through these associations, individuals learn justifications for their illegal downloading.

Although social learning theory has heavily featured as a theoretical explanation for digital piracy in the literature, other criminological theories have also been examined. One of the other primary theories that have been tested for its explanatory value with digital piracy is a general theory of crime. In Gottfredson and Hirschi's (1990) criminological theory, self-control is the ability for an individual to resist engaging in acts that result in negative consequences but have an immediate or near-immediate pleasure associated with the act—it involves the ability for an individual to act in with long-term interests in mind. Levels of self-control, according to

Gottfredson and Hirschi, are stable over the life-course after they have been established in an individual's early life.

In the research literature, findings frequently show that individuals with low self-control have been significantly more likely to engage in illegal downloading (Aaltonen & Salmi, 2013; Higgins et al., 2012). Multiple studies have found low self-control to be significant even when including controls for other prominent theories such as social learning theory (Higgins, 2007; Higgins et al., 2008; Higgins et al., 2012). For instance, the 2012 study by Higgins and colleagues found support for low self-control in explaining illegal music downloading among university students while including differential association measures. In their study of Finnish adolescents, Aaltonen and Salmi (2013) found that respondents with low self-control were more likely to engage in digital piracy. Although individuals with low self-control are typically more likely to engage in illegal downloading, some exceptions to this have been identified when controlling for social learning theory using structural equation modeling. Evidence from Burruss et al. (2012) and Burruss et al. (2018) also supports the existence of a suppression effect in the relationship between low self-control, social learning, and digital piracy—when controlling for social learning theory, increases in the levels of low self-control were associated with a decrease in digital piracy. Low self-control would typically increase the likelihood of engaging in deviant behavior, yet in this case, individuals with low self-control but who lack associations with pirating peers are less likely to engage in digital piracy. According to Gottfredson and Hirschi (1990), low self-control motivates individuals to engage in easy behaviors that don't require much time or skill—digital piracy could require too much technical skill and effort to entice individuals with low self-control (Burruss et al., 2012; Burruss et al., 2018). Individuals with low self-control may not be willing to invest the time and effort into acquiring the skills required to engage in digital piracy without pirating peers from whom they can learn the skills necessary.

Although few empirical studies in the literature have separated uploading and downloading behaviors, Becker and Clement (2006) conducted one such study whereby two surveys were used to examine the motivational factors of participants in peer-to-peer networks. The first of these surveys was posted online with recruitment made through several music-related websites in Germany and the second was administered in-person to German high school and university students. Their second survey included 270 participants who were segmented into three sharing subgroups based on how many files they reported sharing: "free riders," "medium sharer," and "heavy sharer."

They found that willingness to share among individuals in the heavy sharer group was positively correlated with the number of years and the frequency by which these sharers have been using peer-to-peer networks. Additionally, the more an individual believes that it is "cool" to be labeled a sharer, the greater their file-sharing will likely be. The differences identified between these file-sharer groups—particularly between the non-sharing "free riders" and the other two file-sharing subgroups—provide empirical support for the argument that uploading and downloading are influenced by different types of motivators and with different strengths.

Finally, Cenite and colleagues (2009) explored individuals' motivations for both downloading and uploading behavior. Emails were sent out to potential participants among communication students at a university in Singapore and snowball sampling was used to supplement the sample Forty individuals in total were recruited to participate in face-to-face interviews. Individuals were asked to respond only if they (1) had experience with more than one P2P software, (2) possessed a working understanding of their usage, and (3) had purchased a minimum of one original CD or DVD since they began downloading.

Some of the reasons provided for downloading included cost-savings, convenience, the ability to access content that is either hard to find or is not yet available in Singapore, and the ability to sample content before purchasing (Cenite et al., 2009). When discussing uploading, one motivation that some respondents mentioned is a norm of reciprocity—this norm refers to a feeling of obligation within the file-sharing community to give back by uploading their own files or maintaining share rations (ratios of uploaded vs. downloaded). Due to this norm, individuals anticipate a reward for their uploading behavior in the form of others sharing files in the community.

Norm of Reciprocity

The norm of reciprocity refers to the expectation that if one contributes something, then they will receive something in return (Kollock, 2003). As mentioned, for digital piracy, this means that individuals who believe in a norm of reciprocity will share pirated content with the expectation that they will receive pirated content from others. Although not a familiar concept within criminological research, research in the field of economics has found that a significant proportion of people espouse this norm and behave according to it—individuals reciprocate actions, whether friendly or hostile, even when interacting with complete strangers (Fehr & Gåchter, 2000). The norm of reciprocity operates in two primary ways, private reciprocation and public reciprocation (Whatley et al., 1999).

Private reciprocation is the internalized belief that performing good deeds and reciprocating others' good deeds is the right thing to do (Whatley et al., 1999). While this may be developed from various sources, such as through literature or religious teachings, one source could be social interactions with others. In the context of digital piracy, individuals may develop a belief in the norm of reciprocity through their interactions with pirating peers.

The other mechanism through which reciprocity operates is public reciprocation (Whatley et al., 1999). Public reciprocation is a response to the social costs and rewards involved in either following or ignoring the norm of reciprocity. Within the context of digital piracy, an example of the possible social costs of ignoring the norm of reciprocity would be the pirating community's view of sharing ratios. Torrenting websites have sharing ratios which are based on how much an individual downloads and uploads. Individuals who don't maintain good ratios (i.e. they download and never share) are labeled as "free riders" or "leeches" and may even be punished by some online pirating community through ridicules, bans, or the imposition of technical limits to the user's account (i.e. restrict a user's download speed) (Becker & Clement, 2006; Holt & Copes, 2010).

Although reciprocity is not commonly examined in criminological research, reciprocity at face value appears synergistic to social learning theory. Through differential associations with pirating peers, an individual could espouse a belief in the norm of reciprocity within online communities for digital piracy—this would fall under private reciprocation. While private reciprocation can occur through other sources, as mentioned earlier, differential associations could prove to be a significant source of these beliefs. Similarly, for public reciprocation, differential reinforcements such as the negative repercussions associated with bad share ratios could reinforce the individual's belief in reciprocity. Perceived support from other members—a positive social reinforcer—has also been identified as an influence on belief in reciprocity in information-sharing online communities (Pai & Tsai, 2016).

Despite the limited research examining illegal uploading behaviors, some prior qualitative studies have identified reciprocity as an important fact in illegal uploading. As discussed in the previous section, the studies of Becker and Clement (2006) and Cenite and colleagues (2009) both identified reciprocity as a motivator for individuals' illegal uploading behaviors.

Summary of Existing Literature

Several criminological theories have been tested against digital piracy and some have shown promise in their ability to explain variations in digital piracy. Akers' (1985, 1998) social learning theory, in particular, has shown significant promise in its ability to predict multiple forms of digital piracy (Burruss et al., 2012; Burruss et al., 2018; Morris & Higgins, 2010). Of the four elements that comprise Akers' (1985, 1998) social learning theory, differential association—primarily with peers—has garnered the strongest support (Hinduja & Ingram, 2009; Holt & Copes, 2010). While not as strongly supported by the literature as differential association, definitions (Higgins & Wilson, 2006; Holt & Copes, 2010) and differential reinforcement (Burruss et al., 2012; Burruss et al., 2018) both have some empirical support. Imitation has had limited support in the digital piracy literature (Burruss et al., 2012; Burruss et al., 2018), though few studies have included measures for imitation so this may change with future research. Based on the existing digital piracy literature, the empirical strength of each element of social learning theory appears to largely mirror the empirical evidence for social learning theory as a whole.

While significant progress has been made in the study of digital piracy, there are areas where further study is necessary. As mentioned previously, most of the existing literature has focused almost exclusively on downloading behavior or has not differentiated between downloading and uploading. Though related, it has yet to be established whether factors associated with downloading will hold true with uploading as well. Based on the differences presented in benefits, risks, and skills required for uploading and the limited empirical research available, it is argued that digital piracy research should differentiate between illegal uploading and illegal downloading. Given the differences described, significant differences possibly exist between these two elements of digital piracy, and findings within the research literature focusing exclusively on illegal downloading may not prove applicable to illegal uploading as well.

Another limitation of the existing digital piracy literature is the nearly exclusive reliance on university student samples. Although university students have been found to exhibit a high prevalence of digital piracy engagement (Caraway, 2012; Hinduja, 2003), this continued heavy utilization of university student samples limits the generalizability of the findings (Morris & Higgins, 2010). Additionally, even though they have been found to have high engagement in illegal downloading (Caraway, 2012; Hinduja, 2003), it is unknown whether this will also hold true for illegal uploading. Chiu and Chou (2011) postulated that university students may be more likely to engage in illegal downloading due to a lack of disposable income—if this proves to be accurate, university students may be less likely to upload as it requires the uploader to first acquire the files, an act which a lack of disposable income could impair.

As the proportion of uploaders is believed to also be significantly smaller compared to that of downloading (Becker & Clement, 2006), a sample drawn from a different population may be more conducive to studying uploading. According to Cuevas and colleagues (2013), around 100 publishers are responsible for publishing 67% of the copyrighted content available on BitTorrent networks. While this was only based on two publicly accessible BitTorrent websites, it suggests that the number of users uploading is significantly smaller than the number of users who download. Similarly, the majority of Chiu and Chou's (2011) twenty-one university student interviewees, reported exclusively downloading files. Despite the small sample size, this provides further evidence for the low engagement level in uploading compared to downloading. As such, it is important to expand empirical tests relating to digital piracy to other non-university samples both to improve the generalizability of research findings and to possibly increase the likelihood of sampling individuals who engage in illegal uploading.

Lastly, although many studies have partially tested Akers' (1985, 1998) social learning theory, not all components have garnered as much attention. As shown previously, differential association has undergone the bulk of empirical testing regarding social learning theory and has also received the strongest empirical support. Fewer studies have included measures for definitions and differential reinforcement—imitation, in particular, has received sparse attention in the research literature. Although differential association is the component with the strongest evidence in the larger body of criminological research beyond digital piracy, all four components are necessary to truly test the empirical strength of social learning theory. Without more extensive testing in all four components, it is difficult to conclude the overall strength of social learning theory in explaining digital piracy.

CHAPTER 3: METHODOLOGY

This study expands on the existing digital piracy literature in four ways: (1) expanding the sample to include both university students and individuals from an online, general population sample, (2) examining downloading and uploading behavior separately, (3) conducting a full test of social learning theory, and (4) adding and testing an additional concept that was drawn from the qualitative literature on illegal uploading behaviors—reciprocity. Firstly, this study includes a sample of university students as well as a sample of participants that were recruited online from various internet-based discussion forums for digital piracy and other websites. Despite previous findings that university students engage in a significant level of digital piracy (Hinduja, 2003), the nearly exclusive focus on student samples poses a limitation on the generalizability of these findings to non-student populations. Instead, in addition to a university student sample, data for this study was also collected from individuals on multiple websites.

Secondly, the current study expands on the limited empirical research that examines uploading behaviors. Although some studies have begun to explore uploading behavior separate from downloading (Cenite et al., 2009; Cuevas et al., 2013), this study expands on the existing literature by testing the ability of social learning theory to predict variations in self-reported uploading behavior and to compare illegal uploading and downloading behaviors.

Third, although not the first study to test a full model of social learning theory with all four theoretical components (Burruss et al., 2012, Burruss et al., 2018), few studies in the digital piracy literature have done so and the current study provides further empirical evidence about the ability of social learning theory in explaining the likelihood of engaging in digital piracy, more specifically, illegal uploading piracy. The current study includes measures for differential association, differential reinforcement, definitions, and imitation. Finally, drawing from the qualitative literature on illegal uploading behaviors, this study includes the concept of reciprocity as a potential correlate of illegal uploading behaviors. The following hypotheses were tested:

H1: Higher levels in social learning will increase levels of self-reported illegal downloading behaviors. Individuals who self-report more associations with others, that either engage in or approve of engagement in digital piracy, are more likely to self-report engagement in illegal downloading behavior in the past year. Additionally, individuals that self-report having favorable attitudes towards digital piracy and that self-report being rewarded for engaging in digital piracy are more likely to self-report illegal downloading behaviors.

H2: Higher levels in social learning will increase levels of self-reported illegal uploading behaviors. The same mechanisms described for illegal downloading behaviors should also apply to illegal uploading behaviors.

$H3_A$: Higher levels in perceived reciprocity will not increase levels of self-reported illegal downloading behaviors. Individuals with higher self-reported perceptions of reciprocity are not more likely to self-report illegal downloading behavior in the past year.

$H3_B$: Higher levels in perceived reciprocity will increase levels of self-reported illegal uploading behaviors. Individuals with higher self-reported perceptions of reciprocity are more likely to self-report illegal uploading behavior in the past year.

$H4_A$: Higher levels of self-control will decrease levels of self-reported illegal downloading behaviors. Individuals with higher self-reported levels of self-control are less likely to self-report illegal downloading behavior in the past year.

$H4_B$: Higher levels of self-control will not decrease levels of self-reported illegal uploading

behaviors. Individuals with higher self-reported levels of self-control are not less likely to self-report illegal uploading behavior in the past year.

H5: Reciprocity will mediate the relationship between social learning and illegal uploading behaviors. Reciprocity is primarily learned through the social learning process, and high levels of social learning should impact uploading through higher reciprocity.

Sample and Data

This study uses data gathered from both a university student sample and an online sample. Responses from both the in-person and online questionnaires remained anonymous and no identifiers were collected through the surveying process that would allow participants to be identified by their answers. A cover letter was included with the survey that explained the research purpose and informed participants that their responses would remain anonymous. Holt and Copes (2010) encountered reluctance from potential study participants involved in digital piracy without assurances that the researchers were not law enforcement. Given Holt and Copes' difficulties with recruiting participants, ensuring anonymity in the current study may have helped to increase response rates by reducing the perceived cost of participation (Dillman, 1991). Taking steps to ensure the anonymity of the data may have also helped to reduce the risk of response bias. Institutional review board approval was acquired for the current study in spring 2020.[3]

University Sample

A full list of all courses available at a mid-Atlantic urban research-extensive university as of January for the spring 2020 semester was acquired—courses were randomly selected from this list. The list included courses with students enrolled in majors from all units and departments in

[3] IRB ID# HM20017782. The IRB approval process was initiated in September 2019 and completed in February 2020.

the university and included courses from the College of Engineering, the College of Health Professions, the College of Humanities and Sciences, the School of the Arts, the School of Business, the School of Dentistry, the School of Education, the School of Media and Culture, the School of Medicine, the School of Government and Public Affairs, the School of Nursing, the School of Pharmacy, the School of Social Work, the School of World Studies, the University College, and Life Sciences.

The prerequisites for inclusion in the sampling frame were that courses must have on-campus meetings and needed to have at least 25 students registered. After the removal of all courses that didn't meet these requirements, 1,187 courses remained available for selection at both the undergraduate and graduate levels. From these courses, 50 courses were randomly selected and their instructors were emailed an invitation for their classes to participate in the study. If an instructor responded and did not allow access to their class, additional courses were randomly selected resulting in 58 total invitations sent to instructors. Of the instructors emailed, we received email responses (no/yes) from 35%—of the instructors we sent email requests, 12 instructors allowed access to their classes, which resulted in a response rate of 20.7%.[4] To acquire a sufficient sample size for the college sample, a total of 12 instructors provided access to 13 courses for survey administration. Those 13 undergraduate and graduate courses spanned across multiple departments within the university with courses in management, criminal justice, supply chain management and analytics, mathematics, political science, computer science, urban and regional studies, university college, and marketing. Based on enrollment information from January 2020, the 13 classes that were surveyed had a total of 665 enrolled students—approximately 38 students refused to take the survey when asked.

[4] Three instructors permitted access to their courses, but circumstances closer to the survey date prevented survey administration (i.e. class cancelled).

While there are elements of randomization included in the sampling method through the random selection of courses, there are also elements of non-random sampling—for instance, one professor offered an additional class for surveying that was not included in the original randomized selection. The demographic composition (sex, race, and ethnicity) of the university sample is similar to the demographic composition of the university as a whole but the university sample has a larger proportion of individuals who identified as male, Black, and Hispanic/Latino than the university's overall demographic make-up. [5]

Survey administration in classes began in February 2020 and finished in early March 2020. Before distributing the survey instrument, a brief verbal announcement was made concerning the study's purpose and the anonymity of participants' responses. Once all paper instruments were collected, all of the responses were entered manually into SPSS. The survey was initially administered using a scantron form, but the format was switched to paper and pencil with manual data entry due to confusion from respondents.[6] One class was administered the scantron form of the survey (n = 15) and a variable was created to indicate which responses were made using this format. To verify the validity of the data that was manually inputted, 10% of the surveys (40) were randomly selected and verified for accuracy—100% of the surveys checked for validity were accurate. The final sample size for the university sample was 398 students, 59.85% of the total students enrolled from the sampled courses.

Online Sample

For the online sample, a purposive, snowball sampling technique was used given this study's focus on digital pirating. Websites, where recruitment took place, included two torrent

[5]Statistics available at: https://datausa.io/profile/university/virginia-commonwealth-university (Based on 2017 reported statistics for the university)

[6] Respondents reported confusion over how to enter the age on the scantron form, which required respondents to write in their age into the test ID section of the form.

trackers—TorrentLeech and SuprBay—in addition to Reddit.com's Torrents and Pirating subreddits. One of the tracker sites selected, TorrentLeech, is a private tracker which require invitations to join while SuprBay is public. Both public and private trackers were chosen to try to increase the representation of the findings as users of these sites may differ in some meaningful way. The link to the study invitation was also shared by individuals unknown to the researcher on multiple other websites.[7]

During Spring 2020, the researcher created a membership account for each website and posted a new discussion thread explaining the study and requesting participation with a link to the online questionnaire. Every few days, the initial posting was refreshed to increase visibility by replying to the original post. The online survey remained open to responses for four weeks, from March 2020 to April 2020. As compensation for their participation, any individual who completed the survey was allowed to enter into a random drawing for a $25 Amazon.com gift card. At the end of the collection period, the data was exported from the online survey tool into SPSS for analysis. No identifiable data was collected from any respondents in the survey. The online sample consisted of a total of 315 individuals who completed the online questionnaire.

Measures

Several measures are included in the current study including multiple indicators for social learning theory components, digital piracy, low self-control, techniques of neutralization, computer use, computer skill, piracy skill, reciprocity, moral acceptability, punishment certainty,

[7] Based on self-reported responses to a questionnaire item asking respondents where they accessed the survey from, it was identified that the online survey was also posted on Twitter.com, Facebook.com, Slickdeals.net, Tumblr.com, and Mysavings.com.

and individual-level demographics. All of the items detailed in this section are included on a self-administered survey instrument (see Appendix II for exact items).

Social Learning Variables

The current study is a full test of social learning theory. Measures for all four components of Aker's (1985; 1998) social learning theory are assessed. The four social learning components measured are (1) differential association, (2) differential reinforcement, (3) definitions, and (4) imitation. Social learning is measured as a second-order latent factor with first-order latent factors representing each of the four components.

Differential Association

Differential association is measured as a latent factor with two observed items originally adapted for digital piracy research from Krohn et al. (1985) by Morris and Higgins (2010). These items reflect the respondent's perceptions of their peer's approval of and engagement in digital piracy. Respondents are asked to indicate how many of their friends have knowingly used, made, or given to another person "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) within the past year. The second item asks how many of their friends would approve of those same acts (see Appendix II for exact items). Response categories for both items included: none of them, very few of them, about half of them, more than half of them, and all of them. Preliminary internal consistency analysis using Cronbach's alpha indicates both of the differential association items are correlated with each other and are internally consistent ($\alpha = 0.665$). [8]

[8] The purpose of Cronbach's alpha is to indicate the average intercorrelation between the variables that are to be included in a composite scale and to relate this value to the number of variables included in the scale (Frankfort-Nachmias & Nachmias, 1996).

Differential Reinforcement

Differential reinforcement is measured as a first-order latent factor with eight items adapted from measures used by other studies in the literature to include multiple types of piracy (i.e. music, movies). Similar to Burruss et al. (2012), two items are used to measure indirect reinforcement—one item asks how many times a respondent has heard or seen a professor or high school instructor praise or encourage others for digital piracy and one item asks how many times a respondent has heard or seen a professor or higher school instructor offer someone the chance to obtain pirated content (Appendix II for exact items)—the response options were (0) never, (1) 1-2 times, (3) 3-5 times, (4) 6-9 times, and (5) 10 or more times.

Two Likert-type items are included to measure direct reinforcement—these items ask (1) how likely it is that others would praise the respondent for downloading, uploading, or sharing pirated content or (2) how likely it is that others would share pirated content if the respondent uploaded or shared pirated content with them. Four responses are available, anchored with "Very unlikely" and "Very likely".

Four additional items are adapted from Winfree, Mays, and Vigil-Bäckström (1994) to measure positive social reinforcers towards digital piracy. These items ask respondents how strongly they agree with several statements in the hypothetical event that they engage in digital piracy. Statements included "I would feel successful", "I would feel 'cool'", "I would feel excitement", and "I would save money" (see Appendix II for exact items). Available responses are on a 4-point Likert scale anchored with "Strongly agree" and "Strongly disagree". Reliability analysis using Cronbach's alpha indicates that these eight items are strongly correlated with each other and have high internal consistency ($\alpha = 0.845$).

Imitation

Imitation is measured as a latent factor with three observed items asking how much the respondent has learned about the downloading, uploading, and sharing of pirated content from seeing family and friends do them and through Internet chat rooms, IRC, web forums, or social media (Burruss et al., 2012; Burruss et al., 2018). All three Likert-type questions have five response options ranging from "Nothing" to "Everything". Reliability analysis using Cronbach's alpha indicates that the three items measuring imitation are correlated with each other and are internally consistent ($\alpha = 0.605$).

Definitions

The latent factor for definitions includes six observed items that measure participants' attitudes towards digital piracy using Likert-type items that ask respondents how strongly they agree or disagree with statements that indicate positive attitudes towards digital piracy (Higgins & Makin, 2004; Morris & Higgins, 2010). The items include the following statements: (1) "I see nothing wrong in giving people copies of pirated materials to foster friendships", (2) "It is ok for me to pirate media because the creators are really not going to lose any money", (3) "I think it is okay to use copied software for research purposes, because everyone shares the benefits", (4) "I think it is okay to use copied movies for entertainment", (5) "I think it is okay to use copied software because the community at large is eventually benefited", and (6) "I think it is okay to use copied software if it improves my knowledge." Responses range from (0) strongly agree to (3) strongly disagree. Cronbach's analysis indicates that all of the items are strongly correlated with each other and have high internal consistency ($\alpha = 0.942$).

Reciprocity

Qualitative research in digital piracy into the motivations for uploading indicates that reciprocity is an important factor to examine for illegal uploading behavior (Becker & Clement, 2006; Cenite et al., 2009). Reciprocity is measured with four observed items previously used by Becker and Clement (2006). The items included ask respondents how strongly they agree or disagree with four statements: (1) “I expect other users to share digital files online as well”, (2) “I think it is unfair if users don’t share digital files online”, (3) “I feel obliged to share digital files online because I download from others”, and (4) “I think that file sharing is based on reciprocity”. All four of the items are reverse-coded and loaded onto a single first-order latent factor for reciprocity. All of the items measuring reciprocity are strongly correlated with each other and have high internal consistency according to reliability analysis conducted using Cronbach’s alpha ($\alpha = 0.831$).

Self-Control

Several studies have found evidence that levels of self-control impact self-reported illegal downloading, either directly or indirectly (Burruss et al., 2012; Burruss et al., 2018). Low self-control is measured using the Brief Self-Control Scale developed by Tangney, Baumeister, and Boone (2004), which is a 13-item attitudinal measurement of self-control. Items are rated on a 4-point scale, anchored from (0) strongly agree to (3) strongly disagree. The items included in the scale ask respondents how strongly they agree or disagree with a series of statements relating to self-control such as “I am good at resisting temptation”, “I have a hard time breaking bad habits”, “I do certain things that are bad for me, if they are fun”, and “I refuse things that are bad for me” (see Appendix II for exact items). All 13 items are summated to create a composite scale with higher values representing higher self-control ($\alpha = 0.830$).

Outcome Variables: Illegal Downloading and Illegal Uploading

Illegal uploading behavior and illegal downloading behavior are each measured using five items that measure how often during the past year the respondent engaged in various acts of piracy.

Illegal Downloading Behavior

For downloading, respondents are asked how often they (1) downloaded pirated content from a website, (2) used P2P software to download pirated content, (3) used IRC to download pirated content, (4) used a streaming website to illegally watch movies or TV shows, and (5) used software to download media from a website without permission. Response categories ranged from: never, 1-2 times, 3-5 times, 6-9 times, and 10 or more times. Reliability analysis indicated all five measures are correlated with each other and have internal consistency (α = 0.746).

Illegal Uploading Behavior

For uploading, respondents are asked how often they (1) provided copyrighted digital media for others to watch through a streaming website without the owner's permission, (2) uploaded pirated content to a website, (3) used P2P software to seed pirated content after a download has completed, (4) used IRC to share pirated content, and (5) created torrent files to illegally share their own content. Illegal uploading had the same response categories as illegal downloading. The five items for illegal uploading strongly correlated with each other and have internal consistency according to Cronbach's analysis (α = 0.796).

Control Variables

Based on the prior research identifying significant predictors of digital piracy, the following control variables are included: techniques of neutralization, piracy skill, computer skill, computer use, moral acceptability, punishment certainty, age, sex, race, ethnicity, highest education level completed, and current employment status.

Measurement of neutralization techniques is done using a summated scale composed of 14 Likert-type items with 4 response options anchored with (0) strongly agree and (3) strongly disagree. The neutralization techniques captured by the composite scale include: denial of victim, denial of injury, condemnation of the condemner, appeal to higher loyalties, denial of responsibility, and defense of necessity (Maruna & Copes, 2005; Morris & Higgins, 2010). While empirical support has been mixed, there has been some support for neutralization techniques in the digital piracy literature (Steinmetz & Tunnell, 2013). Higher values on the composite scale indicate higher levels of neutralizing attitudes towards digital piracy ($\alpha = 0.911$).

Moral acceptability has also had mixed empirical support in the literature—the current study includes it as a control variable as some research has found support for its inclusion (Tam, Feng, & Kwan, 2019). To capture moral acceptability, a 4-item composite scale is used that measures how morally acceptable the respondent finds copying or sharing software with responses ranging from (0) strongly agree to (3) strongly disagree. As an example, one item included is "unauthorized copying (sharing) of software is not unethical" (see Appendix II for exact items). Items are summated into a scale with higher values indicating higher moral acceptability of digital piracy ($\alpha = 0.728$).

Computer skill is measured using a composite scale ($\alpha = 0.933$) created by summating 12 items asking how knowledgeable the respondent is about a variety of technologies (i.e. browsing the internet, dealing with software problems). Responses are on a 5-point ordinal scale ranging from 0-4 with higher scores indicating an individual is more skilled with computers. In prior research, individuals who report greater computer skills were found to report higher downloading behavior (Burruss et al., 2012; Gunter, 2009; Holt et al., 2010).

To measure piracy skill, a 9-item composite scale ($\alpha = 0.910$) measures how capable the respondent is with skills that relate to digital piracy. Skills included are (1) burning a CD with pirated content, (2) using BitTorrent to illegally download, (3) creating a torrent file to illegally share content, (4) removing DRM or other copyright protection from digital content, (5) using a tool to bypass licensing on commercially sold software, (6) using IRC to illegally download, (7) using a website to download or uploading pirated content, (8) using software to download media from a website without permission, and (9) using a website to illegally stream digital content. Responses to each item ranged from (0) poor to (4) excellent—the 9 items are summated into a composite scale with higher values indicating higher strength of piracy skill.

For computer use, a 6-item scale is used to capture how much time per week over the past 12 months a respondent engaged in a series of computer-related activities (Bossler & Holt, 2009). The activities included: (1) shopping/going to auction sites, (2) checking email, (3) using either chatrooms or IRC, (4) using social media, (5) using instant messaging to chat, and (6) downloading and uploading files. The original 6-item scale developed by Bossler and Holt (2009) is modified and an item to capture social media use is added given its modern popularity. Responses are anchored with (0) never to (4) 6 or more hours—a composite scale is created by summating all of the items so that higher values on the scale indicate higher levels of computer use ($\alpha = 0.701$).

Five measures, drawn from Zhang, Smith, and McDowell (2009), are used to measure perceptions of punishment certainty—respondents are asked to estimate the chance that they would be caught engaging in five activities relating to digital piracy. The five activities are: (1)

duplicate a copyrighted CD, (2) download unauthorized music from the Internet, (3) duplicate a copyrighted DVD, (4) download unauthorized movies from the Internet, and (5) install a pirated copy of software on your computer. All five items are summated to create a composite scale with higher values representing a higher perception of punishment certainty for digital piracy engagement ($\alpha = 0.913$).

Age is collected using a single open-ended item asking participants to enter their exact age in years. In the past, age has been linked to digital piracy with younger individuals being more likely to pirate (Morris & Higgins, 2010). Sex has had mixed support as a predictor of digital piracy with some studies finding no significance when other controls are included (Higgins & Makin, 2004; Morris et al., 2009) while others found that males are more likely to engage in digital piracy (Gunter, 2009; Morris & Higgins, 2010; Skinner & Fream, 1997; Vandiver, Bowman, & Vega, 2012). Sex is measured with a single nominal-level item asking what gender the participant is with the possible responses of (0) male, (1) female, and (2) intersex.[9] Race also has some evidence as a predictor of digital piracy—in some studies, non-White individuals appear to be more likely to engage in digital piracy (Morris & Higgins, 2010; Vandiver et al., 2012; Yu, 2013). To measure race, one item is included that allowed participants to select multiple responses including (0) white/Caucasian, (1) black/African American, (2) Asian, (3) American Indian or Alaskan Native, and (4) Native Hawaiian or other Pacific Islander.[10] A single item asking participants whether or not they identify as Hispanic or Latino is used to measure ethnicity (0 = no/ 1 = yes).

Three additional controls are included measuring current employment status, highest education level, and total household income. One item asks respondents for their current

[9] The response category intersex was dropped due to lack of response.
[10] Recoded to white and non-white.

employment status with three available options: (1) unemployed, (2) employed part-time, and (3) employed full-time. Employment status is collapsed into a binary measuring any employment versus none. Highest educational level is measured using a single item asking respondents to indicate the highest level of education that they have completed with the response options: (1) less than a high school diploma, (2) high school degree or equivalent, (3) some college, no degree, (4) undergraduate degree, and (5) graduate degree. Given that all respondents in the university sample have completed some college, the first two responses are not available to the university sample. This variable is collapsed into a binary with less than an undergraduate degree completed versus an undergraduate degree or higher completed. For total household income, one item asks participants what their total household income was during the past 12 months, these responses included: (1) less than $20,000, (2) $20,000 to $34,999, (3) $35,000 to $49,999, (4) $50,000 to $74,999, and (5) $75,000 or more. The income measure is also collapsed into a binary variable with a total household income of $35,000 or higher versus below $35,000. Although income, employment, and education indicators have not been previously found significant to digital piracy among university samples (Morris & Higgins, 2009; Morris & Higgins, 2010; Yu, 2010), they are included to examine whether this changes with the inclusion of a general population sample.

Analytical Method

In the current study, several structural equation models (SEM) are conducted to examine the effects of social learning on illegal downloading and uploading behaviors separately. Structural equation modeling involves two components: a measurement model and a structural model (Bollen, 1989; Bollen & Lennox, 1991; Muthén & Muthén, 2017). For the measurement models, confirmatory factor analysis (CFA) is utilized to confirm the measurement properties of the social learning latent construct, reciprocity construct, and the outcome factors. All are measured as ordinal latent variables as the items for each are measured at the ordinal level. Then, structural equation modeling techniques are used to model each path and to test the hypotheses. All analyses are conducted using Mplus, version 8 (Muthén & Muthén, 2017). Each of the analytical approaches is described below.

Confirmatory Factor Analyses

The purpose of confirmatory factor analysis is to test for the validity of a measurement model (Byrne, 2000). CFA helps determine the extent to which items that are intended to measure a particular latent factor accomplish this goal. Confirmatory factor analysis is used to examine relationships between a set of continuous latent variables and a set of observed variables (Bollen, 1989). CFA has several advantages over exploratory factor analysis (EFA) including the flexibility to specify the relationships between factors based on theoretical or empirical reasoning and the ability to only load observed indicators onto the factors they're expected to measure (Kenny, 2006; Wang & Wang, 2012).

In SEM techniques, latent variables are used to represent unmeasured variables that refer to theoretical or hypothetical concepts—they are expected to explain covariances among the indicator variables (Wang & Wang, 2012). Each link between the indicator variables and the latent factors is represented by factor loadings, which are the regression paths between the latent factor and the indicator variable. Each latent variable should have statistically significant factor loadings on their respective observed variables, and all factor loadings should be above 0.32 at a minimum but loadings greater than 0.71 are considered excellent (Tabachnick & Fidell, 2013).

Goodness-of-fit Indices

To assess how well the overall conceptual models fit the data, several goodness-of-fit indices reported by Mplus are examined—these fit indices include the chi-square test and its *p*-value, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the standardized root mean square residual (SRMR) (Kline, 2011; Wang & Wang, 2012). When constructing a model using SEM techniques, researchers use goodness-of-fit assessments to determine how well the designed model fits the data.

One of the major goodness-of-fit statistics commonly utilized in SEM is chi-square, which is a global fit statistic that assesses the magnitude of the difference between the fitted covariance matrices and the sample data—a non-statistically significant chi-square indicates that the proposed model's covariance matrix is similar to that of the data's covariance matrix (Hu & Bentler, 1999; Schumacker & Lomax, 2010). The null hypothesis is accepted (fail to reject) when the chi-square is not significant—this indicates a good model fit (Kline, 2011). While chi-square is a useful measure to assess a model, it has limitations—due to how it is calculated, χ^2 is sensitive to sample size and larger sample sizes increase the likelihood of a Type II error, or accepting the null hypothesis when it is actually false (Wang & Wang, 2012). As such, while a significant chi-square statistic indicates that the model is significantly different than a model with a perfect fit, it should not be a reason by itself to reject a model if other fit measures point towards a good fit.

Incremental or relative fit indices were developed to account for potential limitations of the chi-square statistic as an indicator of model fit (Bentler & Bonett, 1980). Several fit indices have been developed to judge model fit including CFI, TLI, RMSEA, and SRMR (Wang & Wang, 2012).

The comparative fit index (CFI) is a relative fit index that compares a model to the null model, assuming the observed measures have zero covariances (Wang & Wang, 2012). For CFI, a value of above 0.90 is recommended for indicating a reasonable fit (Hu & Bentler, 1999). The Tucker-Lewis index (TLI) compares a model's lack of fit to the null model's lack of fit and, like CFI, it is a relative fit index (Wang & Wang, 2012). Hu and Bentler (1999) recommend a cutoff value of 0.90 for TLI with higher values representing a good fit. Root mean square error of approximation (RMSEA) is another test of model fit—it measures the average lack of fit per degree of freedom (Wang & Wang, 2012). An RMSEA value of less than or equal to 0.06 is considered to be a good model fit (Hu & Bentler, 1999). Finally, standardized root mean square residual (SRMR) is a standardized residual-based model fit index based on the square root of the standardized residuals (Wang & Wang, 2012). The model is considered a good fit when SRMR < 0.08 (Hu & Bentler, 1999; Wang & Wang, 2012).

When evaluating a model's fit, it is important to examine multiple fit indices as each index has strengths and weakness—for instance, CFI, TLI, and RMSEA are more sensitive to models with factor loadings that are misspecified whereas SRMR is sensitive to models with misspecified latent structures or factor covariances (Hu & Bentler, 1999). In addition to using a variety of goodness-of-fit measures to evaluate each of the models, the loadings of each latent factor on the observed variables are also examined to ensure that all of those included in the model are valid measures for each factor (Kline, 2005).

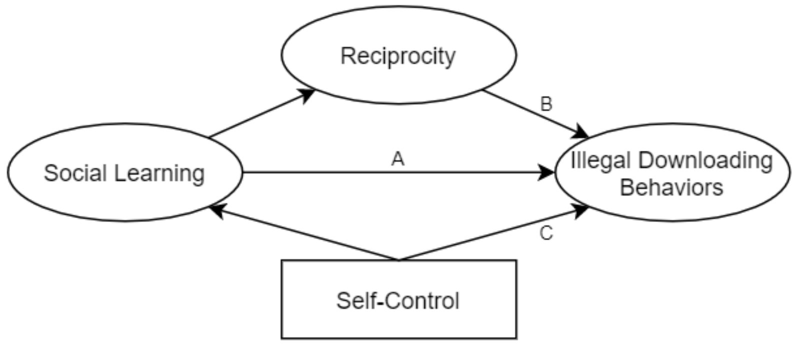
Structural Equation Modeling

After validating the models using CFA weighted least squares mean and variance adjusted estimator (WLSMV) is employed using Mplus, version 8(Muthén & Muthén, 2017). WLSMV is an appropriate estimation method given that our models include ordered-categorical indicators (Brown, 2006; Kline, 2011)—WLSMV also performs well with larger sample sizes. WLSMV is a robust weighted least squares approach that allows for a combination of ordered polytomous, binary, and continuous outcome variables and also allows for multiple-group analysis (Muthén, du Toit, & Spisic, 1997). WLSMV also does not assume that variables are normally distributed (Brown, 2006). Except for small sample sizes (N ~ 200) or highly skewed variables, WLSMV estimation has performed well and saves computation time over similar approaches using categorical outcomes.

Using the two structural models for illegal uploading and downloading behaviors, each of the hypotheses is tested. To test the hypotheses, the following is examined: (H1) whether higher levels in social learning will directly increase levels of self-reported illegal downloading behaviors, (H2) higher levels in social learning will directly increase levels of self-reported illegal uploading behaviors, ($H3_A$) higher levels in perceived reciprocity will not directly increase levels of self-reported illegal downloading behaviors, ($H3_B$) higher levels in perceived reciprocity will directly increase levels of self-reported illegal uploading behaviors, ($H4_A$) higher levels of self-control will directly decrease levels of self-reported illegal downloading behaviors, ($H4_B$) higher levels of self-control will not directly decrease levels of self-reported illegal uploading behaviors, and, finally, (H5) reciprocity will mediate the relationship between social learning and illegal uploading behaviors—social learning will have an indirect effect on uploading behaviors. Figure 1 shows the visual path models for all of the hypotheses.

Figure 1. Conceptual Paths for Hypotheses

Model 3: Illegal Downloading Behaviors

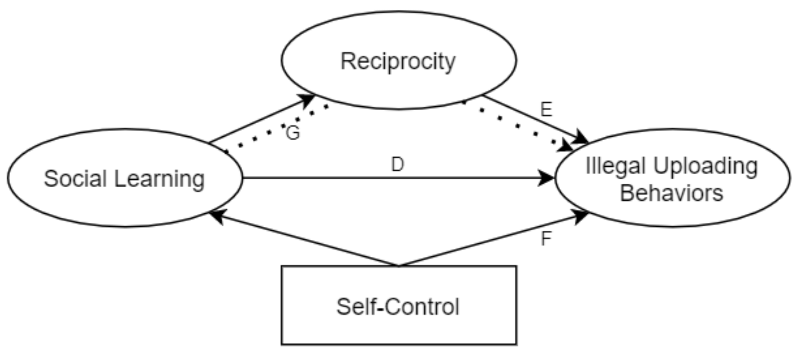


H1: Higher levels in social learning will increase levels of self-reported illegal downloading behaviors (path A is positive).

$H3_B$: Higher levels in perceived reciprocity will not increase levels of self-reported illegal downloading behaviors (path B is not significant).

$H4_A$: Higher levels of self-control will decrease levels of self-reported illegal downloading behaviors (path C is negative).

Model 6: Illegal Uploading Behaviors



H2: Higher levels in social learning will increase levels of self-reported illegal uploading behaviors (path D is positive).

$H3_A$: Higher levels in perceived reciprocity will increase levels of self-reported illegal uploading behaviors (path E is positive).

$H4_B$: Higher levels of self-control will not decrease levels of self-reported illegal uploading behaviors (path F is not significant).

H5: Reciprocity will mediate the relationship between social learning and illegal uploading behaviors (path G is significant).

Multicollinearity

Multicollinearity refers to when two predictor variables are highly correlated, which can have adverse effects on estimation accuracy and lead to Type II errors (Grewal, Cote, & Baumgartner, 2004). One of the consequences of multicollinearity is large standard errors for coefficient estimators (Berry & Feldman, 1985). High multicollinearity can also cause wide confidence intervals for coefficients and low t-statistics for significance tests.

There are multiple methods of identifying potential multicollinearity problems among predictor variables—one method is evaluating the correlations between the independent variables (Grewal et al., 2004; Lewis-Beck, 2016). Generally, a correlation of 0.70 or higher between predictor variables is considered problematic (Lewis-Beck, 2016). Another method to examine multicollinearity is through the variance inflation factor (VIF), which indicates how inflated the variance is (Hair, Black, Babin, Anderson, & Tatham, 2006). Additionally, SEM can incorporate correlated exogenous factors.

CHAPTER 4: RESULTS

The first section of this chapter presents the descriptive statistics for the pooled sample with a discussion of any notable differences in the main variables of interest between the university and online samples. In the second section, the measurement models and confirmatory factor analysis of the latent factors for social learning, reciprocity, and the two piracy outcomes—illegal downloading behaviors and illegal uploading behaviors—are discussed. The final section of the chapter discusses findings from a series of multivariate analyses examining the direct and indirect effects of social learning theory, self-control, and reciprocity on illegal downloading and uploading outcomes, controlling for relevant covariates. Supplemental mediation analyses for self-control and social learning are also discussed.

Descriptive Statistics for Demographic/Control Variables

As mentioned previously, the current study uses two samples—one sampled from a university student population (n = 398) and another from a general, online population (n = 315).[11] The pooled sample has participants ranging in age from 18 to 71 years old with a mean age of 27.1 (*SD* = 10.797).[12] The university sample had much younger participants than the online sample—the university sample had 62.6% of respondents in the 18-21 age range compared to 13.7% of the online sample. The mean age for the university sample was 21.856 (*SD* = 4.409) while it was 33.830 (*SD* = 12.683) for the online sample—overall, the online sample was far more heterogeneous in age compared to the university sample. For sample comparison, the descriptive statistics for the demographic variables for all three samples are presented in Table 1.

[11] For full descriptive statistics of the control variables measured in this study, see Tables 12, 13, and 14 in Appendix I for the pooled, university, and online samples respectively.
[12] Age is measured as a continuous variable in the structural equation models—the categorized age variable is only used in the descriptive statistics.

Table 1. Descriptive Statistics: Demographic Variables by Sample			
Criterion	Pooled	University %	Online
Age ***	N=655	N=368	N=287
18 – 21	40.95	62.56	13.65
22 – 25	17.11	19.60	13.97
26 – 29	9.82	5.53	15.24
30 – 33	5.47	2.26	9.52
34 – 37	5.89	1.26	11.75
38+	12.62	1.26	26.98
Sex	N=681	N=394	N=287
Male	39.55	42.21	36.19
Female	55.96	56.78	54.92
Race	N=698	N=383	N=315
White/Caucasian	69.48	64.82	72.06
Black/African American	14.76	21.11	6.03
Asian	13.32	14.82	10.79
American Indian/Alaskan Native	1.43	1.26	1.59
Native Hawaiian/Pacific Islander	0.84	1.51	0.00
Hispanic/Latino	N=670	N=393	N=277
No	79.38	82.66	75.24
Yes	14.59	16.08	12.70
Highest Education Completed ***	N=670	N=392	N=278
Less than high school diploma	0.70	0.00	1.59
High school diploma	5.19	0.00	11.75
Some college, no degree	54.84	76.38	27.62
Undergraduate degree	23.00	20.85	25.71
Graduate degree	10.24	1.26	21.59
Employment Status ***	N=663	N=394	N=269
Unemployed	31.14	33.42	28.25
Employed - Part-time	37.17	53.52	16.51
Employed - Full-time	24.68	12.06	40.63
Total Household Income ***	N=641	N=397	N=254
Less than $20,000	32.26	42.96	18.73
$20,000 to $34,999	11.78	9.30	14.92
$35,000 to $49,999	9.40	6.03	13.65
$50,000 to $74,999	13.74	11.81	16.19
$75,000 or higher	22.72	27.14	17.14

Note: Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

For sex, the samples were fairly similar; the pooled sample was 55.9% female while the university and online samples were 56.8% and 54.9% female respectively. Both samples were predominately White (pooled = 68.0%, university = 64.8%; online = 72.1%), however the university sample had a higher percentage of Black participants than the online sample (21.1% vs. 6.0%). Individuals who identified as Hispanic or Latino represented 14.6% of the pooled sample and similar percentages were found in both samples (university = 16.1%; online = 12.7%). Unsurprisingly, given the inclusion of a university sample, 88.1% of individuals in the pooled sample had completed some college or higher with 33.2% having completed an undergraduate or graduate degree. The online sample was highly educated with 47.3% having completed an undergraduate or graduate degree compared to 22.1% of the university sample. In the pooled sample, only 0.7% of respondents reported having less than a high school diploma. For employment, 61.9% of pooled respondents were employed either part-time or full-time (university = 65.6%; online = 57.1%). Both samples were fairly similar in regards to total household income—45.9% of the pooled sample reported a total household income of $35,000 or higher with the university and online samples reporting 45.0% and 47.0% respectively. The university sample did have far more respondents who reported a total household income of less than $20,000; 43.0% of the university sample fell into this category compared to only 18.7% of the online sample. Chi-square tests were conducted to test whether there was a statistically significant difference between the samples for each of the demographic variables—age, highest education completed, employment status, and total household income all had significant differences.

The online sample reported higher on average than the university sample on the computer skill index (university *M/SD* = 18.170/10.632; online *M/SD* = 26.971/11.967).[13] Computer use though is fairly similar across both samples—the online sample reported slightly higher computer use on average over the university sample (university *M/SD* = 11.025/4.486; online *M/SD* = 12.050/5.123). While both samples appear to spend similar amounts of time on their computers, on average the online sample reports higher capabilities with various computer skills.

For self-control, the university sample (*M/SD* = 21.038/6.841) has slightly more reported self-control than the online sample (*M/SD* = 19.991/7.067). The online sample had slightly higher levels on the punishment certainty and moral acceptability scales than the university sample. Techniques of neutralization were also slightly higher on average among the online sample as compared to the university sample (university *M/SD* = 20.972/8.907; online *M/SD* = 21.697/9.917). Perceived punishment certainty for digital piracy was low overall (*M/SD* = 4.720/4.983). The online sample also reported higher perceptions of punishment certainty on average (*M/SD* = 5.537/5.491) over the university sample (*M/SD* = 4.292/4.646).

[13] For full descriptive statistics of the control variables for the pooled, university, and online samples, see Tables 14, 15, and 16 in Appendix II respectively.

Descriptive Statistics for Social Learning

Table 2 displays the percentage of respondents across each response category of the differential association measures. Overall, for the differential association measures, the pooled sample did not report very high associations with peers engaging in digital piracy (49.3% reported no association with pirating peers) though perceived approval from their peers for engagement in digital piracy was higher (only 29.1% responded with no peer approval). On average, the online sample reported higher on both measures of differential association.[14] The participants in the online sample reported associating with more pirating peers and perceived that more of their peers would approve if they engaged in digital piracy behaviors in all but one response category—the university sample reported higher on "All of them" under the peer approval item.

Table 2. Sample Comparison for Differential Association

Differential Association Measure	Sample		
	Pooled	University	Online
	%		
Associations with pirating peers [DA1] ***	N=628	N=396	N=232
None of them	49.36	54.80	40.09
Very few of them	34.39	34.34	34.48
About half of them	9.71	6.31	15.52
More than half of them	4.78	3.79	6.47
All of them	1.75	0.76	3.45
Perceived approval for DP from peers [DA2] ***	N=627	N=395	N=232
None of them	29.19	35.95	17.67
Very few of them	21.69	20.00	24.57
About half of them	14.19	12.66	16.81
More than half of them	17.22	13.16	24.14
All of them	17.70	18.23	16.81

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

[14] For full descriptive statistics of the social learning variables for the pooled, university, and online samples, see Tables 17, 18, and 19 in Appendix II respectively.

As shown in Table 3, similar differences are present in the differential reinforcement measures across the two samples. Items DR1-DR4 for differential reinforcement all had significant differences between samples according to chi-square tests. In Table 3, for items DR1, DR3, and DR4, the university sample reported lower levels of differential reinforcement. 70.5% of the university sample reported never seeing a teacher praise or encourage a student for digital

Table 3. Sample Comparison for Differential Reinforcement (DR1-DR4)

Differential Reinforcement Measure	Sample		
	Pooled	University %	Online
Seen teacher praise/encourage students for DP [DR1] *	N=629	N=397	N=232
Never	69.32	70.53	67.24
1-2 times	18.60	19.65	16.81
3-5 times	8.11	5.54	12.50
6-9 times	2.38	2.52	2.16
10 or more times	1.59	1.76	1.29
Seen teacher offer students pirated material [DR2] *	N=630	N=398	N=232
Never	59.05	55.03	65.95
1-2 times	24.44	27.89	18.53
3-5 times	10.95	12.31	8.62
6-9 times	2.86	2.51	3.45
10 or more times	2.70	2.26	3.45
Praised by others for DP [DR3] ***	N=630	N=398	N=232
Very unlikely	44.44	48.49	37.50
Somewhat unlikely	21.75	21.86	21.55
Somewhat likely	23.33	23.37	23.28
Very likely	10.48	6.28	17.67
Others would share pirated materials with you [DR4] ***	N=628	N=396	N=232
Very unlikely	40.92	45.45	33.19
Somewhat unlikely	21.97	22.47	21.12
Somewhat likely	25.16	23.74	27.59
Very likely	11.94	8.33	18.10

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

piracy whereas 67.2% of the online sample did so. Similarly, 48.4% of the university sample reported never receiving praise for digital piracy compared to 37.5% of the online sample. The online sample also reported a higher likelihood overall that others would share pirated materials with them if they shared their own pirated digital materials than the university sample. One exception was on item 2 of the differential reinforcement measures (DR2), which measured how many times the respondent has heard or seen a professor or high school instructor offer students the chance to obtain pirated digital content. For this item, 65.9% of the online sample reported never seeing a teacher offer students the chance to obtain pirated digital content compared to only 55.0% of the university sample. This difference may be explainable by the nature of the samples—the online sample might not have as much interaction with professors as the college sample in the past year.

On all of the remaining differential reinforcement items (DR5-DR8), the online sample reported higher levels of differential reinforcement overall (see Table 4). Also, items DR6 and DR8 had significant differences between samples according to chi-square tests. For the item asking if the respondent would feel successful if they pirated digital content, 43.4% of the university sample strongly disagreed versus 37.8% of the online sample. The item asking if respondents would feel “cool” revealed similar results—55.1% of university respondents and 44.4% of online respondents strongly disagreed. Following this trend, 50.5% of the university sample strongly disagreed that they would feel excitement if they pirated digital content compared to 42.7% of the online sample. While the online sample responded with higher agreement on average for the final differential reinforcement item (DR8), a higher percentage

Table 4. Sample Comparison for Differential Reinforcement (DR5-DR8)			
Differential Reinforcement Measure	Sample		
	Pooled	University	Online
	%		
If DP, I would feel successful [DR5]	N=623	N=396	N=227
Strongly agree	41.41	7.58	9.25
Somewhat agree	22.47	27.53	28.63
Somewhat disagree	27.93	21.46	24.23
Strongly disagree	8.19	43.43	37.89
If DP, I would feel "cool" [DR6] *	N=622	N=395	N=227
Strongly agree	4.34	2.53	7.49
Somewhat agree	16.40	14.43	19.82
Somewhat disagree	27.97	27.85	28.19
Strongly disagree	51.29	55.19	44.49
If DP, I would feel excitement [DR7]	N=623	N=396	N=227
Strongly agree	5.78	5.56	6.17
Somewhat agree	22.95	22.22	24.23
Somewhat disagree	23.60	21.72	26.87
Strongly disagree	47.67	50.51	42.73
If DP, I would save money or make money [DR8] *	N=623	N=396	N=227
Strongly agree	40.61	41.41	39.21
Somewhat agree	33.55	32.32	35.68
Somewhat disagree	7.70	5.81	11.01
Strongly disagree	18.14	20.45	14.10

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

of the university sample responded with both “strongly disagree” and “strongly disagree” than the online sample.

Table 5 shows the percentage of respondents across each response category for the imitation measures. For the imitation measurement items, only one item, IM3, had a significant between samples based on a chi-square test. For IM1, 59.9% of the online sample responded that they’ve learned nothing about digital piracy from seeing family compared to 56.2% of the university sample. The online sample reported much higher on the imitation item that asks

Table 5. Sample Comparison for Imitation			
Imitation Measure	Sample		
	Pooled	University	Online
	%		
Learned about DP from seeing family [IM1]	N=625	N=398	N=227
Nothing	57.6	56.28	59.91
A little	24.8	25.13	24.23
Some	11.68	12.56	10.13
A lot	4.32	4.27	4.41
Everything	1.6	1.76	1.32
Learned about DP from seeing friends [IM2]	N=625	N=398	N=227
Nothing	41.92	43.72	38.77
A little	28.16	28.39	27.75
Some	16.96	16.33	18.06
A lot	10.88	10.05	12.33
Everything	2.08	1.51	3.08
Learned about DP through Internet [IM3] ***	N=625	N=398	N=227
Nothing	43.68	52.26	28.63
A little	25.92	27.64	22.91
Some	11.04	6.78	18.50
A lot	14.4	11.31	19.82
Everything	4.96	2.01	10.13

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

respondents how much they have learned about digital piracy through Internet chat rooms, IRC, web forums, or social media (IM3)—52.2% of university respondents learned nothing about digital piracy through the Internet while only 28.6% of online respondents reported the same. Given that the online sample was recruited primarily through web forums, participants in the online sample may spend significant time on these websites. The university and online sample report fairly similarly for the items that measure learning digital piracy through family and friends, though the online sample was slightly higher.

The percentages of respondents for each response category of items DF1-DF3 for definitions are shown in Table 6. For definitions, the online sample had higher average levels for all of the measures.[15] For definitions items DF1-DF3, a higher percentage of the online sample reported agreement with the statements favorable to digital piracy than the university sample (both "somewhat agree" and "strongly agree" responses).

For the online sample, 13.9% strongly agreed that digital piracy is okay to foster friendships, 13.4% strongly agreed that it is ok because creators don't really lose money, and 19.2% strongly agreed that it is okay for research because everyone benefits—on those same

Table 6. Sample Comparison for Definitions (DF1-DF3)

Definitions Measure	Sample		
	Pooled	University %	Online
DP is ok to foster friendships [DF1] **	N=620	N=397	N=223
Strongly agree	10.32	8.31	13.90
Somewhat agree	27.10	24.18	32.29
Somewhat disagree	27.58	28.72	25.56
Strongly disagree	35.00	38.79	28.25
DP is ok because creators don't really lose money [DF2] ***	N=620	N=397	N=223
Strongly agree	7.58	4.28	13.45
Somewhat agree	20.48	18.89	23.32
Somewhat disagree	31.29	30.23	33.18
Strongly disagree	40.65	46.60	30.04
DP is ok for research because everyone benefits [DF3] ***	N=618	N=395	N=223
Strongly agree	13.43	10.13	19.28
Somewhat agree	34.47	31.90	39.01
Somewhat disagree	22.98	24.30	20.63
Strongly disagree	29.13	33.67	21.08

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

[15] For full descriptive statistics of the social learning variables for the pooled, university, and online samples, see Tables 17, 18, and 19 in Appendix II respectively.

items respectively, 8.3%, 4.2%, and 10.1% of the university sample strongly agreed.

Table 7 shows the percentages of respondents across response categories for the remaining definition items DF4-DF6. As with the previous measurement items for definitions, the online sample also reported higher overall agreement for the remaining three measures—these items also had significant differences between samples. For the item asking respondents how strongly they agree or disagree that movie piracy is okay for entertainment, DF4, 26.4% of the online sample and 17.9% of the university sample strongly agreed. For DF5, 16.1% of online respondents strongly agreed that software piracy is okay because the community benefits while only 8.0% of the university strongly agreed. Finally, 28.2% of online respondents strongly agreed that software piracy is okay if it improves their knowledge compared to 17.1% of

Table 7. Sample Comparison for Definitions (DF4-DF6)

Definitions Measure	Sample		
	Pooled	University %	Online
Movie DP is ok for entertainment [DF4] ***	N=618	N=395	N=223
Strongly agree	21.04	17.97	26.46
Somewhat agree	36.73	33.67	42.15
Somewhat disagree	20.55	24.30	13.90
Strongly disagree	21.68	24.05	17.49
Software DP is ok because community benefits [DF5] **	N=619	N=396	N=223
Strongly agree	10.99	8.08	16.14
Somewhat agree	28.76	27.27	31.39
Somewhat disagree	28.76	29.04	28.25
Strongly disagree	31.50	35.61	24.22
Software DP is ok if it improves my knowledge [DF6] **	N=619	N=396	N=223
Strongly agree	21.16	17.17	28.25
Somewhat agree	32.47	31.31	34.53
Somewhat disagree	20.19	21.21	18.39
Strongly disagree	26.17	30.30	18.83

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

university respondents.

Descriptive Statistics for Reciprocity

Table 8 shows the comparisons for the pooled, university, and online samples for reciprocity— the differences in reciprocity perceptions between the two samples are all significant. Overall, the online sample reported higher levels of perceptions of reciprocity than the university sample. On all four reciprocity items, the online sample had a higher percentage of respondents who somewhat or strongly agreed with the statement about reciprocity in file sharing.

Table 8. Sample Comparison for Reciprocity

Differential Reinforcement Measure	Sample		
	Pooled	University	Online
	%		
I expect other users to share digital files online as well. [RCP1] **	N=598	N=393	N=205
Strongly agree	11.87	8.65	18.05
Somewhat agree	35.62	34.86	37.07
Somewhat disagree	31.61	35.88	23.41
Strongly disagree	20.90	20.61	21.46
I think it is unfair if users don't share digital files online. [RCP2] *	N=598	N=393	N=205
Strongly agree	6.02	4.07	9.76
Somewhat agree	15.72	14.50	18.05
Somewhat disagree	43.65	45.80	39.51
Strongly disagree	34.62	35.62	32.68
I feel obliged to share digital files online because I download from others. [RCP3] ***	N=598	N=393	N=205
Strongly agree	5.69	2.80	11.22
Somewhat agree	15.05	12.47	20.00
Somewhat disagree	37.12	39.44	32.68
Strongly disagree	42.14	45.29	36.10
I think that file sharing is based on reciprocity [RCP4] **	N=596	N=391	N=205
Strongly agree	11.74	8.70	17.56
Somewhat agree	35.07	33.50	38.05
Somewhat disagree	30.87	34.02	24.88
Strongly disagree	22.32	23.79	19.51

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

Descriptive Statistics for Digital Piracy

For the pooled sample, 77.3% of individuals reported engaging in at least some level of illegal downloading behavior in the past year and 33.1% reported illegal uploading behavior. Both samples differ quite significantly in terms of their average reported levels of engagement in illegal downloading and illegal uploading behaviors[16]. Interestingly, while the percentage of the university sample (78.3%) that reported engaging in illegal downloading behavior was close to the online sample (75.7%), this did not hold true for illegal uploading—27.9% of the university sample reported illegal uploading behavior of some kind compared to 41.4% of the online sample.

The comparisons for the pooled, university, and online samples for illegal downloading behaviors are shown in Table 9. All five items had a significant difference between samples based on chi-square tests. For the downloading measures, the online sample reported higher engagement in downloading pirated content from a website (university = 49.9%; online = 62.6%), much higher use of P2P software to downloading pirated content (university = 16.9%; online = 41.4%), higher use of IRC to download pirated digital content (university = 7.1%; online = 17.1%), and higher use of software to download media from a website without permission (university = 41.7%; online = 52.1%). The only downloading measure where the university sample was higher was the use of a streaming website to illegally watch movies

[16] For full descriptive statistics of the digital piracy variables for the pooled, university, and online samples, see Tables 20, 21, and 22 in Appendix II respectively.

Table 9. Sample Comparison for Illegal Downloading Behaviors			
Illegal Downloading Behaviors Measure	Sample		
	Pooled	University %	Online
Downloaded from website [DP1] ***	N=648	N=397	N=251
Never	45.83	51.13	37.45
1-2 times	19.44	20.15	18.33
3-5 times	10.34	10.33	10.36
6-9 times	4.48	3.27	6.37
10 or more times	19.91	15.11	27.49
Used P2P to download [DP2] ***	N=648	N=397	N=251
Never	73.61	83.12	58.57
1-2 times	7.87	8.06	7.57
3-5 times	5.25	3.53	7.97
6-9 times	2.47	1.26	4.38
10 or more times	10.80	4.03	21.51
Used IRC to download [DP3] ***	N=647	N=396	N=251
Never	89.03	92.93	82.87
1-2 times	6.18	4.55	8.76
3-5 times	2.47	1.26	4.38
6-9 times	0.62	0.25	1.20
10 or more times	1.70	1.01	2.79
Used a streaming website to watch illegal [DP4] **	N=648	N=397	N=251
Never	36.27	29.97	46.22
1-2 times	18.21	20.40	14.74
3-5 times	10.80	10.83	10.76
6-9 times	7.72	8.82	5.98
10 or more times	27.01	29.97	22.31
Used software to download without permission [DP5] **	N=647	N=396	N=251
Never	54.25	58.33	47.81
1-2 times	17.16	17.68	16.33
3-5 times	7.57	5.81	10.36
6-9 times	4.02	2.27	6.77
10 or more times	17.00	15.91	18.73
Engaged in any downloading activity	77.31	78.34	75.70

Note: All questions are paraphrased—see Appendix II for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

or television shows—46.2% of the online sample reported never using a streaming website for illegal viewing compared to 29.9% of the university sample.

Table 10 shows the sample comparisons for the illegal uploading behaviors measurement items. Except for the item for providing pirated content on a streaming website, chi-square tests revealed a significant difference between samples for each item. Similar results to illegal downloading are found when examining the descriptive statistics for the illegal uploading behavior measures across the two samples—on every single measure, the online sample reports higher engagement. While engagement in illegal uploading is low across both samples, the online sample reports higher engagement in providing pirated digital content for others to watch through a streaming website without the owner's permission (university = 20.2%; online = 21.9%), higher engagement in uploading pirated content to websites (university = 11.3%; online = 20.7%), higher use of P2P software to seed pirated digital content after they've finished downloading (university = 8.3%; online = 31.8%), higher use of IRC to share pirated content to other users (university = 3.5%; online = 9.5%), and higher engagement with creating torrent files to illegally share their own pirated digital content (university = 4.0%; online = 14.3%).

Table 10. Sample Comparison for Illegal Uploading Behaviors			
Illegal Uploading Behaviors Measure	Sample		
	Pooled	University %	Online
Provided pirated content on a streaming website [DP6]	N=647	N=396	N=251
Never	79.13	79.80	78.09
1-2 times	7.88	9.09	5.98
3-5 times	4.17	3.54	5.18
6-9 times	2.47	1.52	3.98
10 or more times	6.34	6.06	6.77
Uploaded pirated content to a website [DP7] ***	N=647	N=396	N=251
Never	85.01	88.64	79.28
1-2 times	7.57	7.07	8.37
3-5 times	2.47	1.77	3.59
6-9 times	1.55	0.00	3.98
10 or more times	3.40	2.53	4.78
Used P2P to upload/share [DP8] ***	N=647	N=396	N=251
Never	82.53	91.67	68.13
1-2 times	4.79	3.28	7.17
3-5 times	4.17	1.52	8.37
6-9 times	1.24	0.76	1.99
10 or more times	7.26	2.78	14.34
Used IRC to upload/share [DP9] *	N=648	N=397	N=251
Never	94.14	96.47	90.44
1-2 times	2.47	1.26	4.38
3-5 times	1.70	1.01	2.79
6-9 times	0.31	0.00	0.80
10 or more times	1.39	1.26	1.59
Created a torrent file to upload/share [DP10] ***	N=648	N=397	N=251
Never	91.98	95.97	85.66
1-2 times	2.31	1.51	3.59
3-5 times	1.70	0.25	3.98
6-9 times	1.08	0.25	2.39
10 or more times	2.93	2.02	4.38
Engaged in any uploading activity ***	33.18	27.96	41.43

Note: All questions are paraphrased—see Appendix I for exact question-wording. Higher values are highlighted for each sample comparison. Significance between the university and online samples is based on chi-square tests.
*p < .05 **p < .01 ***p < .001

The results of these side-by-side comparisons between the university and online samples highlight the importance of including samples outside of university populations in the study of digital piracy, particularly when investigating illegal uploading behavior. While students may be suitable subjects for the study of digital piracy, students should not be used as surrogates for nonstudents given the differences identified both in prior research and within this study (Lowry, Zhang, & Wu, 2017). Also, given how low engagement is in illegal uploading overall, utilizing samples exclusively from university student populations may not yield a sufficient number of individuals who engage in illegal uploading for study. There may also be qualitative differences between university samples and online-based samples that help account for these differences in digital piracy engagement. The significant difference between the percentage of individuals reporting some level of engagement in illegal uploading behavior for the university and online samples may indicate an important difference in one or more predictors of illegal uploading among these populations.

Confirmatory Factor Analysis of Social Learning Measurement Model

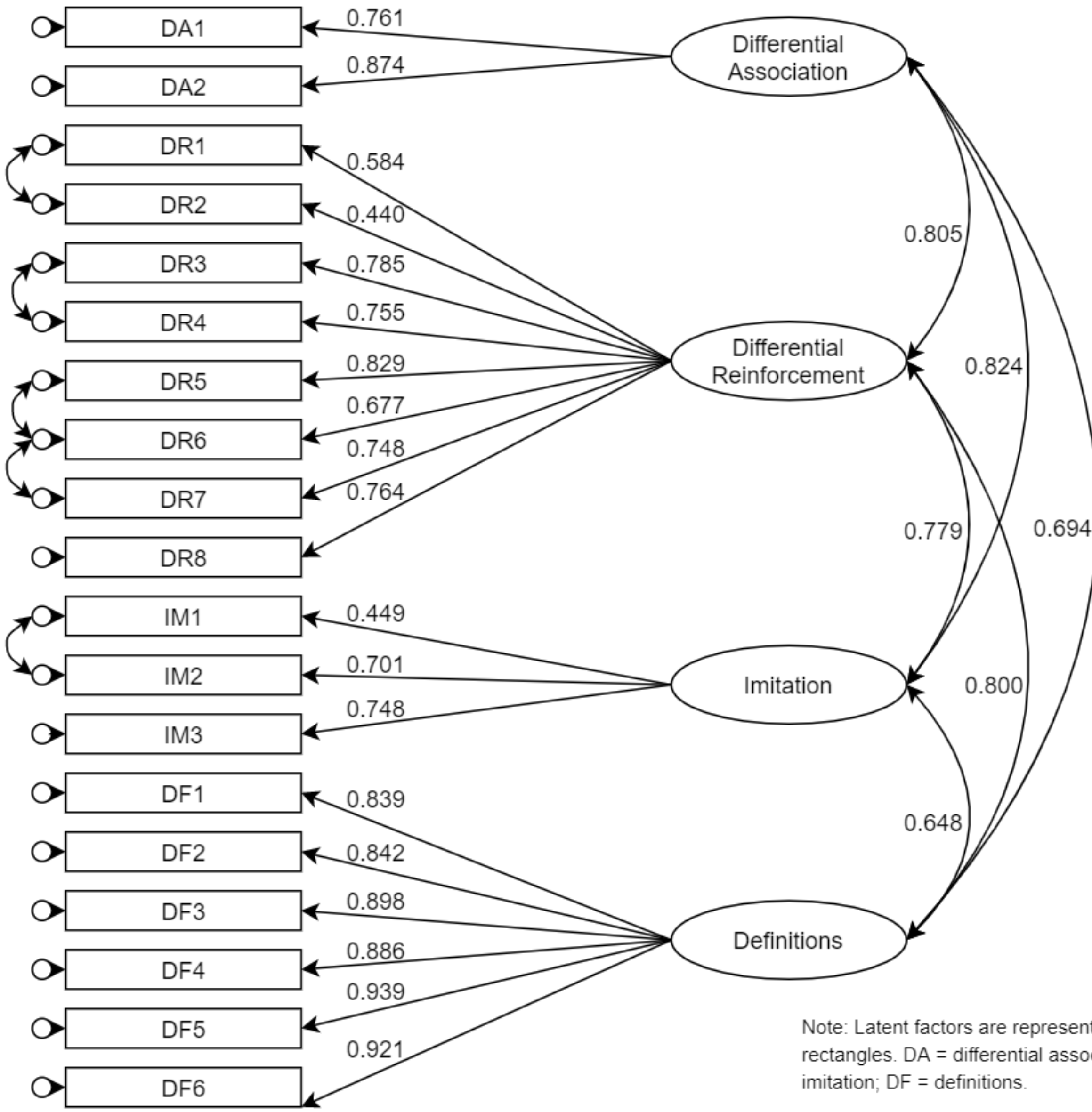
Based on prior theoretical (Akers, 1998) and empirical work (Burruss et al., 2012; Burruss et al., 2018), both first-order and second-order latent constructs for social learning are examined. Proceeding in this manner allows us to address social learning theory as a whole rather than just its individual components (Holt et al., 2010). After fitting several models to the data using all available indicators for each component of social learning, the measurement model is chosen based on the assessment of absolute and relative fit indices. Modification indices, in combination with extant theoretical and empirical work, are used to determine the final model selection and for decision-making regarding correlations of error variances (Brown, 2006; Schumacker & Lomax, 2010). Although correlated errors should not be specified solely to increase model fit, it may be justified based on method effects—common assessment methods and similarly worded items could cause indicator covariation (Brown, 2006). All of the correlated errors in this study's models correspond to items with the same response categories and, in most cases, similar question-wording.

First-Order Social Learning Model

The path diagram for the first-order model with factor loadings and goodness-of-fit indices is displayed in Figure 2.[17] For the first-order social learning model, the fit indices are acceptable to proceed with the model. The chi-square is significant ($\chi^2 = 549.954$, df = 141, $p < 0.000$) and the RMSEA is slightly high (0.069), but CFI (0.982), TLI (0.978), and SRMR (0.043) are all in good ranges. Both of the observed variables for differential association load strongly and significantly on the first-order factor (both loaded at greater than 0.700). All of the observed variables for differential reinforcement also load within acceptable ranges and are significant; three items have loadings of less than 0.700 but are still above the cutoff for acceptable loadings. The three observed variables for imitation also load acceptably and significantly. One observed variable loads close to 0.400 while the remaining two indicators load over 0.700. All six of the observed variables for definitions load strongly and significantly onto the definitions factor (all loadings were greater than 0.800).

[17] Table 30 in Appendix I includes all standardized factor loadings, error covariances, and fit indices for the 1st-order social learning model.

Figure 2. 1st-Order Social Learning Model



Model Fit
$\chi^2 = 549.954, 141, p < 0.000$
RMSEA = 0.069
CFI = 0.982
TLI = 0.978
SRMR = 0.043

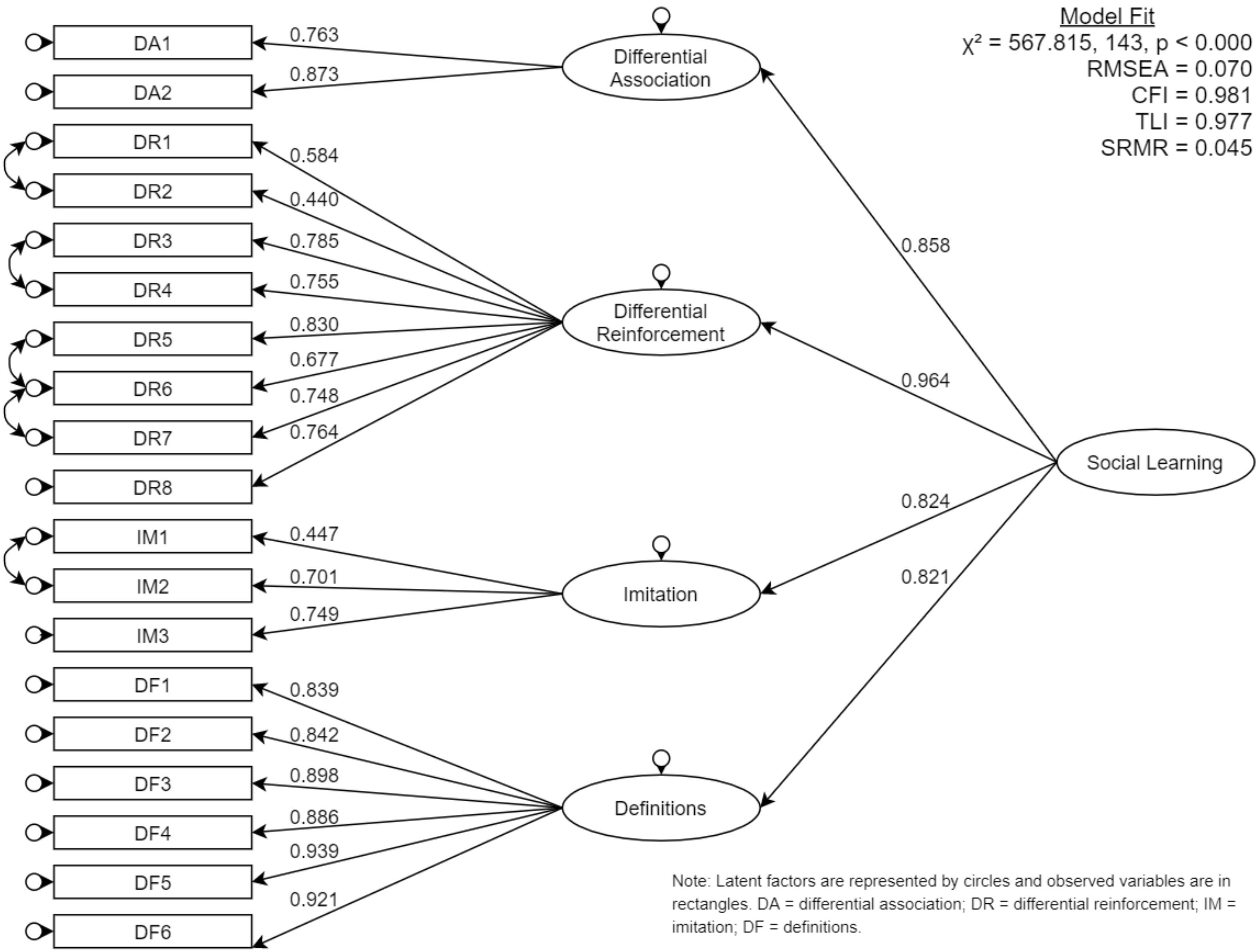
Note: Latent factors are represented by circles and observed variables are in rectangles. DA = differential association; DR = differential reinforcement; IM = imitation; DF = definitions.

Second-Order Social Learning Model

Figure 3 shows the path diagram for the second-order model with factor loadings and goodness-of-fit indices.[18] The second-order social learning measurement model also has acceptable goodness-of-fit indices. While the model χ^2 is significant ($\chi^2 = 567.815$, df = 143, $p < 0.000$)—which, as mentioned earlier, indicates the model is significantly different than a perfect fit model for the data—the CFI (0.981), TLI (0.977), and SRMR (0.045) are all within the thresholds indicating a good fit while the RMSEA was slightly high at 0.070. Although the chi-square indicates that the model is significantly different from a model with an exact fit, this study proceeds with the model as-is due to prior theoretical and empirical research and given that the other fit indices all indicate that the model is a good fit.

[18] Table 31 in Appendix I includes all standardized factor loadings, error covariances, and fit indices for the 2nd-order social learning model.

Figure 3. 2nd-Order Social Learning Model

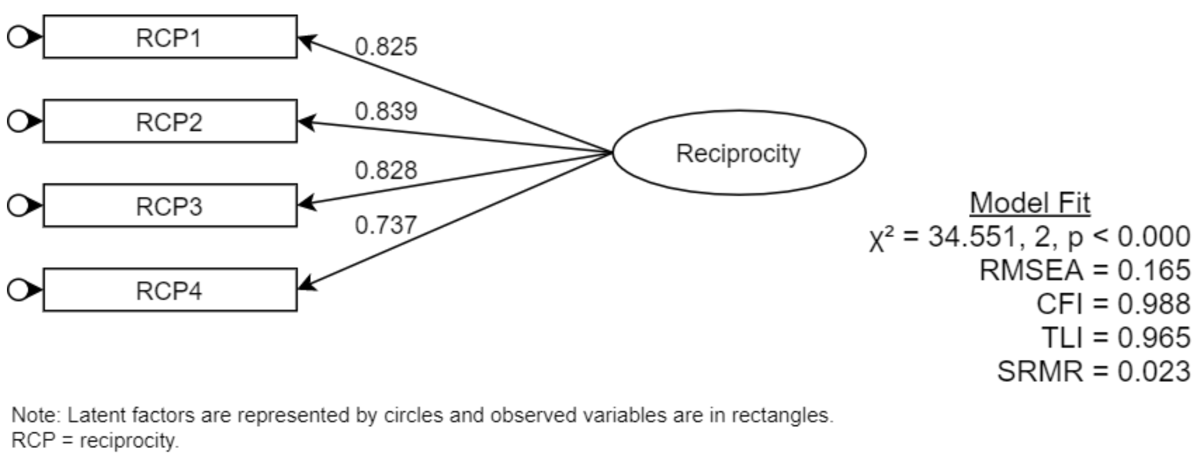


Note: Latent factors are represented by circles and observed variables are in rectangles. DA = differential association; DR = differential reinforcement; IM = imitation; DF = definitions.

Confirmatory Factor Analysis for Reciprocity Measurement Model

The measurement model for reciprocity is displayed in Figure 4 with all factor loadings and fit indices.[19] For reciprocity, a measurement model is designed using four observed, ordered-categorical variables that measure a respondent's levels of perceived reciprocity. The constructed model for reciprocity has a significant chi-square (χ^2 = 34.551, df = 2, p < 0.000) and is therefore significantly different than a model with a perfect fit. While the model's RMSEA is also high (0.165), the remaining goodness-of-fit indices are all indicative of a good model fit (CFI = 0.988; TLI = 0.965; SRMR = 0.023). Additionally, all of the observed items included in the reciprocity model have very high factor loadings (> 0.700).

Figure 4. Measurement Model for Reciprocity



Confirmatory Factor Analysis for Illegal Downloading Measurement Model

The measurement model for illegal downloading behavior with its chi-square test and relevant goodness-of-fit indices is displayed in Figure 5.[20] The measurement model is

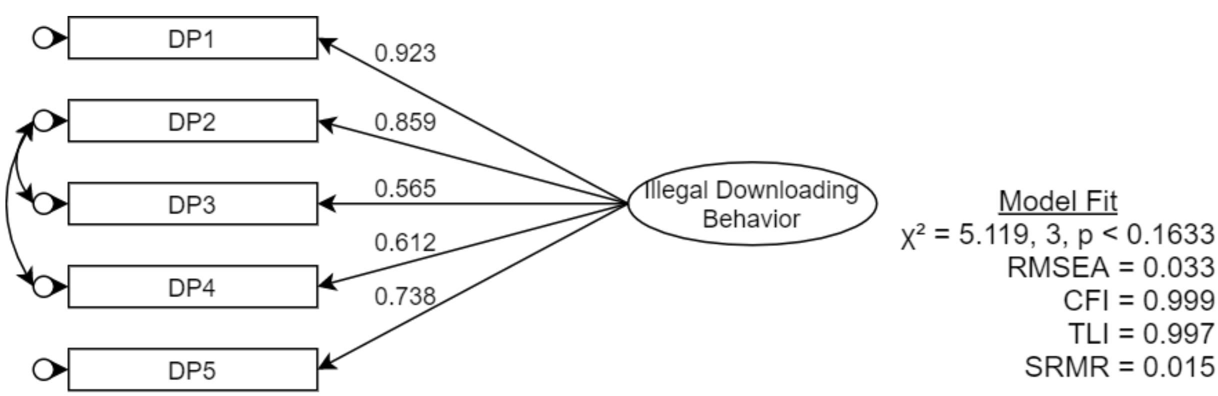
---

[19] Table 32 in Appendix I includes all standardized factor loadings and fit indices for the reciprocity model.
[20] Table 33 in Appendix I includes all standardized factor loadings, error variances, and fit indices for the illegal downloading behaviors model.

constructed using a set of five observed, ordered-categorical variables that capture different forms of downloading behavior. While there are many ways that latent variables and their purpose have been defined, one such definition is that latent variables are a data reduction device—that they are a convenient means for summarizing several observed variables into fewer underlying factors (Bollen, 2002). Digital piracy has been measured as a latent factor frequently in the extant literature, particularly in the business literature (Morris & Higgins, 2010; Taylor, 2012; Yoon, 2011).

All five of the observed measures for illegal downloading behavior have sufficient factor loadings (> 0.400), the chi-square is not significant (χ^2 = 5.119, df = 3, p < 0.163), and goodness-of-fit indices all indicate that the measurement model is a good fit for the data (CFI = 0.999; TLI = 0.997; RMSEA = 0.033; SRMR = 0.015). The lowest loading item is the measure for how often respondents use a streaming website to illegally watch movies or tv shows (0.612) while the item that loads the highest ask about downloading pirated content from a website (0.923).

Figure 5. Measurement Model for Illegal Downloading Behavior

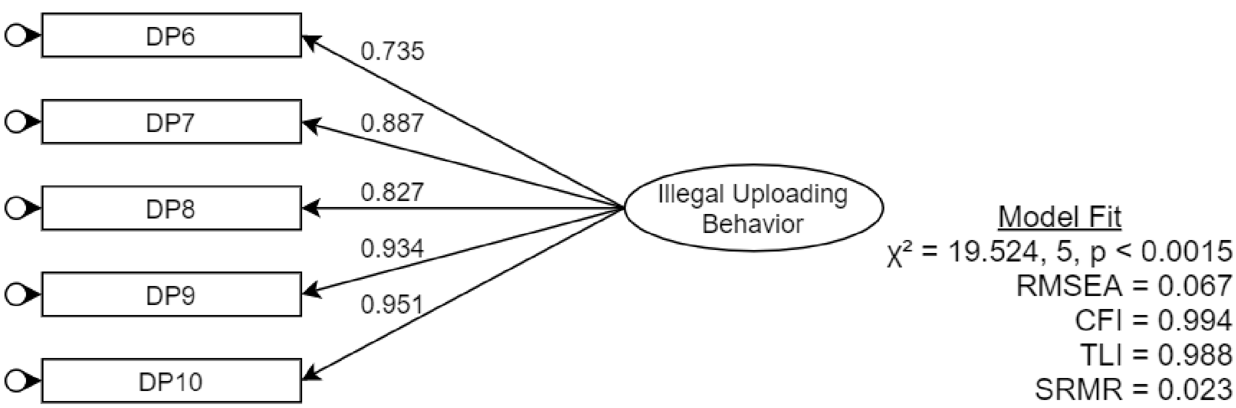


Note: Latent factors are represented by circles and observed variables are in rectangles.
DP = digital piracy.

Confirmatory Factor Analysis for Illegal Uploading Measurement Model

As with illegal downloading behavior, a measurement model is also created for illegal uploading behavior. The measurement model for illegal uploading behavior with its chi-square test and goodness-of-fit indices is displayed in Figure 6.[21] All five observed variables load strongly onto the first-order factor for illegal uploading (> 0.700). Although the chi-square is significant (χ^2 = 19.524, df = 5, p < 0.001), the remaining goodness-of-fit indices all indicate that the measurement model is a good fit for the data (CFI = 0.994; TLI = 0.988; RMSEA = 0.067; SRMR = 0.023). The observed measure variable that loads the highest in the model asked individuals about creating torrent files to illegally share pirated content (0.951). On the other side of the spectrum, the measure with the lowest factor loading asks respondents how often they provided pirated content through a streaming website (0.735).

Figure 6. Measurement Model for Illegal Uploading Behavior



Note: Latent factors are represented by circles and observed variables are in rectangles.
DP = digital piracy.

[21] Table 34 in Appendix I includes all standardized factor loadings and fit indices for the illegal uploading behaviors model.

Multivariate Results: Structural Equation Modeling

Several structural models are examined in this study to evaluate the hypotheses. All of the models include seven demographic variables—age, sex, race, ethnicity, highest education completed, current employment status, and total household income. Additionally, all models control for computer use, techniques of neutralization, computer skill, punishment certainty, and moral acceptability.

Hypothesis 1: Social Learning and Illegal Downloading

The results for all of the models explaining variations in illegal downloading behaviors are shown in Table 11 (Models 1 through 3). Model 3 tests the first hypothesis—social learning increases self-reported illegal downloading behaviors, controlling for all other relevant variables. Figure 7 displays the path diagram for Model 3 with its associated chi-square and goodness-of-fit indices. The results for Model 3 indicate that social learning ($b = 0.633$, $p < 0.001$) has a positive, direct effect on illegal downloading behavior, net of other controls. Unlike prior research, techniques of neutralization are not significantly related to illegal downloading. The only other measure that has a significant direct effect on the latent outcome was computer skill ($b = 0.21$, $p < 0.001$). Higher computer skills increase illegal downloading.

The chi-square for the final structural model on illegal downloading behaviors is significant ($\chi^2 = 1355.021$, df = 662, $p < 0.000$) and SRMR was slightly high (0.087 > 0.08), but CFI (0.938), TLI (0.929), and RMSEA (0.045) are all in acceptable ranges and indicative of a good model fit. Overall, Model 3 explains 59.8% of the variation in the illegal downloading behavior latent variable.

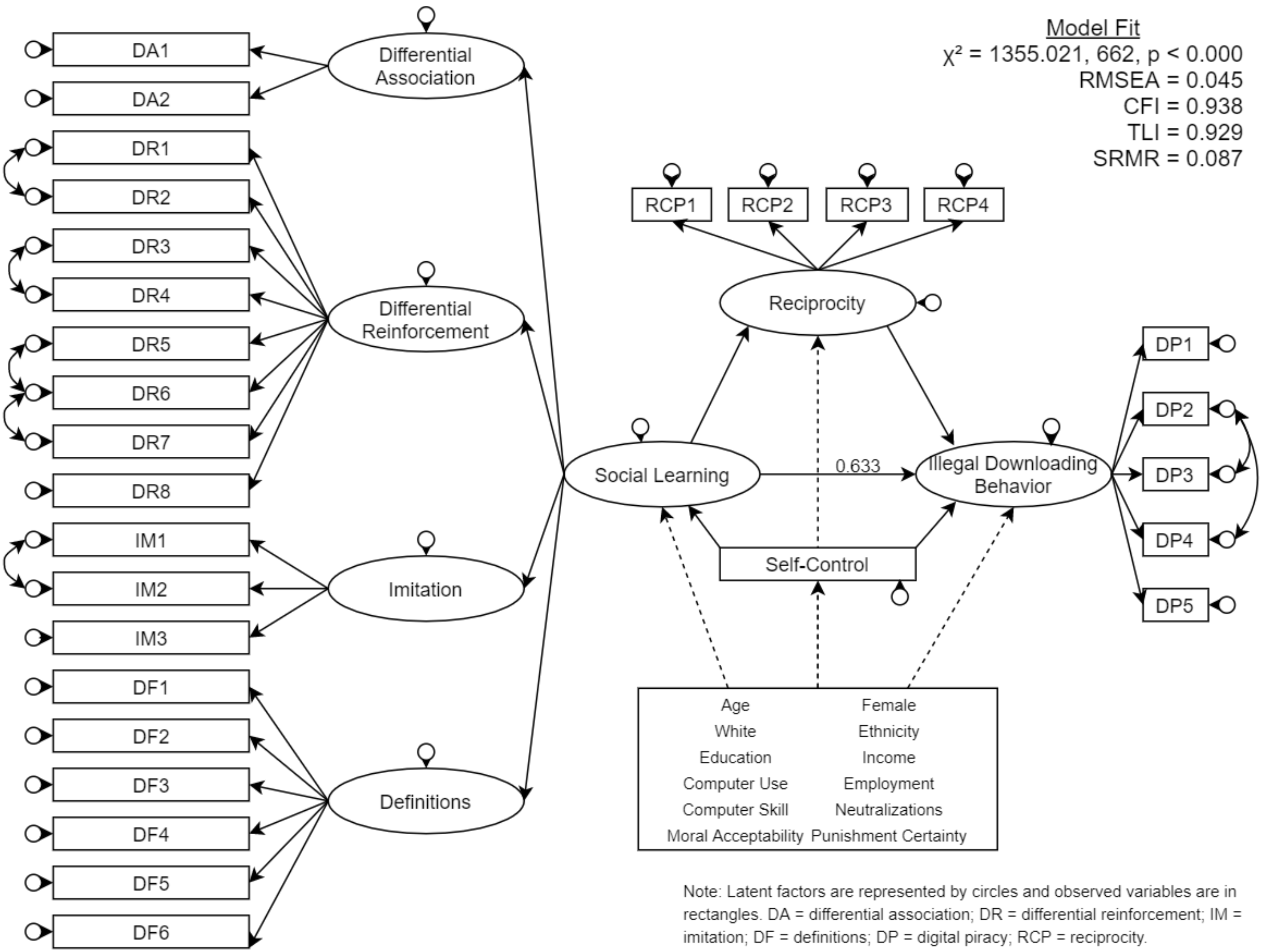
Table 11. Models for Illegal Downloading Behavior (Self-Control and Social Learning)

	Controls only			SC on downloading			SL on downloading			Mediation on downloading		
				Model 1			Model 2			Model 3		
	(n = 520)			(n = 520)			(n = 512)			(n = 512)		
Measures	Estimate	*SE*	β	Estimate	*SE*	β	Estimate	*SE*	β	Estimate	*SE*	β
SL	—	—	—	—	—	—	0.644 ***	0.055	11.676	0.633 ***	0.057	11.109
SC	—	—	—	-0.018 **	0.006	-3.136	—	—	—	-0.005	0.006	-0.910
Age	-0.015 **	0.006	-2.668	0.130 **	0.039	3.331	-0.009	0.005	-1.840	-0.010	0.005	-1.865
Female	-0.136	0.084	-1.623	-0.015 **	0.006	-2.649	-0.124	0.080	-1.553	-0.113	0.080	-1.403
White	-0.065	0.096	-0.678	-0.103	0.084	-1.225	-0.111	0.093	-1.190	-0.116	0.092	-1.253
ETH	0.015	0.117	0.127	-0.094	0.095	-0.988	0.118	0.112	1.053	0.122	0.112	1.084
EDU	-0.009	0.095	-0.095	0.029	0.117	0.245	-0.101	0.093	-1.080	-0.085	0.094	-0.901
EMP	0.031	0.091	0.340	0.025	0.095	0.262	0.034	0.085	0.404	0.036	0.086	0.417
INC	0.011	0.087	0.127	0.037	0.090	0.407	0.025	0.081	0.309	0.017	0.082	0.209
CU	0.009	0.010	0.960	0.009	0.086	0.102	0.006	0.009	0.622	0.004	0.010	0.417
NTZ	0.031 ***	0.006	5.103	0.007	0.010	0.758	-0.004	0.006	-0.546	-0.007	0.007	-0.990
RCP	0.143 ***	0.040	3.574	0.027 ***	0.006	4.315	0.034	0.040	0.857	0.044	0.054	0.822
CS	0.034 ***	0.004	9.554	0.002	0.010	0.227	0.021 ***	0.004	5.668	0.021 ***	0.004	5.688
PCRT	0.001	0.010	0.142	0.044 *	0.019	2.329	0.006	0.009	0.617	0.005	0.009	0.546
MA	0.048 ***	0.004	9.554	0.035 ***	0.004	9.886	-0.005	0.018	-0.273	-0.007	0.018	-0.373
SC via SL	—	—	—	—	—	—	—	—	—	-0.015 ***	0.003	-5.064

Note: SL = social learning; SC = self-control; ETH = Hispanic/Latino; EDU = Education; EMP = unemployed; INC = income; CU = computer use; NTZ = neutralizations; RCP = reciprocity; CS = computer skill; PCRT = punishment certainty; MA = moral acceptability

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

Figure 7. Structural Model for Illegal Downloading Behaviors



<u>Model Fit</u>
$\chi^2 = 1355.021, 662, p < 0.000$
RMSEA = 0.045
CFI = 0.938
TLI = 0.929
SRMR = 0.087

Note: Latent factors are represented by circles and observed variables are in rectangles. DA = differential association; DR = differential reinforcement; IM = imitation; DF = definitions; DP = digital piracy; RCP = reciprocity.

Hypothesis 2: Social Learning and Illegal Uploading Behavior

The results for all of the models explaining variations in illegal uploading behaviors are shown in Table 12 (Models 4 through 6). Model 6 tests the second hypothesis that social learning will increase self-reported illegal uploading behaviors (see Table 12 for the results of Model 6). Figure 8 displays the path diagram for Model 6 with its associated chi-square and goodness-of-fit indices. The results for Model 6 indicate that social learning ($b = 0.433$, $p < 0.001$) has a positive direct effect on illegal uploading behavior, supporting this hypothesis. Social learning has the strongest direct effect on illegal uploading of any variable included in the model. In addition to the main independent variables, computer skill ($b = 0.026$, $p < 0.001$), computer use ($b = 0.027$, $p < 0.05$), and punishment certainty ($b = 0.038$, $p < 0.01$) all have significant direct effects on the illegal uploading outcome.

Although punishment certainty is significant, it should be noted that the direction of this variable's effect is opposite of what is expected based on prior research—higher levels of punishment certainty increase levels of self-reported illegal uploading behaviors. Typically, higher punishment certainty decreases criminal behavior, digital piracy included, but here that is not the case (Peace, Galletta, & Thong, 2003). Despite this anomaly, there is a very low variance in the punishment certainty scale, so while higher punishment levels do increase illegal uploading, those levels are all still extremely low overall.

As with Model 3, the chi-square for the illegal uploading model is significant ($\chi^2 = 1234.605$, $df = 664$, $p < 0.000$) and SRMR is slightly high ($0.084 > 0.08$) but the CFI (0.948), TLI (0.941), and RMSEA (0.041) are all indicative of an acceptable model fit. Overall, Model 3 explains 58.1% of the variation in the illegal downloading behavior latent variable.

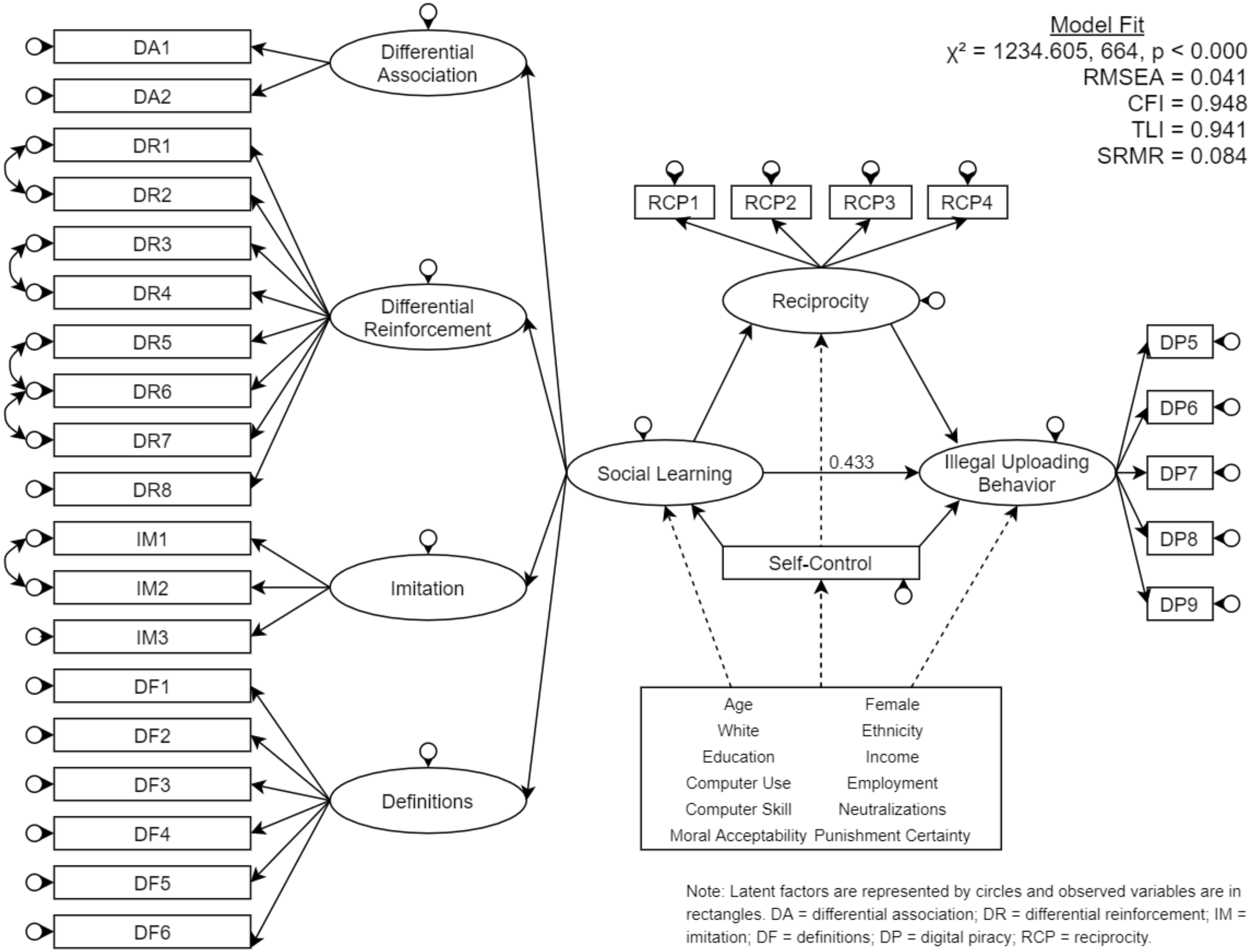
Table 12. Models for Illegal Uploading Behavior (Self-Control and Social Learning)

	Controls only			SC on uploading			SL on uploading			Mediation on uploading		
				Model 4			Model 5			Model 6		
	(n = 519)			(n = 519)			(n = 511)			(n = 511)		
Measures	Estimate	*SE*	β	Estimate	*SE*	β	Estimate	*SE*	β	Estimate	*SE*	β
SL	—	—	—	—	—	—	0.426 ***	0.061	6.967	0.433 ***	0.065	6.705
SC	—	—	—	-0.003	0.007	-0.529	—	—	—	0.004	0.007	0.570
Age	-0.002	0.008	-0.210	-0.002	0.008	-0.201	0.003	0.007	0.480	0.003	0.007	0.432
Female	0.050	0.108	0.461	0.057	0.109	0.521	0.080	0.105	0.768	0.086	0.104	0.825
White	0.025	0.122	0.207	0.020	0.122	0.161	-0.024	0.117	-0.205	-0.007	0.117	-0.057
ETH	-0.004	0.171	-0.025	-0.001	0.170	-0.009	0.077	0.163	0.475	0.087	0.157	0.555
EDU	0.154	0.123	1.251	0.161	0.125	1.291	0.040	0.125	0.319	0.059	0.124	0.473
EMP	-0.119	0.120	-0.995	-0.118	0.120	-0.988	-0.152	0.118	-1.281	-0.151	0.119	-1.266
INC	-0.031	0.117	-0.270	-0.032	0.117	-0.276	-0.016	0.114	-0.140	-0.053	0.113	-0.472
CU	0.032 *	0.013	2.537	0.031 *	0.013	2.499	0.033 **	0.012	2.663	0.027 *	0.012	2.161
NTZ	0.037 ***	0.008	4.877	0.036 ***	0.008	4.699	0.013	0.008	1.632	0.000	0.008	-0.035
RCP	0.253 ***	0.038	6.663	0.251 ***	0.039	6.480	0.169 ***	0.037	4.604	0.227 ***	0.049	4.616
CS	0.036 ***	0.005	7.972	0.036 ***	0.005	8.003	0.029 ***	0.005	6.078	0.026 ***	0.005	5.610
PCRT	0.040 **	0.012	3.278	0.040 **	0.012	3.283	0.042 ***	0.012	3.547	0.038 **	0.012	3.195
MA	0.007	0.025	0.285	0.006	0.025	0.258	-0.025	0.025	-1.027	-0.034	0.025	-1.365
SC via SL	—	—	—	—	—	—	—	—	—	-0.010 ***	0.002	-4.126

Note: SL = social learning; SC = self-control; ETH = Hispanic/Latino; EDU = Education; EMP = unemployed; INC = income; CU = computer use; NTZ = neutralizations; RCP = reciprocity; CS = computer skill; PCRT = punishment certainty; MA = moral acceptability

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

Figure 8. Structural Model for Illegal Uploading Behaviors



Note: Latent factors are represented by circles and observed variables are in rectangles. DA = differential association; DR = differential reinforcement; IM = imitation; DF = definitions; DP = digital piracy; RCP = reciprocity.

Hypothesis 3_A: Reciprocity and Illegal Downloading Behaviors

Model 3 in Table 11 tests hypothesis 3_A, or that higher levels in perceived reciprocity will not increase levels of self-reported illegal downloading behaviors. Model 3 indicates that perceived reciprocity ($b = 0.044$, $p > 0.05$) does not have a significant direct effect on illegal downloading behaviors and, therefore, hypothesis 3_A is supported.

Hypothesis 3_B: Reciprocity and Illegal Uploading Behaviors

In Table 12, Model 6 tests hypothesis 3_B—higher levels in perceived reciprocity will increase levels of self-reported illegal uploading behaviors. The results indicate that the latent variable for reciprocity ($b = 0.227$) has a positive, direct effect on the latent variable for illegal uploading behaviors. In the structural model for illegal uploading, reciprocity has the second strongest direct effect.

In addition to the quantitative results regarding reciprocity, there are also several responses to the open-ended motivations survey question that supported hypothesis 3_A. For instance, one respondent listed their motivations for uploading as, "I like giving back to other users. I download a lot so it feels nice being able to give back with my own stuff." Other responses that support the relationship between reciprocity and illegal uploading include, "To give back what was given to me," "Giving back to the community," and, "I see uploading new content like contributing to a global library. I take pride in making things others need or want available to them. It also expands the ecosystem as a whole, making others more likely to stick around and make contributions of their own. These are also reasons why I seed."

Hypothesis 4_A: Self-Control and Illegal Downloading Behaviors

Model 3 in Table 11 tests hypothesis 4_A, or that higher levels of self-control will decrease levels of self-reported illegal downloading behaviors. The results indicate that levels of self-control do not have a significant, direct effect on the latent factor for illegal downloading behaviors when all other statistical controls are included.

Hypothesis 4_B: Self-Control and Illegal Uploading Behaviors

Hypothesis 4_B states that higher levels of self-control will not decrease levels of self-reported illegal uploading behaviors—this is tested in Model 6 in Table 12. The results from Model 6 support this hypothesis as levels of self-control do not have a significant, direct effect on illegal uploading behaviors ($b = 0.004$, $p > 0.05$).

Hypothesis 5: Reciprocity Mediation

Finally, Hypothesis 5 states that reciprocity will mediate the relationship between social learning and illegal uploading behaviors—this hypothesis is tested in Model 6 in Table 13. The results support hypothesis 5 as the latent factor for social learning has a positive, indirect effect on illegal uploading behaviors through reciprocity. While social learning has a strong indirect effect on illegal uploading through reciprocity ($b = 0.063$, $p < 0.01$), the mediation is only partial and social learning still has a strong direct effect on illegal uploading behaviors ($b = 0.433$, $p < 0.001$) when controlling for the mediation path with reciprocity ($b = 0.227$, $p < 0.001$).

Using Baron and Kenny's (1986) four-step process for mediation analysis confirms these findings (see Table 36 for the results of the additional reciprocity mediation analysis). When social learning is included in a model without reciprocity, social learning has a positive, direct effect on illegal uploading behavior ($b = 0.492$, $p < 0.001$). For the second step, social learning is modeled on reciprocity without the outcome variable—social learning has a positive, direct effect on reciprocity ($b = 0.256$, $p < 0.001$). In a model with social learning and illegal uploading behavior where the mediation path with reciprocity is controlled for, reciprocity has a positive, direct effect on illegal uploading behavior ($b = 0.230$, $p < 0.001$). While reciprocity partially mediates the relationship between social learning and illegal uploading, the mediation effect is small—the coefficient for social learning only changed from 0.492 to 0.429 by including the mediation path with reciprocity.

Table 13. Structural Models for Illegal Uploading Behavior (Social Learning and Reciprocity)

	Controls only			SL on uploading			RCP on uploading			Mediation on uploading		
				Model 7			Model 8			Model 6		
	(n = 520)			(n = 512)			(n = 519)			(n = 511)		
Measures	Estimate	*SE*	β	Estimate	*SE*	β	Estimate	*SE*	β	Estimate	*SE*	β
SL	—	—	—	0.492 ***	0.063	7.789	—	—	—	0.433 ***	0.065	6.705
RCP	—	—	—	—	—	—	0.248 ***	0.039	6.437	0.227 ***	0.049	4.616
SC	-0.011	0.009	-1.197	0.000	0.009	0.019	-0.011	0.009	-1.197	0.004	0.007	0.570
Age	-0.002	0.008	-0.254	0.004	0.007	0.485	-0.002	0.008	-0.257	0.003	0.007	0.432
Female	0.067	0.110	0.608	0.081	0.107	0.759	0.068	0.110	0.613	0.086	0.104	0.825
White	0.005	0.122	0.037	-0.030	0.117	-0.254	0.006	0.122	0.050	-0.007	0.117	-0.057
ETH	0.002	0.170	0.014	0.083	0.163	0.509	0.000	0.171	0.001	0.087	0.157	0.555
EDU	0.178	0.126	1.410	0.039	0.128	0.306	0.179	0.126	1.424	0.059	0.124	0.473
EMP	-0.117	0.118	-0.988	-0.148	0.118	-1.254	-0.117	0.118	-0.992	-0.151	0.119	-1.266
INC	-0.030	0.117	-0.260	-0.015	0.115	-0.128	-0.029	0.117	-0.249	-0.053	0.113	-0.472
CU	0.032 *	0.013	2.552	0.033 **	0.012	2.698	0.032 *	0.013	2.525	0.027 *	0.012	2.161
NTZ	0.035 ***	0.008	4.538	0.010	0.008	1.263	0.035 ***	0.008	4.550	0.000	0.008	-0.035
CS	0.036 ***	0.005	7.969	0.027 ***	0.005	5.646	0.037 ***	0.005	8.009	0.026 ***	0.005	5.610
PCRT	0.040 **	0.012	3.303	0.042 ***	0.012	3.599	0.040 **	0.012	3.314	0.038 **	0.012	3.195
MA	0.005	0.025	0.198	-0.030	0.025	-1.208	0.005	0.025	0.208	-0.034	0.025	-1.365
SL via RCP	—	—	—	—	—	—	—	—	—	0.063 **	0.019	3.404

Note: SL = social learning; SC = self-control; ETH = Hispanic/Latino; EDU = Education; EMP = unemployed; INC = income; CU = computer use; NTZ = neutralizations; RCP = reciprocity; CS = computer skill; PCRT = punishment certainty; MA = moral acceptability

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

Additional Mediation Analysis: Self-Control and Social Learning

Although self-control does not have a significant, direct effect on the outcome variables in either model, mediation analyses show that self-control does have a significant, indirect effect on both outcomes through social learning. Self-control has a negative, indirect effect on illegal downloading behaviors ($b = -0.015$, $p < 0.001$) and illegal uploading behaviors ($b = -0.010$, $p < 0.001$) in Models 3 and 6 respectively (see Table 11 for the results of Model 3; see Table 12 for the results of Model 6). Conducting supplemental mediation analyses using the four-step process described by Baron and Kenny (1986) reveals that social learning fully mediates the relationship between self-control and illegal downloading (see Table 35 for the results of the additional self-control mediation analysis). In a model excluding social learning, self-control has a negative, direct effect on illegal downloading behavior ($b = -0.018$, $p < 0.01$). When self-control and social learning are included together in a model without illegal downloading, self-control has a negative, direct effect on social learning ($b = -0.020$, $p < 0.001$). Finally, in a model with self-control and illegal downloading behaviors where the mediation path with social learning is controlled for, social learning has a positive, direct effect on illegal downloading ($b = 0.633$, $p < 0.001$). Self-control, however, no longer has a significant direct effect when controlling for mediation via social learning ($b = -0.005$, $p > 0.05$)—social learning fully mediates the relationship between self-control and illegal downloading behaviors.

Sensitivity Testing

For sensitivity testing purposes, several additional models are examined to see if the results of this dissertation's analyses would change with alternate model specifications. First, self-reported strength of piracy skill is also included in the model given its significant bivariate correlation with the digital piracy outcomes. The inclusion of self-reported strength of piracy skill did not change the findings for any of the hypotheses. Self-reported piracy skill is significantly related to both illegal downloading and uploading behaviors.

Secondly, although sample-specific models of illegal downloading and uploading behaviors are not modeled in the current analyses, a variable indicating sample membership is included in supplemental analyses to assess if sample membership impacts the findings. The results for all of the hypotheses remain the same.

CHAPTER 5: CONCLUSIONS

Summary

This dissertation sought to answer several research questions relating to digital piracy. The first research question tested whether Akers' (1998) social learning theory could explain variations in illegal downloading behavior. Similarly, the second research question examined whether social learning theory could explain variations in illegal uploading behavior. The third research question examined the relationship between reciprocity and digital piracy, a predictor that existing literature has indicated may play an important role in illegal uploading (Becker & Clement, 2006; Cenite et al., 2009). The fourth research question examined the relationship between self-control and digital piracy, both downloading and uploading. Finally, the fifth research question investigated whether reciprocity mediates the relationship between social learning theory and illegal uploading behavior.

The research questions for this dissertation are important because the existing literature has paid scant empirical examination to illegal uploading behavior separate from illegal downloading. Given the qualitative differences between illegal downloading and uploading, it is important to identify whether theoretical explanations that have been supported for illegal downloading or general digital piracy, are also supported for illegal uploading. If there are significant differences between the mechanisms driving individuals to upload pirated content and to illegally download, existing policies and enforcement strategies developed to address downloading may not be effective for uploading. In answering these questions, the findings of this dissertation can help to better inform the development of policies and strategies that specifically cater to illegal uploading behavior.

Due to the lack of available data on uploading behaviors, data was collected by administering questionnaires on downloading and uploading behaviors to a university (n = 398) and an online sample (n = 315). The university sample was chosen to compare existing findings on illegal downloading with university samples to the current findings on illegal uploading. The online sample was chosen to extend the generalizability of extant research on uploading and downloading beyond that of student populations and to ensure that a sufficient number of respondents that engage in uploading were included in the sample. A combination of random and nonrandom sampling techniques was used to sample among university students and visitors to several websites. Once data collection was completed, a series of multivariate analyses examined social learning and its effect on digital piracy, both illegal downloading and illegal uploading while controlling for relevant covariates.

By examining both uploading and downloading separately, this dissertation sought to provide empirical evidence that illegal uploading and illegal downloading behaviors are qualitatively different behaviors under the larger umbrella of digital piracy. The results indicated that this is correct given that predictors significant with illegal downloading were different than the predictors significant for illegal uploading. While computer use, punishment certainty, and reciprocity were identified as important factors for illegal uploading, they were not for illegal downloading.

This dissertation addressed multiple gaps in the research literature on digital piracy. Firstly, this research addressed the reliance on university samples within the research literature on digital piracy. It is often argued that university samples are suitable for studying digital piracy due to high levels of pirating reported in student populations (Hinduja, 2003). While self-reported digital piracy was high across both of this study’s samples, there were major differences in reported illegal downloading and uploading between the two samples. A higher proportion of the university sample engaged in illegal downloading as compared to the online sample. The reverse was true for uploading—individuals in the online sample were more likely to self-report illegal uploading behaviors. There were also significant differences across both samples in terms of many of the independent variables including age, highest education completed, employment status, total household income, and a majority of the social learning variables.

Another contribution of the current dissertation was that it provided a full theoretical test of Akers' (1998) social learning theory by including measures for all four components of social learning (Burruss et al., 2012; Burruss et al., 2018). This study provided further empirical evidence for social learning theory as a whole and its ability to predict illegal downloading and uploading behaviors. This dissertation also expands the types of criminal behavior that social learning theory can explain by including illegal uploading behavior. While prior criminological research in the digital piracy literature has supported social learning theory's ability to explain digital piracy as a whole and illegal downloading, this is the first study to establish the explanatory value of social learning theory for illegal uploading separate from downloading.

The following section will re-iterate each of the research questions posed by the current dissertation as well as the hypotheses that correspond with each. The limitations of this dissertation, areas for future research, and the policy implications of this dissertation's findings will also be discussed.

Research Question #1

The first question examined the relationship between social learning theory and self-reported illegal downloading behavior. It was hypothesized that higher levels of social learning would increase self-reported illegal downloading behaviors. Stated more fully, individuals who self-report more associations with others who engage in or approve of engagement in digital piracy would be more likely to self-report engagement in illegal downloading within the past 12 months. Also, individuals who self-report having attitudes favorable to digital piracy and that self-report being rewarded for participation in digital piracy would be more likely to self-report illegal downloading behaviors. The results of this dissertation provided strong support for social learning as a predictor of illegal downloading behavior, congruent with past criminological research into digital piracy (Skinner & Fream, 1997). Social learning had, by far, the strongest, positive direct effect on illegal downloading out of the independent variables within the analysis.

This echoes what prior criminological studies into digital piracy have found—that the components of social learning theory are strongly supported in their ability to explain illegal downloading (Burruss et al., 2012; Burruss et al., 2018; Morris & Higgins, 2010). By including all four components of social learning theory, these findings also provided support for two theoretical components that are not as commonly included in research examining social learning theory and digital piracy: differential reinforcement and imitation (Pratt et al., 2010). Additionally, this dissertation controlled for a wide variety of variables that have been found significant in prior research including age (Morris & Higgins, 2010), sex (Hinduja, 2007), race (Hinduja & Higgins, 2011), computer skill (Burruss et al., 2012), low self-control (Hinduja, 2012), and techniques of neutralization (Smallridge & Roberts, 2013)—social learning theory was significant even when these covariates were included and remained the strongest predictor of illegal downloading.

Research Question #2

The second question examined the relationship between social learning theory and self-reported illegal uploading behavior. Hypothesis 2 posited that higher levels of self-reported social learning would increase self-reported illegal uploading behaviors. Mirroring illegal downloading, this means that individuals who self-report more associations with others who approve of or engage in digital piracy would be more likely to self-report illegal uploading in the past year. Individuals who also self-report being rewarded for digital piracy engagement and who self-report having favorable attitudes towards digital piracy would be more likely to self-report illegal uploading. As with illegal downloading, social learning was a significant predictor of illegal uploading and also had the strongest, positive direct effect on illegal uploading behavior of all of the significant variables.

While social learning theory has been strongly supported in the extant digital piracy literature, past studies have focused on illegal downloading (Morris & Higgins, 2009) or have not differentiated between downloading and uploading, often measuring both forms of digital piracy in a single measure (Burruss et al., 2012; Burruss et al., 2018). These findings extend social learning theory to a new type of criminal behavior, illegal uploading. Not only does this advance the existing research into digital piracy, but it also expands social learning theory as a whole by providing empirical evidence of the explanatory value of the theory with a previously untested criminal behavior.

Research Question #3

Research questions 3_A and 3_B for this dissertation investigated the relationship between reciprocity and illegal downloading and uploading behaviors. It was hypothesized that higher self-reported perceptions of reciprocity would increase self-reported illegal uploading behavior within the past year, but would not increase self-reported illegal downloading behavior. The results of this dissertation indicated that reciprocity was not a significant predictor for illegal downloading behaviors. As reciprocity is focused on the act of giving, it was not expected to be a significant motivator for illegal downloading behaviors and the results have supported this conclusion.

While the effect was not as strong as that for social learning, higher self-reported perceptions of reciprocity had a positive, direct effect on self-reported illegal uploading behavior. Individuals who perceive a norm of reciprocity for digital pirating, and therefore believe that they should upload their own pirated content in return for other individuals' uploading (and vice versa), are more likely to engage in illegal uploading behaviors.

This dissertation provides empirical support for a concept that has previously been limited to qualitative digital piracy research—reciprocity. The inclusion of reciprocity was based on the limited computer science literature that has explored motivations for illegal uploading behavior (Becker & Clement, 2006; Cenite et al., 2009). Qualitative evidence from these studies had shown reciprocity as a possible significant factor in illegal uploading. Quantitative evidence now supports reciprocity as a factor as well. Individuals that report perceptions of reciprocity are more likely to engage in illegal uploading behaviors. Given the results of this study, future research focusing on illegal uploading should include reciprocity in their measures. Reciprocity may also be a predictor for other criminal behaviors that rely on a balance of give-and-take of either information or goods within a certain community, whether online or offline.

File-sharing communities rely on the continued sharing of users, without which they would not survive (Becker & Clement, 2006). This reliance on users' willingness to share has fostered a norm of reciprocity in these communities whereby it is expected that individuals who downloading will give back to the community by sharing, whether their own files or through the process of seeding (leaving a torrent open after downloading to continue sharing). The social learning process is one way in which individuals can be exposed to this norm of reciprocity. As discussed earlier, reciprocity involves two main processes—private reciprocity and public reciprocity (Whatley et al., 1999). For private reciprocity, individuals learn about the norm of reciprocity by associating with pirating peers and internalize it. For public reciprocity, individuals experience differential reinforcement for their adherence or non-adherence to this norm (Becker & Clement, 2006; Holt & Copes, 2010).

The concept of reciprocity could prove useful for the study of social learning theory, particularly for deviant behaviors that do not have apparent immediate benefits to the individual such as illegal uploading. While prior research has identified the norm of reciprocity as a motivator for illegal uploading behaviors (Becker & Clement, 2006; Cenite et al., 2009), research has not explored the process through which individuals learn this norm—incorporating social learning theory together with reciprocity can help account for this process. For deviant behaviors that involve the participation or sharing from users of a community, the combination of social learning theory and the norm of reciprocity may be able to account for these behaviors more effectively than on their own. For instance, online child sexual exploitation involves members of virtual communities providing links to distribute illicit content (Westlake & Bouchard, 2016). Similarly, communities of computer hackers have also been identified to utilize similar sharing mechanisms—hacking communities value information sharing within the community (Holt, Strumsky, Smirnova, & Kilger, 2012). Social learning theory together with reciprocity may be able to explain participation in these communities through similar mechanisms as that of file-sharing.

Research Question #4

Research questions 4_A and 4_B investigated the relationship between self-control and illegal downloading and uploading behaviors. It was first hypothesized that higher levels of self-control would decrease levels of self-reported illegal downloading behaviors. Surprisingly, and contrary to prior digital piracy research (Burruss et al., 2012; Burruss et al., 2018; Higgins et al., 2012), the results did not support this hypothesis—self-control did not have a significant direct effect on illegal downloading once social learning was included in the model. It was expected that individuals with low self-control would be more likely to engage in illegal downloading than those individuals with higher self-control because illegal downloading is a relatively easy, low-skill criminal behavior with immediate benefits, but this does not appear to be the case.

This is also contrary to what has been identified in the prior research literature on digital piracy—typically low self-control increases engagement in deviant behaviors, even with controls for other theories (Higgins et al., 2012; Pratt et al., 2010). While self-control did not have a significant direct effect on illegal downloading behaviors, the results did indicate an indirect effect through social learning—individuals with high self-control are less involved in the social learning process and less likely to engage in illegal downloading. This is congruent with past digital piracy research that has found that the indirect effects of low self-control through social learning are stronger than self-control's direct effects (Bossler & Burruss, 2010; Higgins et al., 2006; Higgins & Wilson, 2006).

Although self-control had an indirect effect on illegal downloading through social learning, social learning fully mediated this relationship. While this does not provide much support for self-control on its own, these findings lend support to theoretical integration between social learning and self-control.

The other hypothesis involved in this research question stated that higher levels of self-control would not decrease levels of self-reported illegal uploading behaviors. The results indicated that self-control did not have a significant direct effect on illegal uploading. Given the higher skill and increase time commitment involved with illegal uploading, as well as the lack of an immediate reward, it was anticipated that individuals with low self-control would not have traits suitable to engaging in these behaviors and therefore self-control would not have a significant effect on an individual's engagement in illegal uploading behaviors. As mentioned previously, Gottfredson and Hirschi's (1990) theory posits that individuals with low self-control would be more likely to engage in deviant behaviors that are easy and low-skill and provide an immediate benefit to the individual—illegal uploading fulfills none of these prerequisites. Illegal uploading requires technical skills that an individual with low self-control may not be willing to invest the time and effort into learning. There is also no immediate benefit to illegal uploading—any benefits to the individual would be long-term, which likely would not appeal to someone with low self-control.

Research Question #5

The final research question examined whether reciprocity mediates the relationship between social learning and illegal uploading behaviors. The results indicated that reciprocity does partially mediate this relationship, though social learning still has a large direct effect on illegal uploading as well. Though temporal ordering can only be assumed without longitudinal data, it appears that individuals who associate with pirating peers who also develop a belief in reciprocity are more likely to engage in illegal uploading.

These findings also support reciprocity as a separate concept separate from social learning. Although social learning can help explain the formation of an individual's belief in reciprocity, the lack of full mediation indicates that reciprocity is not just an aspect of the social learning process. As was mentioned previously, individuals are exposed to the norm of reciprocity through their associations with pirating peers and their belief in this norm is further reinforced by the file-sharing community.

While the concept of reciprocity has not been formally articulated in the research literature, these findings support Whatley and colleagues' (1999) description of reciprocity as composed of two operating mechanisms—private reciprocity and public reciprocity. Private reciprocity aligns with the process of developing internalized beliefs in reciprocity through differential associations with pirating peers. Public reciprocity fits with the differential reinforcements that an individual experiences from the file-sharing community due to an individual's cooperation or non-cooperation with the norm of reciprocity. While prior research found reciprocity to be a significant motivator for illegal uploading (Becker & Clement, 2006; Cenite et al., 2009), these findings expand on this by supporting the norm of reciprocity as a concept separate from social learning and helping to explain the mechanisms through which individuals develop their beliefs in this norm.

Limitations

Although this dissertation's research design was chosen to address some of the limitations of existing research in digital piracy, several limitations persist. Firstly, one major limitation of this dissertation is the lack of sample-specific analysis. While the information that was collected provided some descriptive evidence regarding the difference between the online and university samples, it would have been beneficial if the analysis could have been run on each sample of individuals to provide a comparison between the two samples. Given the differences in the samples based on the available data, a sample-specific analysis may have yielded different results.

Another possible limitation of this dissertation may be related to respondent recall error and measurement error. As the questionnaire used in this dissertation relied on self-reported measures of prior criminal activity, there is a risk of social desirability bias (Champion, 2000). Although reported digital piracy engagement was fairly high among the sample (77.3% of participants admitted engaging in digital piracy), individuals may have been hesitant to respond honestly about their criminal behavior despite the data remaining anonymous. Recall bias may have also been an issue as many of the survey items asked respondents to self-report retrospective behaviors—for instance, respondents may underestimate or overestimate how often they've engaged in illegal downloading in the past year (Bradburn, Rips, & Shevell, 1987).

All of the data used was also self-reported, which means that several of the measurement items—specifically those that measured differential reinforcement—relied on participants' perceptions of other individuals' actions or beliefs. As such, participants may have incorrectly judged how their family or peers would react to their digital piracy. Self-reported perceptions of other's attitudes or behaviors are not always accurate measurements and may be based on the respondent's own attitudes or behaviors (Meldrum & Boman, 2013).

The aggregation of multiple types of digital piracy (i.e. music, movies, and software) into composite measures was also a limitation. By combining all of the content types into composite items, this research may be missing important differences between the different types of digital piracy. Some prior research has found differences when the different types of digital piracy are measured individually (Gunter, 2008). Although the results from the CFA indicate that all of the observed items are measuring the same underlying construct, using separate measures for each digital piracy type may have yielded different results and may be more useful for developing policies to address a specific type of digital piracy.

In addition to the limitations of the survey instrument, there are multiple limitations to the sampling techniques used. Although some randomization was involved in the sampling process, the utilization of nonrandom sampling techniques introduced the potential for selection bias. Given that the online sample was selected by purposively selecting websites relating to digital piracy, the amount of digital piracy engagement among the sample may be higher than in the general population. A monetary incentive was also offered for participation in the online sample to try to increase response rates—despite only providing a low possibility of receiving a reward, this incentivization created another potential source of selection bias. Although elements of randomization in the selection of the student sample likely helped reduce possible sampling bias, only one university was included for sampling and the courses selected were only from a few departments within the university. Due to this, this dissertation's findings may not be generalizable to the university as a whole or other university populations.

Finally, this research was cross-sectional in design and—as a result—causality could not be inferred (Frankfort-Nachmias & Nachmias, 1996). Although some extant research has found that the social learning process is fairly time stable for other behaviors (Kabiri, Shadmanfaat, Howell, Donner, & Cochran, 2020; Shadmanfaat, Kabiri, Smith, & Cochran, 2020), it cannot be established that the attitudes and beliefs examined in this dissertation were established before respondents' engagement in digital piracy. This is particularly important for the interpretation of reciprocity's mediation of the relationship between social learning and illegal uploading—since temporal ordering cannot be established, it cannot be stated with certainty that the social learning process occurred before the development of the individual's belief in reciprocity. Akers (2009) has also stated previously that, while differential association leads an individual to deviant behavior, there is also a feedback process in that involvement in certain behaviors increase an individual's associations with those who approve of or engage in the behavior in question. The cross-sectional nature of this dissertation does not allow for the examination of this process.

Future Research

The variations in pirating behaviors between the two samples included in this dissertation indicate that the reliance on university samples in digital piracy research may be problematic. Given the differences in both social learning and digital piracy between the two samples, there may be other important differences that bias research findings that only rely on university student samples. This may be particularly true for research into illegal uploading—the university students in this dissertation's sample engaged in far less illegal uploading compared to the online sample. While the conclusion from prior research regarding university student's high engagement in illegal downloading remains supported (Hinduja, 2007), the same does not appear to be true for illegal uploading. To address this, future digital piracy research should include more varied samples from non-student populations and should include sample-specific analysis to identify whether there is a significant disparity in digital pirating between different populations.

Secondly, the differences between illegal downloading and uploading identified in this dissertation highlight the importance of future research to differentiate between uploading and downloading when measuring digital piracy. While both types of digital piracy share similarities, measurements of digital piracy should not assume the two are equivalent. While significant research has studied illegal downloading behaviors, illegal uploading behaviors are still largely unexamined, and additional differences between these two behaviors may be identified. Future research should examine whether other criminological theories and factors found significant with illegal downloading behavior also extend to illegal uploading behavior.

In addition to the recommendations for future research already mentioned, another future avenue for research would be to explore the role of both offline and online peer influences in illegal uploading behavior. Previously, Hinduja and Ingram (2009) identified that offline and online peers had a differential impact on participation in illegal downloading of music. Future research could test whether this also holds for illegal uploading behavior.

Policy Implications

In addition to the implications for future research based on this dissertation's findings, several policy implications can be gleaned from these results. Many of the existing policies relating to digital piracy in the United States and other countries have focused primarily on reactive measures intended to prosecute digital pirates for prior criminal acts (Castro et al., 2009). Other common policies in the U.S. have focused on targeting websites that hold pirated digital content and other entities that facilitate the distribution of pirated content (Catro et al., 2009; Dey et al., 2018). For instance, both the No Electronic Theft (NET) Act and the Digital Millennium Copyright Act (DMCA) in the United States added civil remedies and criminal penalties for violations of copyright infringement, which extends to digital piracy (U.S. Copyright Office, 1998). Though never successfully passed by the U.S. Congress, the Stop Online Piracy Act (2011) was intended to expand criminal laws to include the unauthorized streaming of digital content and would have allowed websites to be blacklisted or penalized.

While some of these measures increase the severity of penalties that may be applied to individuals, they do little to address digital piracy at the individual-level and focus more on websites hosting pirated materials or other service-providers that facilitate the transfer of pirated content such as Napster (Lane & Healy, 2005). Also, very little is known about how effective these laws are at deterring digital piracy (Piquero, 2005). Some research has suggested that policies that only use legal enforcement as a strategy for addressing digital piracy are ineffective and even counterproductive (Becker & Clement, 2006).

The differences between illegal uploading and downloading identified in this dissertation have important policy implications. The difference in the descriptive statistics for illegal uploading and downloading among the two samples examined indicates that, given the higher reported engagement in illegal downloading among the university sample, policies addressing illegal downloading aimed at university students may be effective. Conversely, policies and enforcement aimed at deterring illegal uploading may have a large impact if they target online communities where reported engagement in illegal uploading behavior is higher. Future development of policies or enforcement strategies for addressing digital piracy should take into account these differences in illegal downloading and uploading among universities and members of online communities.

Based on the findings of this dissertation, policies that also focus on educating individuals about digital piracy may be more effective than those that focus primarily on legal enforcement. Engagement in both illegal downloading and uploading is extremely common and legal action can only affect a small percentage of those who engage in digital piracy. While little is known about how effective legal enforcement is (Piquero, 2005), legal enforcement and technical deterrents have been highly utilized in recent years (Fung & Lakhani, 2013), yet levels of digital piracy engagement are still exceptionally high. Due to the smaller proportion of individuals who engage in illegal uploading as compared to illegal downloading, it may be beneficial to target legal enforcement specifically at illegal uploaders.

In the past, researchers have recommended education as an effective strategy for reducing digital piracy (Morris & Higgins, 2010; Piquero, 2005). Universities have implemented policies such as this that are targeted at educating students about the dangers of digital piracy (Lane & Healy, 2005; Seton Hall University, n.d., Spanier, 2004). Policies at the university level of addressing digital piracy typically involve educating students about copyright infringement, the damage caused by digital piracy, and the possible legal repercussions of pirating digital content (Lane & Healy, 2005). Policies such as these may be effective and should focus on educating students to try to develop attitudes unfavorable to digital piracy and counteract the social learning process.

Given the higher levels of reported illegal uploading behaviors among participants in online communities and the evidence supporting social learning as an explanation for illegal uploading, policies that circulate educational material about the societal costs of illegal downloading and uploading among these communities may be effective by helping to develop attitudes unfavorable to digital piracy. While existing policies aimed at university students may be effective for illegal downloading, additional policies targeted at online communities may prove beneficial as well, particularly for addressing illegal uploading behavior. Information about the consequences and the damages caused by digital piracy could be distributed through online communities and social media to try to instill unfavorable attitudes about pirating digital content among online users. In conclusion, the results of this dissertation strongly support further research on the extent and causes of illegal uploading behavior as part of a larger strategy to reduce digital piracy. Given the widespread prevalence of illegal downloading, targeting illegal uploading among those segments of the population most likely to engage it may be a more effective prevention strategy.

REFERENCES

Aaltonen, M., & Salmi, V. (2013). Versatile delinquents or specialized pirates? A comparison of correlates of illegal downloading and traditional juvenile crime. Journal of Scandinavian Studies in Criminology and Crime Prevention, 14(2), 188-195. http://dx.doi.org/10.1080/14043858.2013.837267

Akers, R. L. (1985). Deviant behavior: A social learning approach. Belmont, CA: Wadsworth.

Akers, R. L. (1998). Social learning and social structure: A general theory of crime and deviance. Boston: Northeastern University.

Akers, R. L. (2009). *Social learning and social structure: A general theory of crime and deviance.* Routledge.

Akers, R. L., & Sellers, C. S. (2004). *Criminological theories: Introduction, evaluation, and application* (4th Ed.). Los Angeles, CA: Roxbury Publishing Company.

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic and statistical considerations. *Journal of Personality and Social Psychology*, *51*, 1173-1182.

Becker, J. U., & Clement, M. (2006). Dynamics of illegal participation in peer-to-peer networks—why do people illegally share media files? Journal of Media Economics, 19, 7-32. http://dx.doi.org/10.1207/s15327736me1901_2

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. Psychology Bulletin, 88, 588-606. http://dx.doi.org/10.1037/0033-2909.88.3.588

Berry, W. D., & Feldman, S. (1985). *Multiple regression in practice*. Thousand Oaks, CA: Sage Publications, Inc. https://dx.doi.org/10.4135/9781412985208

Blackburn, D., Eisenach, J. A., & Harrison, D., Jr. (2019). *Impacts of digital video piracy on the U.S. economy*. The Global Innovation Policy Center. http://www.theglobalipcenter.com/wp-content/uploads/2019/06/Digital-Video-Piracy.pdf

Bollen, K. A. (1989). *Structural equations with latent variables*. New York, NY: John Wiley & Sons, Inc.

Bollen, K. A. (2002). Latent variables in psychology and the social sciences. Annual Review of Psychology, 53, 605-634.

Bollen, K. A., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin, 110*(2), 305-314.

Bossler, A. B., & Burruss, G. W. (2010). 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.

Bossler, A. M., & Holt, T. J. (2009). On-line activities, guardianship, and malware infection: An examination of routine activities theory. International Journal of Cyber Criminology, 3(1), 400-420.

Bradburn, N. M., Rips, L. J., & Shevell, S. K. (1987). Answering autobiographical questions: The impact of memory and inference on surveys. *Science, 236*(4798), 157-161.

Brown, T. (2006). Confirmatory factor analysis for applied research (2nd Ed.). New York, NY: The Guilford Press.

Burgess, R. L., & Akers, R. L. (1966). A differential association-reinforcement theory of criminal behavior. Social Problems, 14(2), 128-147.

Burruss, G. W., & Bossler, A. M., & Holt, T. J. (2012). Assessing the mediation of a fuller social learning model on low self-control's influence on software piracy. Crime & Delinquency, 59, 1157-1184. http://dx.doi.org/10.1177/0011128712437915

Burruss, G. W., Holt, T. J., & Bossler, A. (2018). Revisiting the suppression relationship between social learning and self-control on software piracy. *Social Science Computer Review*, *37*(2), 178-195. http://dx.doi.org/10.1177/0894439317753820

Business Software Alliance. (2010). Policy impact study: The economic benefits of reducing software piracy. Retrieved from http://portal.bsa.org/piracyimpact2010/studies/piracyimpactstudy2010.pdf

Byrne, B. M. (2000). Structural equation modeling with AMOS: Basic concepts, applications, and programming. Mahwah, NJ: Lawrence Erlbaum Associates.

Caraway, B. R. (2012). Survey of file-sharing culture. *International Journal of Communication, 6*, 564-584.

Castro, D., Bennett, R., & Andes, S. (2009). Steal these policies: Strategies for reducing digital piracy. The Information Technology & Innovation Foundation. https://itif.org/files/2009-digital-piracy.pdf

Cenite, M., Wang, M. W., Peiwen, C., & Chan, G. S. (2009). More than just free content: Motivations of peer-to-peer file sharers. Journal of Communication Inquiry, 33, 206-221. http://dx.doi.org/10.1177/0196859909333697

Champion, D. J. (2000). *Research methods for criminal justice and criminology* (2nd Ed.). Upper Saddle River, NJ: Prentice-Hall, Inc.

Chiu, S., & Chou, H. (2011). Investigating the user behavior of peer-to-peer file sharing software. International Journal of Business and Management, 6, 68-78.

http://dx.doi.org/10.5539/ijbm.v6n9p68

Cuevas, R., Kryczka, M., Cuevas, A., Kaune, C. G., & Rejaie, R. (2013). Unveiling the incentives for content publishing in popular BitTorrent portals. IEEE/ACM Transactions on Networking, 21, 1421-1435. http://dx.doi.org/10.1109/TNET.2012.2228224

Dey, D., Kim, A., & Lahiri, A. (2019). Online piracy and the "longer arm" of enforcement. Management Science, 65(3), 1173-1190. http://dx.doi.org/10.1287/mnsc.2017.2984

Dillman, D. A. (1991). The design and administration of mail surveys. Annual Review of Sociology, 17, 225-249.

Fehr, E., & Gächter, S. (2000). Fairness and retaliation: The economics of reciprocity. *Journal of Economic Perspectives*, *14*(3), 159-181.

Fleming, P., Watson, S. J., Patouris, E., Bartholomew, K. J., & Zizzo, D. J. (2017). Why do people file share unlawfully? A systematic review, meta-analysis and panel study. Computers in Human Behavior, 72, 535-548. http://dx.doi.org/10.1016/j.chb.2017.02.014

Frankfort-Nachmias, C., & Nachmias, D. (1996). Research methods in the social sciences (5th Ed.). New York, NY: St. Martin's Press, Inc.

Fung, W. M. J., & Lakhani, A. (2013). Combatting peer-to-peer file sharing of copyrighted material via anti-piracy laws: Issues, trends, and solutions. *Computer Law & Security Review*, *29*, 382-402. http://dx.doi.org/10.1016/j.clsr.2013.05.006

Gil, P. (2019). What is a cyberlocker? Lifewire. Retrieved from https://www.lifewire.com/what-is-a-cyberlocker-2483215

Goode, S., & Cruise, S. (2006). What motivates software crackers? *Journal of Business Ethics, 64*, *65*(2), 173-201. http://dx.doi.org/10.1007/s10551-005-4709-9

Gottfredson, M. R., & Hirschi, T. (1990). A general theory of crime. Stanford, CA: Stanford University Press.

Grewal, R., Cote, J. A., & Baumgartner, H. (2004). Multicollinearity and measurement error in structural equation models: Implications for theory testing. Marketing Science, 23, 519-529. http://dx.doi.org/10.1287/mksc.1040.0070

Gunter, W. D. (2008). Piracy on the high speeds: A test of social learning theory on digital piracy among college students. International Journal of Criminal Justice Sciences, 3, 54-68.

Gunter, W. D. (2009). Internet scallywags: A comparative analysis of multiple forms and measurements of digital piracy. Western Criminology Review, 10, 15-28.

Hair, J. F. Jr., Black, W. C., Babin, B. J., Anderson, R. E. Tatham, R. L. (2006). Multivariate data analysis (6th Ed.). Upper Saddle River, NJ: Prentice-Hall International Inc.

Higgins, G. E. (2007). Digital piracy, self-control theory, and rational choice: An examination of the role of value. International Journal of Cyber Criminology, 1, 33-55.

Higgins, G. E., Fell, B. D., & Wilson, A. L. (2006). Digital piracy: Assessing the contributions of an integrated self-control theory and social learning theory using structural equation modeling. Criminal Justice Studies, 19, 3-22. http://dx.doi.org/10.1080/14786010600615934

Higgins, G. E., & Makin, D. A. (2004). Self-control, deviant peers, and software piracy. Psychological Reports, 95, 921-931.

Higgins, G. E., & Wilson, A. L. (2006). Low self-control, moral beliefs, and social learning theory in university students' intentions to pirate software. Security Journal, 19, 75-92. http://dx.doi.org/10.1057/palgrave.sj.8350002

Higgins, G. E., Wolfe, S. E., & Marcum, C. D. (2008). Music piracy and neutralization: A preliminary trajectory analysis from short-term longitudinal data. International Journal of Cyber Criminology, 2, 324-336.

Hinduja, S. (2003). Trends and patterns among online software pirates. Ethics and Information Technology, 5, 49-61.

Hinduja, S. (2007). Neutralization theory and online software piracy: An empirical analysis. Ethics and Information Technology, 9, 187-204.

Hinduja, S. (2012). General strain, self-control, and music piracy. International Journal of Cyber Criminology, 6, 951-967.

Hinduja, S., & Higgins, G. E. (2011). Trends and patterns among music pirates. *Deviant Behavior*, *32*(7), 563-588. http://dx.doi.org/10.1080/01639625.2010.514202

Hinduja, S., & Ingram, J. R. (2009). Social learning theory and music piracy: The differential role of online and offline peer influences. Criminal Justice Studies, 22, 405-420. http://dx.doi.org/10.1080/14786010903358125

"Hit the uploaders." (2004, October). New Scientist, 184(2469), 4.

Holm, P. (2014). Piracy on the simulated seas: The computer games industry's non-legal approaches to fighting illegal downloads of games. Information & Communications Technology Law, 23(1), 61-76. http://dx.doi.org/10.1080/13600834.2014.899770

Holt, T. J. (2007). subcultural evolution? examining the influence of on- and off-line experiences on deviant subcultures. *Deviant Behavior*, *28*(2), 171-198. http://dx.doi.org/10.1080/01639620601131065

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, 31-61. http://dx.doi.org/10.1080/0735648x.2010.9721287

Holt, T. J., & Copes, H. (2010). Transferring subcultural knowledge on-line: Practices and beliefs of persistent digital pirates. Deviant Behavior, 31, 625-654. http://dx.doi.org/10.1080/01639620903231548

Holt, T. J., Strumsky, D., Smirnova, O., & Kilger, M. (2012). Examining the social networks of malware writers and hackers. *International Journal of Cyber Criminology, 6*(1), 891-903.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1-55. http://dx.doi.org/10.1080/10705519909540118

Ingram, J. R., & Hinduja, S. (2008). Neutralizing music piracy: An empirical examination. Deviant Behavior, 29, 334-366. http://dx.doi.org/10.1080/01639620701588131

Kabiri, S., Shadmanfaat, S. M., Howell, C. J., Donner, C., & Cochran, J. K. (2020). Performance-enhancing drug use among professional athletes: A longitudinal test of social learning theory. *Crime & Delinquency, 2020-01-22*, p.001112871990111. http://dx.doi.org/10.1177/0011128719901111

Kenny, D. A. (2006). Confirmatory factor analysis for applied research. New York, NY: The Guilford Press.

Kipnis, J. (2005, January). Targeting illicit uploaders: New service identifies piracy source. Billboard, 117(3), 35.

Klepper, S., & Nagin, D. (1989). The deterrent effect of perceived certainty and severity of punishment revisited. *Criminology*, *27*(4), 721-746.

Kline, R. B. (2011). Principles and practice of structural equation modeling (3rd Ed). New York, NY: The Guilford Press.

Kollock, P. (2003). The economies of online cooperation: Gifts and public goods in cyberspace. In M. Smith & P. Kollock (Eds.), *Communities in cyberspace* (pp. 219-237). London: Routledge.

Krohn, M. D., Skinner, W. F., Massey, J. L., & Akers, R. L. (1985). Social learning theory and adolescent cigarette smoking: A longitudinal study. Social Problems, 32, 455-473. http://dx.doi.org/10.1525/sp.1985.32.5.03a00050

Lai, E. (2009). What's replacing P2P, BitTorrent as pirate hangouts? Computerworld. Retrieved from https://www.computerworld.com/article/2528930/what-s-replacing-p2p--bittorent-as-pirate-hangouts-.html

Lewis-Beck, M. S. (2016). Applied regression: An introduction. Thousand Oaks, CA: Sage.

Liptak, A. (2019). *Poland has filed a complaint against the European Union's copyright directive*. The Verge. Retrieved from https://www.theverge.com/2019/5/25/18639963/poland-european-union-copyright-directive-filed-complaint-court-of-justice

Lowry, P. B., Zhang, J., & Wu, T. (2017). Nature or nurture? A meta-analysis of the factors that maximize the prediction of digital piracy by using social cognitive theory as a framework. *Computers in Human Behavior, 68*, 104-120. http://dx.doi.org/10.1016/j.chb.2016.11.015

Marcum, C. D., Higgins, G. E., Wolfe, S. E., & Ricketts, M. L. (2011). Examining the intersection of self-control, peer association and neutralization in explaining digital piracy. Western Criminology Review, 12, 60-74.

Maruna, S., & Copes, H. (2005). What have we learned from five decades of neutralization research? Crime and Justice: An Annual Review of Research, 32, 221-320. http://dx.doi.org/10.1086/655355

Marx, N. (2013). Storage wars: Clouds, cyberlockers, and media piracy in the digital economy. *Journal of e-Media Studies, 3*(1). http://dx.doi.org/10.1349/PS1.1938-6060.A.426

Meldrum, R. C., & Boman, J. J. IV. (2013). Similarities and differences between perceptions of peer delinquency, peer self-reported delinquency, and respondent delinquency: An analysis of friendship dyads. *Journal of Criminal Justice, 41*(2013), 395-406. https://doi.org/10.1016/j.jcrimjus.2013.07.005

Moore, R., & McMullan, E. C. (2009). Neutralizations and rationalizations of digital piracy: A qualitative analysis of university students. International Journal of Cyber Criminology, 3, 441-451.

Morris, R. G., & Higgins, G. E. (2009). Neutralizing potential and self-reported digital piracy: A multitheoretical exploration among college undergraduates. Criminal Justice Review, 34, 173-195. http://dx.doi.org/10.1177/0734016808325034

Morris, R. G., & Higgins, G. E. (2010). Criminological theory in the digital age: The case of social learning theory and digital piracy. Journal of Criminal Justice, 38, 470-480. http://dx.doi.org/10.1016/j.jcrimjus.2010.04.016

Morris, R. G., Johnson, M. C., & Higgins, G. E. (2009). The role of gender in predicting the willingness to engage in digital piracy among college students. Criminal Justice Studies, 22(4), 393-404. http://dx.doi.org/10.1080/14786010903358117

Muthén, L. K., & Muthén, B. O. (2017). Mplus user’s guide: Statistical analysis with latent variables. Los Angeles, CA: Muthén & Muthén.

Muthén, B. O., du Toit, S. H. C., & Spisic, D. (1997). Robust inference using weighted least squares and quadratic estimating equations in latent variable modeling with categorical and continuous outcomes. Retrieved on November 2, 2020 from https://www.statmodel.com/download/Article_075.pdf

Nazer, D. (2013). The copyright alert system FAQ. Electronic Frontier Foundation. Retrieved from https://www.eff.org/deeplinks/2013/02/six-strikes-copyright-alert-system-faq

Offer, A. (2003). Between the gift and the market: The economy of regard. *The Economic History Review, 50*(3), 450-476. http://dx.doi.org/10.1111/1468-0289.00064

Pai, P., & Tsai, H. (2016). Reciprocity norms and information-sharing behavior in online consumption communities: An empirical investigation of antecedents and moderators. *Information & Management*, *53*(1), 38-52. http://dx.doi.org/10.1016/j.im.2015.08.002

Paternoster, R. (1987). The deterrent effect of the perceived certainty and severity of punishment: A review of the evidence and issues. *Justice Quarterly*, *4*(2), 173-217

Peace, A. G., Galletta, D., & Thong, J. Y. L. (2003). Software piracy in the workplace: a model and empirical test. *Journal of Management Information Systems, 20*(1), 153-177.

Piquero, N. L. (2005). Causes and prevention of intellectual property crime. *Trends in Organized Crime, 8*, 40-61.

Pratt, T. C., Cullen, F. T., Sellers, C. S., Winfree, L. T., Jr., Madensen, T. D., Daigle, L. E., Fearn, N. E., & Gau, J. M. (2010). The empirical status of social learning theory: A meta-analysis. Justice Quarterly, 27(6), 765-802. http://dx.doi.org/10.1080/07418820903379610

Quintais, J. P. (2018). *Global online piracy study: Legal background report*. Institute for Information Law. Retrieved from http://www.ivir.nl/publicaties/download/Global-Online-Piracy-Study-Legal-Background-Report.pdf

Rahim, M. M., Seyal, A. H., & Rahman, M. N. A. (2001). Factors affecting softlifting intention of computing students: An empirical study. Journal of Educational Computing Research, 24, 385-405. http://dx.doi.org/10.2190/2U2D-30LC-R3YM-T364

Recording Industry Association of America. (2017). About piracy. Retrieved from https://www.riaa.com/resources-learning/about-piracy/

Schumacker, R. E., & Lomax, R. G. (2010). A beginner's guide to structural equation modeling (3rd Ed.). New York, NY: Routledge.

Seton Hall University. (n.d.). Pirates against piracy. Retrieved November 3, 2020, from https://www.shu.edu/technology/piracy.cfm

Shadmanfaat, S. M., Kabiri, S., Smith, H., & Cochran, J. K. (2020). A longitudinal study of Iranian fans' cyberbullying: The utility of social learning theory. *Deviant Behavior, 41*(12), 1616-1635. https://doi.org/10.1080/01639625.2019.1637996

Shore, B., Venkatachalam, A. R., Solorzano, E., Burn, J. M., Hassan, S. Z., & Janczewski, L. J. (2001). Softlifting and piracy: Behavior across cultures. Technology in Society, 23, 563-581.

Siwek, S. (2007). The true cost of copyright industry piracy to the U.S. economy. IPI Policy Report, #189: Institute for Policy Innovation.

Skågeby, J., & Pargman, D. (2005). File-sharing relationships: Conflicts of interest in online gift-giving. *Communities and Technologies*, *2005*, 111-127. http://dx.doi.org/10.1007/1-4020-3591-8_7

Skinner, W. F., & Fream, A. M. (1997). A social learning theory analysis of computer crime among college students. Journal of Research in Crime and Delinquency, 34, 495-518.

Smallridge, J. L., & Roberts, J. R. (2013). Crime specific neutralizations: An empirical examination of four types of digital piracy. International Journal of Cyber Criminology, 7, 125-140.

Steinmetz, K. F., & Tunnell, K. D. (2013). Under the pixelated Jolly Roger: A study of on-line pirates. Deviant Behavior, 34, 53-67. http://dx.doi.org/10.1080/01639625.2012.707536

Stop Online Piracy Act, H.R. 3261, 112th Cong. (2011).

Sun, D., Easley, R., & Kim, B. C. (2015). Optimal digital rights management with uncertain piracy. Decision Sciences, 46(1), 165-191. http://dx.doi.org/10.1111.deci.12120

Sutherland, E. H. (1947). Principles of criminology (4th ed.). Oxford, England: J. B. Lippincott.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th Ed.). Boston, MA: Pearson Education, Inc.

Tam, K. Y., Feng, K. Y., & Kwan, S. (2019). The role of morality in digital piracy: Understanding the deterrent and motivational effects of moral reasoning in different piracy contexts. *Journal of the Association for Information Systems, 20*(5), 604-628.

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. Journal of Personality, 72(2), 271-324. http://dx.doi.org/10.1111/j.0022-3506.2004.00263.x

Taylor, S. (2012). Evaluating digital piracy intentions on behaviors. The Journal of Services Marketing, 26, 472-483. http://dx.doi.org/10.1108/08876041211266404

U.S. Copyright Office. (1998, October 28). *The Digital Millennium Copyright Act of 1998*. Retrieved from https://www.copyright.gov/legislation/dmca.pdf

Vandiver, D. M., Bowman, S., & Vega, A. (2012). Music piracy among college students: An examination of low self-control, techniques of neutralization, and rational choice. The Southwest Journal of Criminal Justice, 8, 92-111.

Virginia Commonwealth University. (n.d.). Data USA. Retrieved December 2, 2020, from https://datausa.io/profile/university/virginia-commonwealth-university

Wang, J., & Wang, X. (2012). Structural equation modeling: Applications using Mplus. West Sussex, UK: John Wiley & Sons, Inc.

Westlake, B. G., & Bouchard, M. (2016). Linking and hyperlinking: Community detection in online sexual exploitation networks. *Social Science Research, 59*, 23-26. http://dx.doi.org/10.1016/j.ssresearch.2016.04.010

What is IRC (Internet Relay Chat)? (n.d.) Radware. Retrieved October 22, 2020, from https://security.radware.com/ddos-knowledge-center/ddospedia/irc-internet-relay

Whatley, M. A., Webster, M., Smith, R. H., & Rhodes, A. (1999). The effect of a favor on public and private compliance: How internalized is the norm of reciprocity? *Basic and Applied Social Psychology, 21*(3), 251-259.

Winfree, L. T., Jr., Mays, G. L., & Vigil-Bäckström, T. (1994). Youth gangs and incarcerated delinquents: Exploring the ties between gang membership, delinquency, and social learning theory. Justice Quarterly, 11(2), 229-256.

Yoon, C. (2011). Theory of planned behavior and ethics theory in digital piracy: An integrated model. Journal of Business Ethics, 100, 405-417. http://dx.doi.org/10.1007/s10551-010-0687-7

Yu, S. (2010). Digital piracy and stealing: A comparison on criminal propensity. International Journal of Criminal Justice Sciences, 5, 239-250.

Yu, S. (2013). Digital piracy justification: Asian students versus American students. International Criminal Justice Review, 23, 185-196. http://dx.doi.org/10.1177/1057567713485416

Zhang, L., Smith, W. W., & McDowell, W. C. (2009). Examining digital piracy: Self-control, punishment, and self-efficacy. International Resource Management Journal, 22(1), 24-44. http://dx.doi.org/10.1109/TPDS.2010.123

APPENDIX I: ADDITIONAL TABLES

Table 14. Descriptive Statistics (Controls) (Pooled Sample)

Variable	N	Minimum	Maximum	*M*	*SD*
Age	655	18	71	27.100	10.797
Female	681	0	1	0.586	0.493
White	698	0	1	0.695	0.461
Hispanic/Latino	670	0	1	0.155	0.362
Undergraduate	670	0	1	0.354	0.478
Unemployed	663	0	1	0.335	0.472
35k Income	641	0	1	0.510	0.500
PS	643	0	36	9.400	9.232
CU	618	0	24	11.392	4.745
SC	615	1	39	20.667	6.934
NTZ	605	0	42	21.225	9.270
PCRT	596	0	20	4.720	4.983
MA	594	0	12	5.236	2.661
CS	597	0	48	21.178	11.856
Reciprocity					
RCP1	598	0	3	1.385	0.945
RCP2	598	0	3	0.931	0.860
RCP3	598	0	3	0.843	0.881
RCP4	596	0	3	1.362	0.956

Note: Undergraduate = completed undergraduate degree or higher; 35k income = total household income is $35,000 or higher; PS = piracy skill; CU = computer use; SC = self-control; NTZ = neutralizations; RCP = reciprocity; PCRT = punishment certainty; MA = moral acceptability; CS = computer skill.

Table 15. Descriptive Statistics (Controls) (University Sample)

Variable	N	Minimum	Maximum	*M*	*SD*
Age	368	18	54	21.856	4.409
Female	394	0	1	0.574	0.495
White	383	0	1	0.674	0.469
Hispanic/Latino	393	0	1	0.163	0.370
Undergraduate	392	0	1	0.224	0.418
Unemployed	394	0	1	0.338	0.473
35k Income	387	0	1	0.463	0.499
CU	397	0	24	11.025	4.486
SC	397	1	39	21.038	6.841
NTZ	394	0	42	20.972	8.907
PCRT	391	0	20	4.292	4.646
MA	390	0	12	4.951	2.456
CS	393	0	48	18.170	10.632
Reciprocity					
RCP1	393	0	3	1.316	0.896
RCP2	393	0	3	0.870	0.806
RCP3	393	0	3	0.728	0.785
RCP4	391	0	3	1.271	0.922

Note: Undergraduate = completed undergraduate degree or higher; 35k income = total household income is $35,000 or higher; PS = piracy skill; CU = computer use; SC = self-control; NTZ = neutralizations; RCP = reciprocity; PCRT = punishment certainty; MA = moral acceptability; CS = computer skill.

Table 16. Descriptive Statistics (Controls) (Online Sample)

Variable	N	Minimum	Maximum	*M*	*SD*
Age	287	18	71	33.830	12.683
Female	287	0	1	0.600	0.490
White	315	0	1	0.720	0.449
Hispanic/Latino	277	0	1	0.140	0.352
Undergraduate	278	0	1	0.540	0.500
Unemployed	269	0	1	0.330	0.471
35k Income	254	0	1	0.580	0.494
PS	246	0	36	13.276	10.096
CU	221	0	24	12.050	5.123
SC	218	3	39	19.991	7.067
NTZ	211	0	42	21.697	9.917
PCRT	205	0	20	5.537	5.491
MA	204	0	12	5.779	2.945
CS	204	0	48	26.971	11.967
Reciprocity					
RCP1	205	0	3	1.517	1.022
RCP2	205	0	3	1.049	0.948
RCP3	205	0	3	1.063	1.005
RCP4	205	0	3	1.537	0.997

Note: Undergraduate = completed undergraduate degree or higher; 35k income = total household income is $35,000 or higher; PS = piracy skill; CU = computer use; SC = self-control; NTZ = neutralizations; RCP = reciprocity; PCRT = punishment certainty; MA = moral acceptability; CS = computer skill.

Table 17. Descriptive Statistics (Social Learning Variables) (Pooled Sample)					
	N	Minimum	Maximum	*M*	*SD*
Differential Association					
DA1	628	0	4	0.752	0.938
DA2	627	0	4	1.726	1.481
Differential Reinforcement					
DR1	629	0	4	0.483	0.864
DR3	630	0	4	0.657	0.970
DR5	630	0	3	0.998	1.048
DR6	628	0	3	1.081	1.065
DR7	623	0	3	1.029	1.011
DR8	622	0	3	0.738	0.885
DR10	623	0	3	0.868	0.960
DR11	623	0	3	1.966	1.100
Imitation					
IM1	625	0	4	0.675	0.952
IM2	625	0	4	1.030	1.101
IM3	625	0	4	1.110	1.249
Definitions					
DF1	620	0	3	1.127	1.010
DF2	620	0	3	0.950	0.956
DF3	618	0	3	1.322	1.035
DF4	618	0	3	1.571	1.049
DF5	619	0	3	1.192	1.003
DF6	619	0	3	1.486	1.095

Note: DA = differential association; DR = differential reinforcement; IM = imitation; DF = definitions.

Table 18. Descriptive Statistics (Social Learning Variables) (University Sample)					
	N	Minimum	Maximum	*M*	*SD*
Differential Association					
DA1	396	0	4	0.610	0.827
DA2	395	0	4	1.580	1.525
Differential Reinforcement					
DR1	397	0	4	0.450	0.850
DR3	398	0	4	0.690	0.940
DR5	398	0	3	0.870	0.978
DR6	396	0	3	0.950	1.013
DR7	396	0	3	0.990	1.008
DR8	395	0	3	0.640	0.820
DR10	396	0	3	0.830	0.960
DR11	396	0	3	1.950	1.136
Imitation					
IM1	398	0	4	0.700	0.965
IM2	398	0	4	0.970	1.068
IM3	398	0	4	0.830	1.095
Definitions					
DF1	397	0	3	1.020	0.982
DF2	397	0	3	0.810	0.890
DF3	395	0	3	1.180	1.015
DF4	395	0	3	1.460	1.045
DF5	396	0	3	1.080	0.974
DF6	396	0	3	1.350	1.087

Note: DA = differential association; DR = differential reinforcement; IM = imitation; DF = definitions.

Table 19. Descriptive Statistics (Social Learning Variables) (Online Sample)					
	N	Minimum	Maximum	*M*	*SD*
Differential Association					
DA1	232	0	4	0.990	1.063
DA2	232	0	4	1.980	1.369
Differential Reinforcement					
DR1	232	0	4	0.530	0.887
DR3	232	0	4	0.600	1.019
DR5	232	0	3	1.210	1.129
DR6	232	0	3	1.310	1.115
DR7	227	0	3	1.090	1.015
DR8	227	0	3	0.900	0.968
DR10	227	0	3	0.940	0.957
DR11	227	0	3	2.000	1.035
Imitation					
IM1	227	0	4	0.630	0.929
IM2	227	0	4	1.130	1.152
IM3	227	0	4	1.600	1.351
Definitions					
DF1	223	0	3	1.320	1.032
DF2	223	0	3	1.200	1.018
DF3	223	0	3	1.570	1.028
DF4	223	0	3	1.780	1.028
DF5	223	0	3	1.390	1.025
DF6	223	0	3	1.720	1.071

Note: DA = differential association; DR = differential reinforcement; IM = imitation; DF = definitions.

Table 20. Descriptive Statistics (Dependent Variables) (Pooled Sample).

	N	Minimum	Maximum	*M*	*SD*
Illegal Downloading Behavior					
DP1	648	0	4	1.332	1.558
DP2	648	0	4	0.690	1.329
DP3	647	0	4	0.198	0.671
DP4	648	0	4	1.710	1.646
DP5	647	0	4	1.124	1.516
Illegal Uploading Behavior					
DP6	647	0	4	0.490	1.115
DP7	647	0	4	0.308	0.874
DP8	647	0	4	0.459	1.131
DP9	648	0	4	0.123	0.573
DP10	648	0	4	0.207	0.785

Note: DP = Digital Piracy

Table 21. Descriptive Statistics (Dependent Variables) (University Sample)

	N	Minimum	Maximum	*M*	*SD*
Illegal Downloading Behavior					
DP1	397	0	4	1.110	1.449
DP2	397	0	4	0.350	0.927
DP3	396	0	4	0.120	0.517
DP4	397	0	4	1.880	1.638
DP5	396	0	4	1.000	1.473
Illegal Uploading Behavior					
DP6	396	0	4	0.450	1.067
DP7	396	0	4	0.210	0.710
DP8	396	0	4	0.200	0.754
DP9	397	0	4	0.080	0.498
DP10	397	0	4	0.110	0.600

Note: DP = Digital Piracy

Table 22. Descriptive Statistics (Dependent Variables) (Online Sample)					
	N	Minimum	Maximum	*M*	*SD*
Illegal Downloading Behavior					
DP1	251	0	4	1.680	1.660
DP2	251	0	4	1.230	1.654
DP3	251	0	4	0.320	0.846
DP4	251	0	4	1.430	1.624
DP5	251	0	4	1.320	1.563
Illegal Uploading Behavior					
DP6	251	0	4	0.550	1.187
DP7	251	0	4	0.470	1.067
DP8	251	0	4	0.870	1.459
DP9	251	0	4	0.190	0.670
DP10	251	0	4	0.360	0.992

Note: DP = Digital Piracy

Table 23. Item Measurement (Differential Association & Differential Reinforcement)

Differential Association		
	DA1	During the past 12 months, how many of your friends have knowingly used, made, or given to another person "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks)?
	DA2	During the past 12 months, how many of your friends would approve if you knowingly used, made, or given to another person "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks)?
Differential Reinforcement		
	DR1	How many times have you heard or seen a professor or high school instructor praise or encourage students for downloading, uploading or sharing '"pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with them or others?
	DR2	How many times have you heard or seen a professor or high school instructor offer students the chance to obtain free copies of commercially sold computer software or digital media (e.g. music, movies, eBooks)?
	DR3	How likely is it that you would be praised by others for downloading, uploading or sharing "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with them or others?
	DR4	How likely is it that others would share pirated material with you if you uploaded or shared 'pirated' copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with them or others?
	How much do you agree with the following statements? If I engaged in downloading, uploading or sharing of "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with others:	
*	DR5	I would feel successful
*	DR6	I would feel "cool"
*	DR7	I would feel excitement
*	DR8	I would save money or make money

* Items reverse-coded

Table 24. Item Measurement (Imitation & Definitions)

Imitation		
	IM1	How much have you learned about the downloading, uploading and sharing of “pirated” copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) from seeing family do them?
	IM2	How much have you learned about the downloading, uploading and sharing of ‘pirated’ commercially sold computer software or digital media (e.g. music, movies, eBooks) from seeing friends do them?
	IM3	How much have you learned about the downloading, uploading and sharing of ‘pirated’ commercially sold computer software or digital media (e.g. music, movies, eBooks) through Internet chat rooms, IRC, web forums, or social media?
Definitions		
*	DF1	I see nothing wrong in giving people copies of pirated materials to foster friendships.
*	DF2	It is ok for me to pirate media because the creators are really not going to lose any money.
*	DF3	I think it is okay to use copied software for research purposes, because everyone shares the benefits.
*	DF4	I think it is okay to use copied movies for entertainment.
*	DF5	I think it is okay to use copied software because the community at large is eventually benefited.
*	DF6	I think it is okay to use copied software if it improves my knowledge.

* Items reverse-coded

Table 25. Item Measurement (Self-Control)

*	SC1	I am good at resisting temptation.
	SC2	I have a hard time breaking bad habits.
	SC3	I am lazy.
	SC4	I say inappropriate things.
	SC5	I do certain things that are bad for me, if they are fun.
*	SC6	I refuse things that are bad for me.
	SC7	I wish I had more self-discipline.
*	SC8	People would say that I have iron self-discipline.
	SC9	Pleasure and fun sometimes keep me from getting work done.
	SC10	I have trouble concentrating.
*	SC11	I am able to work effectively towards long-term goals.
	SC12	Sometimes I can't stop myself from doing something, even if I know it is wrong.
	SC13	I often act without thinking through all the alternatives.

* Items reverse-coded

Table 26. Item Measurement (Neutralization Techniques)

*	NTZ1	If a college student gets in trouble for using a software file from an illegitimate source instead of paying for it, it is more the university's responsibility because they should provide the software to students.
*	NTZ2	The university should be responsible for providing access to software or other digital media; this way people would not have to download it illegally.
*	NTZ3	I shouldn't have to pay for music and software when most of the people I know download for free.
*	NTZ4	Music and software companies are not really harmed when someone download their products for free. Those companies have so much money, it doesn't really matter.
*	NTZ5	Artists make so much money from concerts, videos, sponsors, and other sources, they aren't really hurt by illegal downloading.
*	NTZ6	If music and software companies don't want someone to download their products for free, they should have better online security.
*	NTZ7	I don't really buy into the idea that music companies lose much from illegitimate downloaders and file sharing; my (or others') downloading doesn't really hurt them.
*	NTZ8	Illegitimate downloading is a victimless crime.
*	NTZ9	Music and software companies have been ripping people off for years, so illegitimate downloading is justified.
*	NTZ10	It's really not anyone's fault that they download music and software rather than paying for it; prices are just too high these days.
*	NTZ11	If I had to pay for all the music and software that I listen to or use, I would likely have to work more to pay for things like food, tuition, clothes, and so on.
*	NTZ12	Illegitimate downloading should not be frowned on when people need those programs to do their job or their class work and the university doesn't make the software as available as it should be.
*	NTZ13	People who download necessary software because they can't afford it should not be held liable for doing such things.
*	NTZ14	I think it is okay to use copied software for research purposes, because everybody shares the benefits.

* Items reverse-coded

Table 27. Item Measurement (Additional Independent Variables)

Punishment Certainty		
	Please estimate the chance that you may get caught if you…	
	PCRT1	Duplicate a copyrighted CD.
	PCRT2	Download unauthorized music from the Internet.
	PCRT3	Duplicate a copyrighted DVD.
	PCRT4	Download unauthorized movies from the Internet.
	PCRT5	Install a pirated copy of software on your computer.
Moral Acceptability		
	MA1	Unauthorized copying (sharing) of software goes against moral principles.
*	MA2	Unauthorized copying (sharing) of software is not unethical.
	MA3	People ought not to copy (share) software without authorization.
*	MA4	It would be morally acceptable to copy (share) software without authorization.
Computer Skill		
	How knowledgeable are you on using the following technologies on a range from novice (a) to expert (e). Novice can mean you have no knowledge about activity.	
	CS1	Browsing the Internet
	CS2	Dealing with software problems
	CS3	Removing malware from your computing devices (e.g., computer viruses)
	CS4	Dealing with computer hardware problems
	CS5	Identifying if your computer is infected with spyware
	CS6	Modifying the firewall on your computing devices
	CS7	Establishing a virtual proxy network on your computing devices.
	CS8	Storing digital information on a cloud-based platform (e.g., Dropbox, Onedrive, Box)
	CS9	Identifying a phishing email
	CS10	Securing digital information (files, documents) through encryption
	CS11	Surfing the web through anonymous browsers (e.g., TOR)
	CS12	Surfing the Darkweb
Computer Use		
	How much time do you spend on the computer each week over the past 12 months engaging in each of the following activities?	
	CU1	Shopping/ going to auction sites
	CU2	Playing video games
	CU3	Checking email
	CU4	Using either chatrooms or IRC
	CU5	Using social media
	CU6	Using Instant Messaging to chat
	CU7	Downloading and uploading files

* Items reverse-coded

Table 28. Item Measurement (Demographic Variables)

	Age	How old are you? ______ years old
*	Sex	What is your sex?
*	Race	What is your race? (Choose all that apply)
*	Ethnicity	Are you of Hispanic or Latino origin?
*	Education	What is the highest level of education that you have completed?
*	Employment	What is your current employment status?
*	Income	What was your total household income during the past 12 months?

* Items recoded into binary variables for data analysis

Table 29. Item Measurement (Dependent Variables)

Illegal Downloading Behaviors	
During the past 12 months, how often have you engaged in the following behaviors?	
DP1	Downloaded pirated software or digital media files (e.g. music, movies, eBooks) from a website.
DP2	Used P2P software such as BitTorrent to download pirated software or digital media.
DP3	Used IRC to download pirated software or digital media.
DP4	Used a streaming website to illegally watch movies or television shows.
DP5	Used software to download media from a website without permission (e.g. YouTube, Instagram).
Illegal Uploading Behaviors	
During the past 12 months, how often have you engaged in the following behaviors?	
DP6	Provided copyrighted digital media for others to watch through a streaming website without the owner’s permission.
DP7	Uploaded pirated software or digital media files (e.g. music, movies, eBooks) to a website?
DP8	Used P2P software (e.g. BitTorrent) to seed pirated software or digital media after a download has fully completed?
DP9	Used IRC to illegally share pirated software or digital media with other users?
DP10	Created torrent files to illegally share my own software or digital media.

Table 30. Factor Loadings: 1st-Order Social Learning Model

(n = 610)				
Measures	Estimate	*SE*	β	P-Value
DA1 ← DA	0.761	0.026	28.829	0.000
DA2 ← DA	0.874	0.025	35.529	0.000
DR1 ← DR	0.584	0.037	15.765	0.000
DR2 ← DR	0.440	0.040	11.046	0.000
DR3 ← DR	0.785	0.023	34.082	0.000
DR4 ← DR	0.755	0.025	30.562	0.000
DR5 ← DR	0.829	0.017	47.856	0.000
DR6 ← DR	0.677	0.029	23.545	0.000
DR7 ← DR	0.748	0.022	34.312	0.000
DR8 ← DR	0.764	0.025	30.194	0.000
IM1 ← IM	0.449	0.045	9.902	0.000
IM2 ← IM	0.701	0.029	24.216	0.000
IM3 ← IM	0.748	0.031	24.302	0.000
DF1 ← DF	0.839	0.015	57.039	0.000
DF2 ← DF	0.842	0.015	57.788	0.000
DF3 ← DF	0.898	0.010	87.644	0.000
DF4 ← DF	0.886	0.012	73.244	0.000
DF5 ← DF	0.939	0.007	134.539	0.000
DF6 ← DF	0.921	0.009	106.179	0.000
DA ↔ DR	0.805	0.028	29.134	0.000
DA ↔ IM	0.824	0.037	22.489	0.000
DA ↔ DF	0.694	0.032	21.365	0.000
DR ↔ IM	0.779	0.034	22.952	0.000
DR ↔ DF	0.800	0.020	40.499	0.000
IM ↔ DF	0.648	0.040	16.280	0.000
Errors				
DR1 ↔ DR2	0.481	0.037	13.113	0.000
DR3 ↔ DR4	0.225	0.030	7.433	0.000
DR5 ↔ DR6	0.233	0.029	7.956	0.000
DR6 ↔ DR7	0.267	0.029	9.113	0.000
IM1 ↔ IM2	0.193	0.038	5.067	0.000

Goodness-of-Fit	
χ^2	549.954, 141, $p < 0.000$
RMSEA	0.069
CFI	0.982
TLI	0.978
SRMR	0.043

Note: All factor loadings are standardized.

Table 31. Factor Loadings: 2nd-Order Social Learning Model

(n = 610)					Goodness-of-Fit	
Measures	Estimate	*SE*	β	P-Value	χ^2	567.815, 143, p < 0.000
DA ← SLT	0.858	0.027	32.254	0.000	RMSEA	0.070
DA1 ← DA	0.763	0.027	28.778	0.000	CFI	0.981
DA2 ← DA	0.873	0.025	35.517	0.000	TLI	0.977
DR ← SLT	0.964	0.020	47.593	0.000	SRMR	0.045
DR1 ← DR	0.584	0.037	15.795	0.000		
DR2 ← DR	0.440	0.040	11.071	0.000		
DR3 ← DR	0.785	0.023	34.252	0.000		
DR4 ← DR	0.755	0.025	30.703	0.000		
DR5 ← DR	0.830	0.017	47.976	0.000		
DR6 ← DR	0.677	0.029	23.562	0.000		
DR7 ← DR	0.748	0.022	34.353	0.000		
DR8 ← DR	0.764	0.025	30.181	0.000		
IM ← SLT	0.824	0.030	27.145	0.000		
IM1 ← IM	0.447	0.045	9.835	0.000		
IM2 ← IM	0.701	0.029	24.131	0.000		
IM3 ← IM	0.749	0.031	24.216	0.000		
DF ← SLT	0.821	0.021	38.604	0.000		
DF1 ← DF	0.839	0.015	57.033	0.000		
DF2 ← DF	0.842	0.015	57.789	0.000		
DF3 ← DF	0.898	0.010	87.748	0.000		
DF4 ← DF	0.886	0.012	73.256	0.000		
DF5 ← DF	0.939	0.007	134.510	0.000		
DF6 ← DF	0.921	0.009	106.205	0.000		
Errors						
DR1 ↔ DR2	0.481	0.037	13.141	0.000		
DR3 ↔ DR4	0.226	0.030	7.521	0.000		
DR5 ↔ DR6	0.233	0.029	7.937	0.000		
DR6 ↔ DR7	0.266	0.029	9.111	0.000		
IM1 ↔ IM2	0.195	0.038	5.076	0.000		

Note: All factor loadings are standardized.

Table 32. Factor Loadings: Reciprocity

(n = 596)					Goodness-of-Fit	
Measures	Estimate	*SE*	β	P-Value	χ^2	34.551, 2, p < 0.000
RCP1 ← RCP	0.825	0.020	40.565	0.000	RMSEA	0.165
RCP2 ← RCP	0.839	0.019	44.775	0.000	CFI	0.988
RCP3 ← RCP	0.828	0.018	44.843	0.000	TLI	0.965
RCP4 ← RCP	0.737	0.023	31.720	0.000	SRMR	0.023

Note: All factor loadings are standardized.

Table 33. Factor Loadings: Illegal Downloading Behavior Model

(n = 648)					Goodness-of-Fit	
Measures	Estimate	*SE*	β	P-Value	χ^2	5.119, 3, p < 0.1633
DP1 ← IDB	0.923	0.023	40.767	0.000	RMSEA	0.033
DP2 ← IDB	0.859	0.025	34.773	0.000	CFI	0.999
DP3 ← IDB	0.565	0.059	9.573	0.000	TLI	0.997
DP4 ← IDB	0.612	0.033	18.418	0.000	SRMR	0.015
DP5 ← IDB	0.738	0.027	27.367	0.000		
Errors						
DP2 ↔ DP3	0.198	0.052	3.793	0.000		
DP2 ↔ DP4	-0.232	0.038	-6.040	0.000		

Note: All factor loadings are standardized.

Table 34. Factor Loadings: Illegal Uploading Behavior Model

(n = 648)					Goodness-of-Fit	
Measures	Estimate	*SE*	β	P-Value	χ^2	19.524, 5, p < 0.0015
DP6 ← IUB	0.735	0.036	20.391	0.000	RMSEA	0.067
DP7 ← IUB	0.887	0.024	36.463	0.000	CFI	0.994
DP8 ← IUB	0.827	0.029	28.796	0.000	TLI	0.988
DP9 ← IUB	0.934	0.028	33.909	0.000	SRMR	0.023
DP10 ← IUB	0.951	0.021	44.241	0.000		

Note: All factor loadings are standardized.

Table 35. Mediation Analysis for Self-Control and Illegal Downloading Behavior

	Self-control on piracy (n = 520)				Self-control on social learning (n = 513)				Mediation on piracy (n = 512)			
Measures	Estimate		*SE*	β	Estimate		*SE*	β	Estimate		*SE*	β
SL	—		—	—	—		—	—	0.633	***	0.056	11.234
SC	-0.018	**	0.006	-3.136	-0.020	***	0.005	-4.309	-0.005		0.006	-0.924
RCP	0.130	**	0.039	3.331	0.141	***	0.033	4.307	0.032		0.040	0.808
Age	-0.015	**	0.006	-2.649	-0.008		0.004	-1.855	-0.009		0.005	-1.852
Female	-0.103		0.084	-1.225	0.004		0.068	0.058	-0.115		0.081	-1.428
White	-0.094		0.095	-0.988	0.029		0.073	0.396	-0.118		0.092	-1.279
ETH	0.029		0.117	0.245	-0.160		0.100	-1.599	0.120		0.113	1.062
EDU	0.025		0.095	0.262	0.108		0.079	1.363	-0.090		0.094	-0.957
EMP	0.037		0.090	0.407	-0.029		0.070	-0.417	0.035		0.085	0.416
Income	0.009		0.086	0.102	0.019		0.068	0.289	0.025		0.081	0.302
CU	0.007		0.010	0.758	0.005		0.008	0.660	0.005		0.009	0.566
NTZ	0.027	***	0.006	4.315	0.051	***	0.005	11.219	-0.004		0.006	-0.640
PCRT	0.002		0.010	0.227	-0.005		0.006	-0.726	0.006		0.009	0.633
MA	0.044	*	0.019	2.329	0.076	***	0.016	4.794	-0.005		0.018	-0.285
CS	0.035	***	0.004	9.886	0.019	***	0.003	6.511	0.021	***	0.004	5.750
SC→SL	—		—	—	—		—	—	-0.021	***	0.005	-4.462

Note: SL = social learning; SC = self-control; RCP = reciprocity; ETH = ethnicity; EDU = education; EMP = employment; CU = computer use; NTZ = neutralizations; PCRT = punishment certainty; MA = moral acceptability; CS = computer skill

*p < 0.05 **p < 0.01 *** p < 0.001

Table 36. Mediation Analysis for Reciprocity and Illegal Uploading Behavior

	Social learning on piracy (n = 512)				Social learning on reciprocity (n = 513)				Mediation on piracy (n = 511)			
Measures	Estimate		*SE*	β	Estimate		*SE*	β	Estimate		*SE*	β
SL	0.492	***	0.063	7.789	0.256	***	0.058	4.384	0.429	***	0.062	6.928
RCP	—		—	—	—		—	—	0.230	***	0.050	4.626
SC	0.000		0.009	0.019	-0.007		0.006	-1.246	0.002		0.009	0.193
Age	0.004		0.007	0.485	0.004		0.005	0.716	0.003		0.007	0.372
Female	0.081		0.107	0.759	-0.033		0.079	-0.418	0.089		0.106	0.842
White	-0.030		0.117	-0.254	-0.081		0.086	-0.939	-0.010		0.118	-0.085
ETH	0.083		0.163	0.509	0.002		0.106	0.021	0.083		0.158	0.527
EDU	0.039		0.128	0.306	-0.121		0.090	-1.356	0.067		0.125	0.538
EMP	-0.148		0.118	-1.254	0.004		0.081	0.052	-0.149		0.118	-1.262
Income	-0.015		0.115	-0.128	0.157	*	0.078	2.007	-0.049		0.113	-0.435
CU	0.033	**	0.012	2.698	0.027	**	0.008	3.235	0.027		0.012	2.196
NTZ	0.010		0.008	1.263	0.045	***	0.006	8.213	0.000		0.008	0.003
PCRT	0.042	***	0.012	3.599	0.019	*	0.008	2.364	0.038	**	0.012	3.209
MA	-0.030		0.025	-1.208	0.016		0.019	0.836	-0.033		0.025	-1.349
CS	0.027	***	0.005	5.646	0.004		0.004	1.143	0.026	***	0.005	5.590
SL→RCP	—		—	—	—		—	—	0.258	***	0.059	4.408

Note: SL = social learning; SC = self-control; RCP = reciprocity; ETH = ethnicity; EDU = education; EMP = employment; CU = computer use; NTZ = neutralizations; PCRT = punishment certainty; MA = moral acceptability; CS = computer skill

*p < 0.05 **p < 0.01 *** p < 0.001

APPENDIX II: QUESTIONNAIRE MATERIAL

COVER LETTER FOR UNIVERSITY QUESTIONNAIRE

Dear Participant:

You are invited to participate in a survey about your experiences with sharing copyrighted files online without permission. This study is being conducted by Cydney Lowenstein (lowensteincj@vcu.edu), a doctoral student in the Wilder School of Government and Public Administration at Virginia Commonwealth University, under the supervision of Dr. Nancy A. Morris, Associate Professor (Criminal Justice Program, Wilder School). You must be 18 years or older to participate. Your participation is completely voluntary, you are not obligated to participate and will not be penalized for not participating. Your responses are anonymous and you will never be personally identified in this study. This research has received approval through VCU's IRB (ID#: HM20017782). We appreciate your willingness to help us in our research effort.

Purpose of the Study

The purpose of this study is to examine factors associated with individuals sharing copyrighted files online without permission. Your participation in this survey will help develop a better understanding of the sharing.

Procedures

In this study, a paper survey questionnaire and a scantron form to record your answers on with be distributed to you during class time. You will be asked to read through each of the survey questions and mark your answers using the corresponding bubbles on the scantron form using a #2 pencil. Once you have completed the survey, both the questionnaire and the scantron will be collected from you. It is estimated that the survey will take around 20 minutes to complete.

Potential Risk and Harms

There are no potential risk or harms from participating in this study.

Potential Benefits

There will be no direct benefits from participating in this study. Your response have the potential to expand current theoretical and scientific knowledge on digital piracy.

Compensation

For participation in this research study, you will be provided a piece of candy.

Confidentiality

The survey is anonymous and no names or personally identifiable information will be collected. No individual responses will be identifiable in any resulting reports and data collected will only be reported in the aggregate. The completed scantron forms will be submitted to VCU Technology Services for scanning into a digital database. After scanning is completed and the data is verified for accuracy, the paper scantron forms will be destroyed. The resulting digital database containing participants' responses will be stored indefinitely and may be used in future unspecified research or shared with other researchers. Consent forms will be collected separately from the scantron forms and will not be associated with your responses. Consent forms will be kept in a secured location and only accessible by the researchers. Once the research study has completed, the consent forms will be destroyed.

Potential Conflicts of Interest

The researchers involved in this research study have no conflict of interest.

Rights of Research Subjects

Your participation in this research study is completely voluntary and you have the right to refuse to participate, to stop participation at any time, or to skip any questions that you do not wish to answer with absolutely no penalty for doing so. Withdrawal from the research study will not affect your compensation.

If you have any questions or concerns regarding this research study, you may ask now or at a later time by contacting the researchers using one of the contact methods below.

If you have general questions about your rights as a participant in this or any other research, or if you wish to discuss problems, concerns or questions, to obtain information, or to offer input about research, you may contact:

Virginia Commonwealth University Office of Research

800 East Leigh Street, Suite 3000, Box 980568, Richmond, VA 23298

(804) 827-2157; https://research.vcu.edu/human_research/volunteers.htm

Identification of PIs

The investigator and study staff named below are the best people to contact if you have any questions, complaints, or concerns about your participation in this research:

Cydney Lowenstein

lowensteincj@vcu.edu – (804)495-1349

Dr. Nancy Morris

nmorris@vcu.edu – (804)827-0484

COVER LETTER FOR ONLINE QUESTIONNAIRE

Dear Participant:

You are invited to participate in a survey about your experiences with sharing copyrighted files online without permission. This study is being conducted by Cydney Lowenstein (lowensteincj@vcu.edu), a doctoral student in the Wilder School of Government and Public Administration at Virginia Commonwealth University, under the supervision of Dr. Nancy A. Morris, Associate Professor (Criminal Justice Program, Wilder School). You must be 18 years or older to participate. Your participation is completely voluntary, you are not obligated to participate and will not be penalized for not participating. Your responses are anonymous and you will never be personally identified in this study. This research has received approval through VCU's IRB (ID#: HM20017782). We appreciate your willingness to help us in our research effort.

Purpose of the Study

The purpose of this study is to examine factors associated with individuals sharing copyrighted files online without permission. Your participation in this survey will help develop a better understanding of the sharing.

Potential Risk and Harms

There are no potential risk or harms from participating in this study.

Potential Benefits

There will be no direct benefits from participating in this study. Your response have the potential to expand current theoretical and scientific knowledge on digital piracy.

Compensation

For participation in this research study, you will be able to enter into a drawing to with a $25 Amazon.com gift card. In order to enter, you must provide an email address at the requested after the survey is complete. The email address provided will not be connected to the responses you provide in the survey and will only be used to contact you if you are selected as the winner of the drawing.

Confidentiality

The survey is anonymous and no names or personally identifiable information will be collected. The form to collect email addresses for the gift card drawing will be collected separately from the survey and will not be linked to your responses. The email addresses will not be kept after the drawing is complete. No individual responses will be identifiable in any resulting reports and data collected will only be reported in the aggregate. The data collected will be stored indefinitely and may be used in future unspecified research or shared with other researchers.

Potential Conflicts of Interest

The researchers involved in this research study have no conflict of interest.

Rights of Research Subjects

Your participation in this research study is completely voluntary and you have the right to refuse to participate, to stop participation at any time, or to skip any questions that you do not wish to answer with absolutely no penalty for doing so. Withdrawal from the research study will not affect your compensation.

If you have any questions or concerns regarding this research study, you may ask now or at a later time by contacting the researchers using one of the contact methods below.

If you have general questions about your rights as a participant in this or any other research, or if you wish to discuss problems, concerns or questions, to obtain information, or to offer input about research, you may contact:

Virginia Commonwealth University Office of Research

800 East Leigh Street, Suite 3000, Box 980568, Richmond, VA 23298

(804) 827-2157; https://research.vcu.edu/human_research/volunteers.htm

Identification of PIs

The investigator and study staff named below are the best person(s) to contact if you have any questions, complaints, or concerns about your participation in this research:

Cydney Lowenstein

lowensteincj@vcu.edu – (804)495-1349

Dr. Nancy Morris

nmorris@vcu.edu - (804)827-0484

If you agree to participate in this study, please start now by clicking on the Continue button below.

QUESTIONNAIRE ITEMS

Demographic Measures

1. How old are you? _______ years old

2. What is your sex?

   (0) Male

   (1) Female

   (2) Intersex

   (9) Prefer not to say [Online only]

3. What is your race? (Choose all that apply)

   a. White/Caucasian

   b. Black/African American

   c. Asian

   d. American Indian or Alaskan Native

   e. Native Hawaiian or other Pacific Islander

   f. Prefer not to say [Online only]

3. Are you of Hispanic or Latino origin?

   (0) No

   (1) Yes

   (3) Prefer not to say [Online only]

4. What is the highest level of education that you have completed?

   (0) Less than a high school diploma [Online only]

   (1) High school degree or equivalent [Online only]

   (2) Some college, no degree

(3) Undergraduate degree

(4) Graduate degree

(9) Prefer not to say [Online only]

5. What is your current employment status?

(0) Unemployed

(1) Part-time employed

(2) Full-time employed

(9) Prefer not to say [Online only]

6. What was your total household income during the past 12 months?

(0) Less than $20,000

(1) $20,000 to $34,999

(2) $35,000 to $49,999

(3) $50,000 to $74,999

(4) $75,000 or more

(9) Prefer not to say [Online only]

7. What website did you access this survey from? [Online only]

(1) Speed.cd

(2) Torrentleech

(3) SuprBay

(4) Reddit

(5) Prefer not to say

(6) Other __________________

Digital Piracy

During the past 12 months, how often have you engaged in the following behaviors?

8. Used either your own computer resources or another person's to knowingly use, make, or give to another person a 'pirated' copy of commercially sold computer software or digital media (e.g. music, movies, eBooks)?
    (0) Never
    (1) 1-2 times
    (2) 3-5 times
    (3) 6-9 times
    (4) 10 or more times

Downloading-Specific Digital Piracy

9. Downloaded pirated software or digital media files (e.g. music, movies, eBooks) from a website. [DP1]
    (0) Never
    (1) 1-2 times
    (2) 3-5 times
    (3) 6-9 times
    (4) 10 or more times
10. Used P2P software such as BitTorrent to download pirated software or digital media. [DP2]
11. Used IRC to download pirated software or digital media. [DP3]
12. Used a streaming website to illegally watch movies or television shows. [DP4]
13. Used software to download media from a website without permission (e.g. YouTube, Instagram). [DP5]

Uploading-Specific Digital Piracy

14. Provided copyrighted digital media for others to watch through a streaming website without the owner's permission. [DP6]
    (0) Never
    (1) 1-2 times
    (2) 3-5 times
    (3) 6-9 times
    (4) 10 or more times
15. Uploaded pirated software or digital media files (e.g. music, movies, eBooks) to a website? [DP7]
16. Used P2P software (e.g. BitTorrent) to seed pirated software or digital media after a download has fully completed? [DP8]
17. Used IRC to illegally share pirated software or digital media with other users? [DP9]
18. Created torrent files to illegally share my own software or digital media. [DP10]

Piracy Skill [PS]

How capable are you in performing the following activities on a range from Poor (a) to Excellent (e).

19. Burn a CD that contains an illegal copy of commercially sold software or digital media.
    (0) Poor
    (1) Fair
    (2) Good
    (3) Very Good
    (4) Excellent

20. Use BitTorrent to illegally download software or digital media.
21. Create torrent files to illegally share my own software or digital media.
22. Remove DRM or other copy protection from software or digital media.
23. Use a tool to bypass the licensing of commercially sold software.
24. Use IRC to illegally download software or digital media.
25. Use a website to download or upload pirated software or digital media.
26. Use software to download media from a website without permission (e.g. YouTube, Instagram).
27. Use a website to illegally stream movies, music, or television shows.

Cyber Deviance

How often have you engaged in the following activities in the past 12 months?

28. Uploaded or posted hurtful information about someone from an online community.
    (0) Never
    (1) 1-2 times
    (2) 3-5 times
    (3) 6-9 times
    (4) 10 or more times
29. Purposefully excluded someone from an online community.
30. Threatened or harassed someone through e-mail or instant messaging.
31. Threatened or harassed someone through online gaming.
32. Uploaded or posted nude or sexually explicit images of someone online without his/her permission.

33. Committed any type of hacking by gaining access to unauthorized areas of the Internet or another person's secure account.
34. Uploaded or helped distribute malicious software.
35. Uploaded or posted someone else's personal information, e.g. credit card, without his/her permission to obtain goods or services through the Internet.

Social Learning

Differential Association

36. During the past 12 months, how many of your friends have knowingly used, made, or given to another person "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks)? [DA1]

    (0) None of them

    (1) Very few of them

    (2) About half of them

    (3) More than half of them

    (4) All of them

37. During the past 12 months, how many of your friends would approve if you knowingly used, made, or given to another person "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks)? [DA2]

Differential Reinforcement

38. How many times have you heard or seen a professor or high school instructor praise or encourage students for downloading, uploading or sharing '"pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with them or others? [DR1]

(0) Never

(1) 1-2 times

(2) 3-5 times

(3) 6-9 times

(4) 10 or more times

39. How many times have you heard or seen a boss or colleague praise or encourage employees for downloading, uploading or sharing ‘pirated” copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with them or others?

40. How many times have you heard or seen a professor or high school instructor offer students the chance to obtain free copies of commercially sold computer software or digital media (e.g. music, movies, eBooks)? [DR2]

41. How many times have you heard or seen a boss or colleague offer someone the chance to obtain free copies of commercially sold computer software or digital media (e.g. music, movies, eBooks)?

42. How likely is it that you would be praised by others for downloading, uploading or sharing “pirated” copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with them or others? [DR3]

(0) Very unlikely

(1) Somewhat unlikely

(2) Somewhat likely

(3) Very likely

43. How likely is it that others would share pirated material with you if you uploaded or shared 'pirated' copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with them or others? [DR4]

How much do you agree with the following statements? If I engaged in downloading, uploading or sharing of "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) with others:

44. [22] I would feel successful [DR5]
   (0) Strongly agree
   (1) Somewhat agree
   (2) Somewhat disagree
   (3) Strongly disagree
45. [*] I would feel "cool" [DR6]
46. [*] I would be more like someone else
47. [*] I would feel excitement [DR7]
48. [*] I would save money or make money [DR8]

Imitation

49. How much have you learned about the downloading, uploading and sharing of "pirated" copies of commercially sold computer software or digital media (e.g. music, movies, eBooks) from seeing family do them? [IM1]
   (0) Nothing
   (1) A little

[22] Reverse-coded for analysis.

(2) Some

(3) A lot

(4) Everything

50. How much have you learned about the downloading, uploading and sharing of 'pirated' commercially sold computer software or digital media (e.g. music, movies, eBooks) from seeing friends do them? [IM2]

51. How much have you learned about the downloading, uploading and sharing of 'pirated' commercially sold computer software or digital media (e.g. music, movies, eBooks) through Internet chat rooms, IRC, web forums, or social media? [IM3]

Definitions

52. * I see nothing wrong in giving people copies of pirated materials to foster friendships. [DF1]

    (0) Strongly agree

    (1) Somewhat agree

    (2) Somewhat disagree

    (3) Strongly agree

53. * It is ok for me to pirate media because the creators are really not going to lose any money. [DF2]

54. * I think it is okay to use copied software for research purposes, because everyone shares the benefits. [DF3]

55. * I think it is okay to use copied music for entertainment.

56. * I think it is okay to use copied movies for entertainment. [DF4]

---

* Reverse-coded for analysis.

57. * I think it is okay to use copied software because the community at large is eventually benefited. [DF5]

58. * I think it is okay to use copied software if it improves my knowledge. [DF6]

Computer Count

59. How many computers do you own?

    (0) None

    (1) 1-2 computers

    (2) 3-4 computers

    (3) 5 or more

Computer Use [CU]

How much time do you spend on the computer each week over the past 12 months engaging in each of the following activities?

60. Shopping/ going to auction sites

    (0) Never

    (1) Less than 1 hour

    (2) 1-2 hours

    (3) 3-5 hours

    (4) 6 or more hours

61. Playing video games

62. Checking email

63. Using either chatrooms or IRC

* Reverse-coded for analysis.

64. Using social media

65. Using Instant Messaging to chat

66. Downloading and uploading files

Low Self-Control [SC]

How strongly do you agree or disagree with the following statements?

67. I am good at resisting temptation.

    (0) Strongly agree

    (1) Somewhat agree

    (2) Somewhat disagree

    (3) Strongly disagree

68. I have a hard time breaking bad habits.

69. I am lazy.

70. I say inappropriate things.

71. I do certain things that are bad for me, if they are fun.

72. I refuse things that are bad for me.

73. I wish I had more self-discipline.

74. People would say that I have iron self-discipline.

75. Pleasure and fun sometimes keep me from getting work done.

76. I have trouble concentrating.

77. I am able to work effectively towards long-term goals.

78. Sometimes I can’t stop myself from doing something, even if I know it is wrong.

79. I often act without thinking through all the alternatives.

Neutralizations [NTZ]

80. [25] If a college student gets in trouble for using a software file from an illegitimate source instead of paying for it, it is more the university's responsibility because they should provide the software to students.

(0) Strongly agree

(1) Somewhat agree

(2) Somewhat disagree

(3) Strongly disagree

81. * The university should be responsible for providing access to software or other digital media; this way people would not have to download it illegally.

82. * I shouldn't have to pay for music and software when most of the people I know download for free.

83. * Music and software companies are not really harmed when someone download their products for free. Those companies have so much money, it doesn't really matter

84. * Artists make so much money from concerts, videos, sponsors, and other sources, they aren't really hurt by illegal downloading.

85. * If music and software companies don't want someone to download their products for free, they should have better online security.

86. * I don't really buy into the idea that music companies lose much from illegitimate downloaders and file sharing; my (or others') downloading doesn't really hurt them.

87. * Illegitimate downloading is a victimless crime.

88. [26] Music and software companies have been ripping people off for years, so illegitimate downloading is justified.

---

[25] Reverse-coded for analysis.
[26] Reverse-coded for analysis.

89. * It's really not anyone's fault that they download music and software rather than paying for it; prices are just too high these days.

90. * If I had to pay for all the music and software that I listen to or use, I would likely have to work more to pay for things like food, tuition, clothes, and so on.

91. * Illegitimate downloading should not be frowned on when people need those programs to do their job or their class work and the university doesn't make the software as available as it should be.

92. * People who download necessary software because they can't afford it should not be held liable for doing such things.

93. * I think it is okay to use copied software for research purposes, because everybody shares the benefits.

Reciprocity

94. * I expect other users to share digital files online as well. [RCP1]
    (0) Strongly agree
    (1) Somewhat agree
    (2) Somewhat disagree
    (3) Strongly disagree

95. * I think it is unfair if users don't share digital files online. [RCP2]

96. * I feel obliged to share digital files online because I download from others. [RCP3]

97. * I think that file sharing is based on reciprocity. [RCP4]

98. [27] I think it's ok to accept help without thinking of reciprocating it immediately.

99. * I can understand other users who don't share digital files online.

[27] Reverse-coded for analysis.

100. * I value the appreciation of others users.

101. * I don't care what other users think of me.

Punishment Certainty [PCRT]

Please estimate the chance that you may get caught if you…

102. Duplicate a copyrighted CD.

    (0) About zero

    (1)

    (2)

    (3)

    (4) Almost certain

103. Download unauthorized music from the Internet.

104. Duplicate a copyrighted DVD.

105. Download unauthorized movies from the Internet.

106. Install a pirated copy of software on your computer.

Punishment Severity

How severe do you think the punishment would be if you get caught by…

107. Duplicate a copyrighted CD.

    (0) Not severe at all

    (1)

    (2)

    (3)

    (4) Very severe

108. Download unauthorized music from the Internet.

109. Duplicate a copyrighted DVD.

110. Download unauthorized movies from the Internet.

111. Install a pirated copy of software on your computer.

Moral Acceptability [MA]

112. Unauthorized copying (sharing) of software goes against moral principles.

    (0) Strongly agree

    (1) Somewhat agree

    (2) Somewhat disagree

    (3) Strongly disagree

113. * Unauthorized copying (sharing) of software is not unethical.

114. People ought not to copy (share) software without authorization.

115. * It would be morally acceptable to copy (share) software without authorization.

Computer Skill [CS]

How knowledgeable are you on using the following technologies on a range from novice (a) to expert (e). Novice can mean you have no knowledge about activity.

116. Browsing the Internet

    (0) Novice

    (1)

    (2)

    (3)

    (4) Expert

117. Dealing with software problems

118. Removing malware from your computing devices (e.g., computer viruses)

119. Dealing with computer hardware problems

120. Identifying if your computer is infected with spyware

121. Modifying the firewall on your computing devices

122. Establishing a virtual proxy network on your computing devices.

123. Storing digital information on a cloud-based platform (e.g., Dropbox, Onedrive, Box)

124. Identifying a phishing email

125. Securing digital information (files, documents) through encryption

126. Surfing the web through anonymous browsers (e.g., TOR)

127. Surfing the Darkweb

128. What reasons do you have for uploading pirated software or digital media files (e.g. music, movies, eBooks)? Please include any reasons you can think of. [Online only]