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Social Learning and Digital Piracy: Do Online Peers Matter?

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SOCIAL LEARNING AND DIGITAL PIRACY: DO ONLINE PEERS MATTER?

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This study examined the relationship between digital piracy and social learning theory. To the knowledge of this researcher, only one study had tested a full model of social learning theory in relation to digital piracy (Skinner and Fream, 1997). The current study expanded on past work by testing all four components of social learning theory (differential association, differential reinforcement, imitation, definitions). In addition, to being a full test of the theory this dissertation made many additional contributions to the literature; including the creation of new neutralization techniques (DRM defiance, and claim of future patronage), and the examination of the influence of online sources of social learning on digital piracy. Very few studies have examined online social learning in the past (Holt and Copes, 2010, Hinduja and Ingram, 2009).

Data for the study was collected through the use of an online survey. The survey was administered via email to a random sample of college students at two eastern universities. The results from this study suggested that offline sources of differential association have a stronger influence on digital piracy than online sources. However, online sources of differential association were also important predictors of digital piracy in multiple models. Other important predictors of digital piracy included positive reinforcement and various neutralization techniques, including one of the new neutralization techniques created for this study.

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CHAPTER I

INTRODUCTION

Computers have affected life in ways hard to imagine 100 or even 20 years ago. The advent of digital technologies has dramatically changed the world at the social, occupational, and business levels. The changes brought on by digital technology have led to improvements in quality of life for many people. However, with the positive changes new threats have emerged. One of these new threats is digital piracy.

Digital piracy has a large societal cost, for this reason it is important to better understand the factors that contribute to an individual's participation in digital piracy. It is possible that many theories relevant to street crimes may not be as relevant to computer crimes such as digital piracy (Wall, 2005). Thus, it is important to test theories developed for traditional forms of crime on emerging digital crimes. This dissertation tested the applicability of social learning theory as a predictor of participation in digital piracy. Social learning theory is considered a general theory of crime. Therefore, it should apply equally well to computer crimes, such as digital piracy, as it does to more traditional street crimes. However, new questions arise when applying social learning theory to digital piracy. Most notably, how much do online sources of social learning contribute to participation in digital piracy? The current study sought to answer this question, as well as determine the relationship between offline social learning variables and digital piracy.

To answer the research questions, this dissertation utilized quantitative methods whereby students at two eastern universities were asked about their level of participation in movie, music, software, and video game piracy. In addition, the students were asked multiple questions representing key concepts from social learning theory.

Definition of Key Terms

For the purposes of this study the following definitions were defined.

Cyber-lockers.

Cyber-lockers are online sites were password protected files can be stored remotely and accessed from anywhere using a computer. They can be used for legitimate purposes, but are often used to facilitate digital piracy.

Digital Piracy.

Digital piracy is the illegal act of copying digital goods that are copyrighted, without the permission or compensation to the copyright holder (Gopal, Sanders, Bhattacharjee, Angrawal, and Wagner, 2004).

Digital Rights Management Software (DRM).

Digital rights management software refers to a wide range of software designed to stop digital piracy.

Peer to Peer Torrent Program.

Peer to peer torrent programs are programs that allow for files to be transferred easily from other users who are sharing a file rather than a server. This method of file sharing can increase download speeds by downloading multiple parts of the file simultaneously.

What is Digital Piracy?

Many have argued that legally digital piracy is not theft, but rather a form of copyright infringement. A copyright refers to a form of protection for original works granted to the author/creator of a work to protect their interests (U.S. Copyright Office, 2006). Within U.S. law, the creator of an original work is granted the exclusive rights to copy; create derivative works of the original, distribute copies to the public through sale, lease, and rent; and perform or display the work in public (U.S. Copyright Act of 1976). Copyright infringement occurs when the exclusive rights of the copyright holder are carried out without the permission of the copyright holder (U.S. Copyright Office, n.d.). The term piracy is often used interchangeably with copyright infringement.

Many changes have been made to U.S. copyright law in response to new challenges brought by changing technology, such as digital technology. In 1982, the Piracy and Counterfeiting Amendments Act expanded the law to cover mass-copyright violations of movies and music, making such violations a felony. The act was once again amended in 1997 with the No Electronic Theft Act, which expanded the 1976 Copyright Act by imposing liability on individuals who do not profit from the distribution of pirated goods (Gasser, 2005). This removed a loophole in the law that made it hard to prosecute most digital pirates because they did not seek to profit from the illegal copies they distribute and receive. The Digital Millennium Copyright Act of 1998 added an additional layer of protection for copyright holders by making it illegal to circumvent technologies designed to control access to a digital work (Gasser, 2005).

Digital piracy differs in many ways from traditional forms of copyright infringement such as commercial piracy. Panethiere (2005) states,

> Traditional definitions, particularly as embodied in national criminal codes, generally view piracy in the context of acts intentionally committed with the goal of obtaining a commercial advantage of some kind. More modern formulations, however, recognise that the essential *sine qua non* of piracy consists in significant damage to the interests of those rightsholders whose protection is the aim of intellectual property regimes and that this damage increasingly is sustained by conduct with little or no commercial motivation. (p. 2).

A major distinction between traditional and digital piracy is that most digital pirates do not seek to profit from participation in digital piracy. In the past, pirated copies were expensive to make and in many ways inferior in quality to the original product. However, the emergence of digital technology has enabled high quality reproductions of copyrighted works to be made at little or no cost. In addition, the internet has made it easy to find and distribute digital goods quickly (Belleflamme & Peitz, 2010). This has led to a change in the scale of piracy and in the makeup of individuals who participate in it.

Multiple definitions of digital piracy have been offered in the literature. For the purpose of this study, digital piracy was defined as "… the illegal act of copying digital goods – software, digital documents, digital audio (including music and voice) and digital video – for any reason other than backup without explicit permission from and compensation to the copyright holder" (Gopal, Sanders, Bhattacharjee, Angrawal, and Wagner, 2004, p. 90). This would include downloading a file from the internet, as downloading the file constitutes making a copy.

Defining digital piracy is difficult as the strategies used vary significantly and change over time. The preferred methods used by pirates have changed multiple times over the years. As previously stated, digital piracy is much easier today than it was in the past. Two of the most popular methods of pirating today are through the use of torrent programs and cyber-lockers (Holt & Copes, 2010). Peer-to-peer (P2P) torrent programs have easy- to- use graphic user interfaces, making piracy a relatively easy task. However, torrent program still require that a program is installed and run from the user's computer.

Recently the use of cyber-lockers has begun to overtake torrent sites in regards to internet traffic. Cyber-lockers are online sites which allow password protected data to be stored online. Data on these sites can be shared by providing the password to others. The top three cyber-locker websites generated over 21 billion visits last year (BBC News, 2011). Accessing materials on cyber-locker websites is very easy, and usually does not require the installation of a program. Cyber-lockers have many legitimate purposes, and many legitimate files are shared using such websites. Thus, it is difficult to tell how much of the material on these sites is pirated.

The Cost of Digital Piracy

Like many other forms of crime it is difficult to obtain accurate estimates regarding the scope of digital piracy. A few recent studies have attempted to estimate piracy rates worldwide and by nation. According to a study conducted by the International Data Corporation (2010), the global software piracy rate hit 43% in 2009. This means that nearly half of all computer software distributed in 2009 was pirated. This study indicates that software piracy is a large problem. Such high rates of piracy can have a negative effect on legitimate sales.

The same report gives some indication of the high cost of piracy. The report indicates that the worldwide value of pirated software reached $51.4 billion dollars in 2009. Additionally, the United States has the highest commercial value of pirated computer software at $8.3 billion. These values represented the commercial value of pirated computer software if all the pirated software was sold on the commercial market. Thus, it is not a completely accurate estimation of lost revenue resulting from computer software piracy, as it is unlikely that every pirated copy removed a legitimate sale from the market.

The software industry is not the only industry to suffer due to digital piracy. Digital piracy has also negatively affected the music, movie, and video game industries. According to a study by International Federation of Phonographic Industries (2011), the revenue of global music sales declined an estimated 31% from 2004 to 2010. This is despite the rapid increase in sales through digital distributors such as ITunes. Within the United States, losses resulting from music piracy were estimated at over 12 billion dollars a year (Siwek, 2007). Movie companies have also suffered heavy losses. In 2005, the worldwide losses of the movie industry were estimated at over 20 billion dollars annually (Siwek, 2006). Finally, while few studies have examined the negative impact of game piracy, many in the video game industry have claimed that piracy hurts their sales and that game piracy is common (Kalning, 2007).

A few studies have attempted to measure the amount of business lost as a result of digital piracy. Rafael and Waldfogel (2006) surveyed a group of college students to provide information regarding the music albums they had bought as well as those they had pirated. The students were also asked to indicate how much they valued each music album. Rofael and Waldfogel found that for every one album bought, five were pirated. However, students were more likely to buy albums that they valued more. Meaning it is likely that some of the pirated content would never have been purchased as the students did not value it enough to warrant a legitimate purchase. This study provided clearer information regarding the number of lost sales resulting from piracy. However, the study was conducted on a specific population, and only examined one type of piracy. Thus, the findings are not generalizable to other forms of piracy or other populations.

Despite these measurement problems it is clear that digital piracy has caused harm to multiple stakeholders. A 2010 report by the United States Government Accountability Office (GOA) found that piracy produced many negative effects for the stakeholders involved. Those who pirate (consumers) can be negatively affected when the pirated product fails. In addition, the consumers may receive viruses from pirated goods, which can cause damage to computer hardware and software, incurring costs for repairs and time lost. Industry can be negatively affected due to loss sales, lost brand value, increased cost of piracy protection, and a decreased incentive to innovate. Governments can be negatively affected due to lost tax revenue. Lastly, the economy as a whole can be negatively affected, as piracy may contribute to stagnated economic growth as companies become hesitant to innovate.

Dissertation Layout

In chapter II of this dissertation, the past literature on digital piracy and social learning theory is presented. This section starts with a discussion of the methods of measuring digital piracy utilized in the past. The second section focuses on social learning theory, the theoretical focal point of the study, which contains subsections discussing both deterrence and neutralization theory, both of which are subsumed under social learning theory for the purposes of this study. Next a section is presented covering empirical evidence regarding multiple demographic characteristics that were used in the current study. This is followed by a review of the unique contributions the current study will add to the literature on digital piracy and social learning theory. Finally the literature review concludes with the presentation of the research questions and hypotheses for the current study.

Chapter III provides a detailed description of the methods used for this study. The chapter covers site selection and sampling, survey administration, survey design, reliability and validity, human subject protections, strengths and limitations of the study, and the analysis plan for both the quantitative and qualitative portion. Chapter IV provides the results from the analyses used for this study. Chapter V provides a discussion of the results, strengths and weaknesses of the study, and directions for future research.

CHAPTER II

LITERATURE REVIEW

In this chapter, the past literature on digital piracy is explored. This literature review begins with an overview of the measurement of digital piracy. In the next section, the theoretical propositions and empirical support for social learning theory are discussed. This is followed by a short overview of deterrence and neutralization theory. A discussion of these two theories is included because they were subsumed under social learning theory for the current study.

The next section presents an overview of the empirical literature regarding the demographic variables included in the study. This is followed by a section discussing how the current study expanded on past studies to advance the understanding of the causes of participation in digital piracy. The literature review will conclude with the research questions and hypotheses for the current study.

Measuring Digital Piracy

Past studies have examined three forms of digital piracy: software, music, and movie piracy. Early studies usually only examined one type of digital piracy, such as software piracy (Skinner and Fream, 1997) or utilized a general piracy measure designed to cover any form of digital piracy (Hinduja, 2001). However, recent studies have demonstrated the value of testing multiple forms of digital piracy together (Morris and Higgins, 2009; 2010; Gunter, 2009). Depending on the type of piracy examined, digital pirates may differ along demographic lines. Additionally, theoretical variables may affect diverse types of digital piracy differently. Morris and Higgins (2009) found this to be the case with movie and music pirates.

For this reason, the current study examined four different types of digital piracy, including measures for software, video, music, and video game piracy. Video game piracy appears to be less explored in the literature. In the past, it may have been subsumed under software piracy as computer games represent a type of software. However, traditional software (e.g., Microsoft Office, Photoshop) was designed to serve a different purpose than computer games. In addition, the retail prices differ significantly between the two. For these reasons, software and computer game pirates may differ significantly. Thus, it was warranted to examine the two types of piracy separately.

Studies of digital piracy have often measured piracy in one of two ways; self-report measures of actual piracy, or scenarios designed to gauge an individual's willingness to engage in digital piracy. A study by Higgins, Wolfe, and Ricketts (2009) utilized both forms of measurement. Based on the results of the study they concluded that scenario based measures of digital piracy produce more conservative estimates. Higgins, Wolfe, and Ricketts recommend measuring digital piracy both ways in future studies. Following Higgins, Wolfe, and Ricketts recommendation the current study included both measures for actual digital piracy and willingness to commit digital piracy in response to vignettes.

Digital Piracy and Criminological Theory

According to Wall, (2005) applying existing criminological theories to computer crime (including piracy) may be problematic because of the varying qualities between street crime and computer crime. However, specific theories may apply equally well to both types of crime. For example, theories considered general theories of crime, such as social learning theory, should apply equally well to online crimes as they do to traditional street crimes.

In recent years, numerous criminological theories have been tested in relation to computer crime. Two forms of computer deviance or criminality have received the most attention in criminology. Namely, hacking and digital piracy (Glass, & Wood, 1996; Higgins, Fell, & Wilson, 2006; Hinduja, 2007; Holt, & Bossler, 2009; Lee, Lee, & Yoo, 2004; Morris, & Blackburn, 2009; Skinner, & Fream, 1997; Rogers, 2001). As previously noted the current study sought to increase the breadth of knowledge on the later of these two behaviors, although parallels are drawn between hacking and digital piracy literature where applicable.

The following section on the application of theory to digital piracy mainly explores the developmental history, and empirical support of social learning theory. However, neutralization and deterrence theory are also be discussed in two separate subsections, as these two theories will be subsumed under social learning theory for the purposes of this study.

First this section covers the theoretical propositions and empirical evidence of social learning theory; including, a subsection discussing the past literature related to the influence of online sources of social learning. Next the theoretical propositions and empirical evidence of neutralization and deterrence theory are reviewed. In addition, the reasons why the two theories should be subsumed under social learning theory are provided.

Learning Theories

Learning theories explore the process of learning behaviors. Multiple theories of learning have been developed in the fields of social, psychology, and criminology. However, the most well-known learning theory in criminology is Sutherland’s (1947) differential association theory, and its expansion by Burgess and Aker’s (1966) social learning theory. Social learning theory is largely an extension of Sutherland’s (1947) differential association theory. Social learning theory though, is not meant to be a rival theory of differential association theory, but is instead a broader theory, which integrates the processes set forth in differential association with psychological learning principles. Before discussing social learning theory a brief review of Sutherland’s theory is warranted.

Sutherland's (1947) differential association theory states that criminal behavior like any other behavior is learned. It is learned through symbolic interactionism, which emphasizes that learning takes place through interaction and communication within close intimate groups. It is within these close intimate groups that individuals learn how to commit crimes, as well as the motivations for doing so. The motivation to commit crime comes from how a person views legal codes. A person can define the law as positive or negative. An individual is more likely to be delinquent if they possess an abundance of definitions favorable towards crime.

According to Sutherland (1947), definitions can vary along four dimensions: frequency, duration, priority, and intensity. Frequency refers to how often an individual is exposed to definitions favorable or unfavorable to law violation. A definition favorable to crime will have a larger impact on a person's behavior the more frequently they are exposed to it. Duration reflects the length of time a person is exposed to a definition. A definition will have a larger impact on a person if they are exposed to it for longer periods of time. Priority refers to how early in life a person was exposed to a definition, the earlier the exposure, the greater influence that definition will have on a person. Intensity refers to the level of closeness between an individual and the person(s) who are exposing them to a definition. A definition has a stronger effect on an individual if it is transferred from a person with whom they have a stronger relationship (Sutherland, 1947). These four dimensions can overlap. For example, if an individual was exposed to a definition early in life (priority) it is also likely they were exposed to it often (frequency). If an individual has high exposure to a definition in frequency, duration, priority, and intensity it will have a larger effect on their behavior than a definition they are exposed to less. Sutherland (1947) noted that definitions can be crime specific; meaning that a person could believe that one type of crime is acceptable while another is not. Or they could believe that most crimes are wrong but make an exception for a particular type of crime.

Although Sutherland’s theory was a pivotal advancement in the field of criminology and was extremely popular, it was criticized for many reasons. According to Cressey (1952), the central tenants of the theory were stated in a manner that makes testing of the theory difficult. In his discussion of differential association theory Sutherland does not go into detail regarding what positive and negative definitions of criminality would look like. Responding to this deficiency, Cressey (1952) noted that such conceptualizations must be created before the theory can move forward. Another criticism of the theory is that it does not specify how criminal behavior is learned (Kubrin, Stucky, & Krohn, 2009). To an extent, both of these issues have been addressed as the theory has been expanded over the years.

Burgess and Akers (1966) expanded differential association theory to create what they originally referred to as differential reinforcement theory. After this, Akers continued to develop the theory eventually renaming it social learning theory (Akers, 1973; 1985; 2009). Social learning theory maintains many aspects of Sutherland’s (1947) differential association theory. For example, the theory preserves the claim that definitions favorable and unfavorable to crime are important in determining criminality. However, Burgess and Akers adaptation is more attentive to how criminal behavior is learned, drawing influence from psychological learning theories and principles. Notably, Burgess and Akers incorporate the process of operant conditioning into their theory, drawing influence from Skinner (1959).

As Akers (1973; 1985; 2009) continued to develop the theory he simplified it into four main concepts. By simplifying the main concepts Akers created a more parsimonious theory with clearer concepts compared to differential association theory. This made social learning theory much easier to test. The four components include definitions, differential association, differential reinforcement, and imitation (Akers, 2009). Each of these four components are discussed in greater detail below.

Differential association. Differential association refers to the people and groups with whom an individual associates. According to Akers (2009),

> The groups with which one is in differential association provide the major social context in which all the mechanisms of social learning theory operate. Not only do they expose one to definitions, they present models to imitate and mediate differential reinforcement (source, schedule, value, and amount) for criminal and conforming behavior (p. 62).

Thus, differential association is one of the most important aspects of social learning theory.

The majority of research on social learning theory focuses on the influence of “intimate personal groups” as emphasized by Sutherland. According to Akers, “Sutherland’s emphasis of ‘intimate personal groups’ is well founded because they are the ones that are most significant to the individual, especially the primary groups of family and friends” (2009, p. 60). Early in a person’s life, family supplies the majority of interactions that shape a person’s behavior. As a person gets older and approaches adolescence, peer influence increases in importance. The most significant associations for adults are generated from spouses, friends, and coworkers (Akers, 2009).

Although, the majority of studies focus on the influence of these “intimate personal groups”, Akers contends secondary and reference groups are also important. Secondary and reference groups could include interactions with neighbors, church groups, teachers, and many other individuals a person interacts with in their life. According to Akers, the aforementioned secondary groups, and even the mass media can influence an individual’s propensity to participate in delinquent or criminal behavior (Akers, 2009). Considering the ever increasing importance of technology today, the influences of virtual peers may also be important. According to Warr (2002), advances in technology have greatly increased opportunities for communication. Through these advances in technology individuals can now interact with people within their social network with greater ease. In addition, individuals may also be exposed to completely online peer groups that they never interact with outside of online venues. Thus, it is clear that online peer groups could have a strong influence on behavior, especially for computer based crimes. However, this is an area of research which has received little attention. For this reason, the importance of online peer groups remains largely unknown. This issue is discussed further in a subsequent section on online peer groups.

Imitation. Imitation refers to the modeling of a behavior an individual observes others doing (Akers, 2009). Multiple factors determine whether a behavioral model will be imitated. For example, individuals are more likely to model the behaviors of people they like or respect. In addition, the modeled behavior may be vicariously reinforced if the observer witnesses the molder’s behavior being rewarded. The environment can also affect the potential for imitation. If an individual is in an environment where imitating a behavior is encouraged, they may be more likely to imitate the modeled behavior (Bandura, 1986; Akers, 2009).

Imitation is more important in the initiation of primary deviance, as compared to cessation or continuation of a behavior (Akers, 2009). Once a behavior is initiated for the first time, other aspects of social learning theory (differential reinforcement and definitions) become more important in determining the continuation of the behavior in the future. However, the effect of imitation on behavior does not completely cease. Rather, imitation does facilitate the maintaining or changing of behavior to a minor extent. The weakening importance of imitation after the initiation of a behavior may explain the low level of support often found for imitation measures in empirical tests of the theory (Kubrin, Stucky, & Khron 2009; Akers, 2009).

Definitions. Definitions are conceptually similar to those discussed in Sutherland's differential association theory. Akers stated, definitions "… are orientations, rationalizations, definitions of the situation, and other attitudes that label the commission of an act as right or wrong, good or bad, desirable or undesirable, justified and unjustified" (2009, p. 78). If an individual holds definitions favorable to crime violation, they are more likely to commit crime. Conversely, if an individual holds definitions unfavorable to crime or favorable to conventional behavior they will be less likely to commit a crime (Akers, 2009).

Definitions can be either general or specific. General definitions refer to moral, religious, normative, and conventional values that influence a person's broad disposition toward behaviors. Specific definitions are focused on a particular behavior or set of behaviors (Akers, 2009; Akers and Sellers, 2004). An individual could hold the general definition that one should not commit crime, but still hold specific definitions that state a specific behavior such as digital piracy is permissible. According to Akers, specific definitions trump general definitions, in that general definitions will have a weaker effect on behavior when compared to specific definitions (Akers, 2009).

Definitions favorable to criminality can take two forms: positive or neutralizing. Positive definitions occur less frequently than neutralizing definitions. Positive definitions refer to rationalization or beliefs that view a criminal or deviant act as desirable (Akers, 2009). Past studies have demonstrated that some digital pirates deny that digital piracy is wrong. These individuals often view the transference of digital good illegally as a virtue. They rationalize that the free exchange of information and media is a noble endeavor. Thus, they exhibit a positive definition of digital piracy (Holt & Copes, 2010). Similar ideology is often exhibited by hackers, and is transferred through subcultural means (Holt &Copes, 2010).

Positive definitions are most often transferred through participation in a subculture with values that run counter to that of the conventional societal norms. Thus, social learning theory covers the influence of subcultures on behavior. However, Akers (2009) stresses that social learning theory is not a deviant subculture theory. To cast it as such would be too limiting and overlook the socialization processes that form the base of the theory. Recent research on digital piracy by Holt and Copes (2010) indicated that digital pirate subcultures can form and foster the transfer of definitions favorable to committing digital piracy. Expectedly, once formed, these subcultures facilitate the transfer of definitions and techniques online. Subcultures can be either an “intimate” or secondary group depending on an individual’s level of association and identification with the group.

Neutralizing definitions are considered more common than positive definitions. Neutralizing definitions are not used to justify criminal behavior as positively desirable. Instead, they are best described as excuse or justification a person may make for their behavior with full knowledge that the behavior is viewed as undesirable (Akers, 2009). One of the most recognized sources of neutralizing definitions is Sykes and Matza’s (1957) techniques of neutralization theory.

Techniques of neutralization. As previously stated Sykes and Matza’s (1957) neutralization theory will be subsumed under social learning theory for the purposes of this study. Sykes and Matza’s theory was originally developed as an expansion of Sutherland’s differential association theory. For this reason, it applies equally well as a component of social learning theory. Thus, neutralization theory will be treated as part of the definitions component of social learning theory for the current study, allowing the current study to test multiple neutralizing definitions.

Sykes and Matza (1957) proposed five techniques of neutralization. The first technique was the denial of responsibility. As part of this technique, the offender views the actions as being controlled by forces beyond their control, and thus not their fault; for example, growing up in a bad neighborhood, or not having enough money due to bad life situations. The second technique was the denial of injury. An offender utilizing this technique would rationalize that what they did caused no real harm or lasting damage. The third technique was the denial of the victim. This technique has two forms; (1) when the deviant shifts blame to the victim, making them into a person deserving of the harm done, or (2) by diminishing awareness of the victim.

The fourth technique was the condemning of the condemners. In utilization of this technique, deviants shift the blame from themselves to those who disapprove of the act. For example, the delinquent may rationalize that their condemners participate in the same behavior and are thus, hypocrites. The last technique proposed by Sykes and Matza was the appeal to higher loyalties. For this technique the deviant rationalizes that they put the needs of some group over society, be it family or friends. This technique seems to have a great deal of overlap with delinquent subculture theories.

Over the year's theorist have expanded on Sykes and Matza's five original techniques. Four of these additional techniques were included in the current study (metaphor of the ledger, claim of normalcy, claim of entitlement, and the defense of necessity). The metaphor of the ledger was developed by Klockars (1974) from a qualitative study in which he conducted in-depth interviews with and observations of a professional fence. Klockars found that the fence justified his actions by stating that the good he had done in his life outweighed the bad. Klockars called this justification the metaphor of the ledger, making an analogy between a ledger for business transactions and a ledger for life.

Coleman (1985) likewise, developed three new techniques in a study of white-collar criminals. Two of these techniques will be utilized in this dissertation, the claim of normalcy and entitlement. For the claim of normalcy offenders rationalize that their behavior was not wrong because they perceive that everyone does the behavior. Coleman also developed the claim of entitlement. This technique is common in instances of employee theft. For this technique, offenders rationalize that they were entitled to what they took for reasons such as feeling cheated by their employer. Finally, Minor (1981) developed a new technique called the defense of necessity. With this neutralization technique, an individual argues that their behavior was not wrong because the act was deemed necessary.

According to Murana and Copes (2005) neutralization techniques should be crime specific. For this reason two new techniques of neutralization, specific to digital piracy, were developed for this study. These two techniques were developed specifically for the current study, and have not appeared in any past literature. However, the development of these two techniques is based on findings from past studies of digital piracy. The first new technique is called “the claim of future patronage”. “The claim of future patronage” is based on excuses made by digital pirates to explain their behavior in past qualitative studies. More specifically, digital pirates often indicate that they would eventually buy the product, and that they are only trying out the pirated copy (Holt and Copes, 2010). Thus, they minimize the harm of the act by rationalizing that the piracy is only temporary.

The second new technique focuses on individual perceptions of digital rights management software (DRM) as it relates to digital piracy. This technique is called “DRM defiance". To better understand the potential influence of this rational, the history and impact of DRM must be discussed. DRM is an umbrella term used to describe software designed to protect digital products from copyright infringement. According to Sinha, Machado, Sellman, (2010) "…DRM, is a term used to refer to the technical systems and technologies that digital publishers and copyright holders use to exert control over how consumers may use digital works" (41). DRM controls the ways in which a consumer can use the digital goods they purchased.

The behaviors of hacking and digital piracy are often intrinsically linked. The reason for this is simple. Most variants of digital goods come equipped with some form of digital management software (DRM) packaged with it. In order for protected software to be usable by people who download or exchange digital goods, it must first be cracked to remove the protection. It only takes a small number of individuals who are technologically knowledgeable enough to bypass DRM to make the cracked content available to a large user base (Haber, Horne, Pato, Sander, & Tarjan, 2003).

The cracking of DRM software and subsequent dissemination of the cracked digital product over illicit distribution is nearly inevitable, nearly all forms of DRM are eventually hacked (Myska, 2010). This has led to a digital arms race between hackers and companies attempting to protect their digital goods. The result of which has contributed to the development and use of DRM systems considered increasingly "draconian" by consumers. Past literature from economics indicates that DRM considered "draconian" might actually increase piracy (Sinha, Machoado, & Sellman, 2008).

These "draconian" DRM measures can have a negative effect on legitimate customers by restricting the utility of a digital product or making its use more cumbersome (Sinha, Machado,

& Sellman, 2010). In addition, these increased restrictions may begin to be perceived as a punishment. Individuals may act negatively if they perceive that their personal freedoms are being infringed upon unjustly. According to Milligan, Han, and Burestein (2003) DRM restricts the personal use of products in a manner that is not consistent with the norms of use established through traditional media consumption styles such as DVDs. The combination of these factors may lead to a rejection of DRM, leading to “DRM defiance”. With this neutralization technique digital pirates rationalize that piracy is okay because it allow them to circumvent the draconian DRM. Thus, the piracy becomes acceptable as the digital pirates vilify the DRM.

Differential reinforcement. Differential reinforcement plays a large part in determining whether an individual will initiate, continue, or desist from committing a particular behavior. According to Akers, “Differential reinforcement refers to the balance of anticipated or actual rewards and punishments that follow or are consequences of behavior” (2009, p.67). Whether an individual will commit a crime in either the future or the present largely depends on the rewards and punishments an individual has received in the past and present, as well as anticipated future rewards and punishments.

If an act produces rewarding outcomes, such as obtaining money, status, or pleasant sensations, it is more likely to be repeated. This refers to positive reinforcement. An act is also more likely to be repeated when it allows an individual to escape an unpleasant or negative event. This refers to negative reinforcement. As previously stated, rewards and punishments can be anticipated or actually received (Akers, 2009).

An individual is less likely to initiate or continue a behavior if they receive a punishment or perceive punishment as a likely outcome of their behavior. Punishment can also be positive or negative. According to Akers (2009) when referring to punishment the terms “positive” and “negative” are not meant to be evaluative. Instead, positive refers to the introduction of a stimulus, and negative refers to the removal of a stimulus. Positive punishment occurs when a behavior produces a painful or unpleasant response, and negative punishment occurs when the outcome of a behavior is the removal of something positive such as a reward.

Both punishment and reinforcement vary in frequency, amount, and probability. A behavior is more likely to occur if reinforcement occurs frequently, the amount of positive reward is high, and the probability of receiving the reward is high. Likewise if punishment occurs frequently, is considered severe, and is likely to occur, the punishment producing behavior is less likely. Because of the partial focus on punishment, it has been argued that the differential reinforcement aspect of social learning theory subsumes deterrence theory (Akers, 1990). Differential reinforcement covers a wider range of punishment and reinforcing outcomes making it a more comprehensive theoretical explanation for behavior than deterrence theory. For that reasons deterrence theory was subsumed under differential association for the current study. The rationale for this decision is discussed further in a subsequent section on deterrence.

Deterrence theory. Deterrence theory is largely influenced by the work of the 18^{th} century utilitarian philosophers Cesare Beccaria (1963/1764) and Jeremy Bentham (2010/1781). Bentham and Beccaria were primarily concerned with legal penal reform. The work of Beccaria and Bentham along with many of their contemporaries was instrumental in reforming the justice system, with many of the ideas they advocated remaining central components of our justice system today (Kubrin, Stucky, and Krohn, 2009: 22).

The classical view of deterrence is built on the principle that people are rational beings and can exercise free will. Being rational, people want to obtain pleasure and avoid pain. Thus, people will act in a way that maximizes pleasure and minimizes pain. An individual may find crime attractive, because it offers easy access to pleasurable things. However, a person's desire to commit crime may be countered by their fear of punishment. If a legal penalty threatens more pain proportionately to the potential gains of a crime, individuals will be less likely to commit crime. Thus, the more severe, certain, and swift the punishment the better it controls crime. (Kubrin, Stucky, & Krohn, 2009: 22).

Modern formulations of deterrence have changed little from the classical version. According to Gibbs, "Deterrence occurs when a potential offender refrains from or curtails criminal activity because he or she perceives some threat of a legal punishment for contrary behavior and fears that punishment" (1986: 87). Thus, the driving factor behind deterrence theory is fear of legal punishment. According to Akers the threat of legal punishment "is one source or indicator of aversive stimulus under the general concept of differential reinforcement (balance of rewarding and aversive stimuli)" (1990, p. 658). Therefore, the main components of deterrence theory (all of which represent the fear of legal punishment) correspond to a partial statement of differential reinforcement, representing positive punishment. For this reason, parts of deterrence were subsumed under social learning theory for the current study.

General Empirical Validity of Social Learning Theory

Past studies have demonstrated that social learning variables are some of the strongest predictors of crime and deviance (Matsueda, 1982; Warr, 2002; Akers & Jensen, 2006) leading some researchers to conclude that it is the most strongly and consistently supported theory in criminology (Akers and Jensen, 2006). In addition, Akers has noted that all studies that support Sutherland's differential association theory also support social learning theory (Akers and Sellers, 2004). However, the theory is rarely tested with a full model containing measures representing all four of its central components.

When social learning theory is tested in multivariate models against other criminological theories, it often has the strongest effect on criminality (Matsueda, 1982; Agnew, 1991; Jang, 2002; Neff & Waite, 2007; Hwang, & Akers, 2006). Additionally, being a general theory of crime, social learning theory has been successfully applied to a wide range of deviant and criminal behaviors. Most of the studies examine minor forms of criminality such as drug use (Hwang & Akers, 2006; Akers et. al. 1979; Akers & Lee, 1999) however; it has also been applied to more serious forms of criminality such as rape (Boeringer, Shenham, & Akers: 1991). With the rise of the digital age, researchers have begun to apply social learning theory to emerging crimes such as digital piracy (Skinner & Fream, 1997).

Like general tests of the theory, multivariate tests of digital piracy generally find moderate support for social learning theory even after controlling for other theoretical perspectives (Morris & Higgins, 2009; Gunter, 2009; Higgins, Fell & Wilson, 2006; 2007). In Gunter's (2009) multivariate tests of social learning and deterrence theory, the social learning variables were significant for all three types of piracy examined. The significance of the social learning variables remained after the control variables and competing theories were entered into each model. Gunter's study included one measure of differential association, asking respondents how many of their friends pirate. The study also included one differential reinforcement variable, asking if their parents would approve of them pirating. Another multivariate test of digital piracy was conducted by Morris and Higgins (2009). In their study, they included variables from social learning theory, neutralizations, self-control, microanomie, and strain theory. Out of the theories examined, the social learning variables were found to be the strongest predictors of digital piracy. Higgins, Fell, and Wilson (2006) examined digital piracy utilizing social control theory and social learning theory. They gave a self-report questionnaire to college students with measures of low self-control, social learning theory, and digital piracy. From their results, the authors concluded that digital piracy is attractive to people who have low self-control and have learned digital piracy through social learning. Based on these findings it is clear that social learning theory is a moderately good predictor of digital piracy.

As the reviewed literature indicated social learning, theory is a promising theory for explaining individual involvement in digital piracy. However, most digital piracy studies only include measures of differential association and definitions, meaning the preponderance of studies have only been partial tests of the theory. To date, the only study to test a full model of social learning on digital piracy was conducted by Skinner and Fream (1997). The results of a regression model with all the social learning variables included indicated that social learning theory accounted for 37% of the variance explained in software piracy. The current study will improve on Skinner and Fream's methods by including more measures of social learning theory.

All of the studies previously reviewed in this section only tested offline sources of social learning. However, the current study tested both online and offline sources of differential association and imitation. For this reason, the literature related to online sources of social learning are examined in the following section.

Learning from Online Peers

As previously discussed, few studies have examined the influence of online peers in relation to digital piracy. In this section the small amount of research regarding online peers is reviewed. Some studies examining online communities have demonstrated that online communities share many characteristics with offline communities (Etzioni & Etzioni, 1999; Miller & Gergen, 1998). However, according to Etzioni and Etzioni (1999), communal sharing of culture is more easily achieved online. In many forms of online communication, such as chat rooms, discussions are saved. Accordingly, they are easily retrieved and remembered later. This creates greater exposure in duration and frequency to both definitions and differential reinforcement, as well as easy access to modeled behaviors. Based on surveys with 164 known hackers, Chantler (1996) concluded that computer related crimes might require a greater dependence on peer learning sources, with much of the transference of knowledge occurring online. Studies examining hackers have also indicated that techniques and definitions in favor of hacking are transferred through online peer groups and communities, such as message boards, internet relay chats (IRCs), and chat rooms (Rogers, 2001; Holt, 2007). These studies demonstrate the possible importance of online learning sources.

Many studies that address online learning focus on deviant subcultures. Cooper and Harrison (2001) conducted an online ethnography aimed at identifying the social organization of a subculture of online audio pirates. They found that the audio pirate subculture has many similarities to hacker subcultures. For example, the members of the subculture interacted almost exclusively online. In addition, subculture members with highly developed technical skills often received a higher level of respect. These high status individuals were often those who crack protected software, and hosted file sharing servers. Although Cooper and Harrison's study did not specifically examine online social learning, their study does hint at its potential importance.

While some studies have examined the characteristics of online deviant cultures (Cooper & Harrison, 2001), few have examined the influence of online peers on the social learning processes that lead to digital piracy. This is a significant gap in the literature when you consider that the behaviors are largely carried out online. Considering the technological nature of digital piracy, it is possible that online peer groups are just as important as offline peer interaction in the transference of definitions favorable to piracy, as well as providing models to imitate and reinforcing behavior.

Although studies have demonstrated the potential importance of online peer influence on behavior, only two studies have specifically examined the effect of online social learning variables on digital piracy. They first study, by Holt and Copes (2010), examined the transference of subcultural knowledge online by interviewing 34 persistent digital pirates, and conducting a non-participant ethnography of online message boards devoted to piracy. The study examined themes not considered in the previous literature. First, the study examined how the transmissions of norms, values, and beliefs within a group of like-minded individuals can lead to the formation of a criminal subculture. Second, it is the only study to date that examined the influence of online interactions in the facilitation of norm transmission. In other words, this is the only study to date to examine how definitions favorable to piracy can be transmitted and reinforced through online interactions which eventually leads to a subculture of digital pirates.

The second study to examine online peer influences was conducted by Hinduja and Ingram (2009). Hinduja and Ingram examined the influence of both on and offline peer interactions on digital piracy. For the study, a questionnaire was administered to approximately 2,000 university students within randomly selected classrooms. The dependent variable for the study was a composite scale of music piracy measures. The main independent variables included multiple measures of peer influence, both online and offline. For the study, offline peer influences were conceptualized as real life friends (real life peers), and popular media that may instruct an individual (popular media). Online peer influences were conceptualized as individuals who one may interact with online (online peers), and social artifacts one might interact with on the internet such as blogs, or news stories (online media).

The results of this study showed that all four of the peer interaction variables had a significant effect on music pirating behavior. The four variables combined to explain 13% of the variance in music piracy. Out of the peer influence variables, it was found that real life peers had the strongest effect on pirating behavior followed by online media, online peers, and popular media. Music piracy scores were significantly higher if a participant reported learning the behaviors from both online peers and online media. When control variables were introduced into the model all of the peer variables except popular media remained significant (Hinduja & Ingram, 2009).

As previously stated, deterrence and neutralization theory are subsumed under social learning theory for the purposes of this study. For this reason, the empirical evidence of both theories are examined in the following two sections.

Empirical Evidence of Deterrence Theory

Overall, the empirical validity of deterrence theory is mixed (Pratt, Cullen, Blevins, Daigle, & Madenson, 2006; Cook, 1980; Greensburg, & Kessler, 1982; Paternoster, 1985; 1987). Deterrence theory has been tested at both the macro and individual level. At the individual level, studies often test deterrence theory based on individual perceptions and responses to scenarios.

Pratt et. al. (2006) conducted a meta-analysis of deterrence studies utilizing perceptual measures. Perceptual deterrence measures often ask respondents how likely they would be caught committing a crime (certainty), or what would be the likely punishment for a crime (severity). The results indicated that on average, severity of punishment did not produce a deterrent effect, while certainty did produce a deterrent effect. However, it was weak producing a low mean effect size. It was also found that celerity of punishment is rarely measured. Pratt et. al. also found, that the effect sizes of deterrence variables are greatly reduced in multivariate models that include variables from other theories such as social control or social learning. Interestingly, the deterrence estimates from the study conducted by Pratt et. al. (2006) found higher levels of support for white color offenses. This was particularly true for the certainty of punishment estimates. This may indicate that white-collar offenders take risk into greater consideration when committing a crime.

Few studies have examined the effect of deterrence on the crime of digital piracy. Like the literature for deterrence theory in general, studies have found mixed results applying deterrence variables to digital piracy (Gopal & Sanders, 1997; Peace, Gellata, & Thong, 2003; Higgins, Wilson, & Fell, 2005; Skinner & Fream, 1997; Sinha and Mandel, 2008; Gunter, 2009). Qualitative statements made by digital pirates clearly support deterrence theory. Through ethnographic observations within the online digital piracy community, Cooper and Harrison (2001) found that digital pirates are not afraid of being prosecuted for their actions because they view the chances of detection and prosecution as low. In addition, many thought the most likely punishment they would receive if caught was the deactivation of their internet. Thus, the digital pirates in Cooper and Harrison’s sample perceived the severity and certainty of punishment for digital piracy as low. However, Cooper and Harrison’s observations were based on interactions with individuals deeply imbedded in the digital piracy subculture at the time. Thus, their findings may not be generalizeable to the current population under study.

Quantitatively, the relationship between deterrence theory and digital piracy has been tested multiple ways. Multiple studies have utilized a factorial design. Gopal and Sanders (1997), for example, administered two sets of questionnaires to 123 M.B.A. students. For the study, the dependent variable was a scale based on the respondent’s willingness to engage in four different software piracy scenarios. Half of the participants in the study (61) were provided with information regarding the copyright laws at the time of the study including, the consequences of being caught, the negative effects of piracy on consumers and the industry, and actions taken by the Software Publishers Association to curtail piracy. The presence of the deterrence information was considered a treatment variable. The results of an OLS regression indicated that individuals who received the deterrence information demonstrated lower levels of piracy acceptance.

Other studies of digital piracy have tested deterrence theory as the respondent's perceived certainty and severity of punishment if they were caught pirating digital goods. Gunter (2009) conducted multiple multivariate tests of digital piracy, examining the impact of social learning theory, deterrence theory, and multiple control variables. Surveys were administered to 513 undergraduate students in a non-random selection of classes at a Mid-Atlantic Public University. Three different types of piracy were measured as separate independent variables (music, software, and movie piracy). Certainty of punishment was measured by asking respondents what they thought the chances of being caught and punished were for each piracy type, with responses ranging from extremely likely to unlikely. To capture severity, respondents were asked what they thought the punishment was for each type of piracy if they were to be caught. For severity, five response categories were used ranging from "no punishment" to "jail/ prison time". However, the variables were recoded as a dichotomous variable representing severe and not severe punishment. The only social learning theory variables included related to differential association, measuring peer involvement and parental approval. This study is more complete than many other digital piracy studies because many more control variables were included, such as parental income, personal income, internet speed, and technical ability.

The results from Gunter's (2009) study demonstrated strong support for social learning theory, but only marginal support for deterrence theory. Deterrence variables were only significant in the software piracy model. In addition, when the control variables were entered into the model the significance of certainty of punishment was lost. Thus, this study indicated that deterrence theory is a weaker predictor of digital piracy than social learning. The current study tested the effects of certainty and severity of punishment as perceptual measures in a similar manner to Gunter (2009).

Empirical Evidence of Techniques of Neutralization

In this section, the empirical evidence of Sykes and Matza's (1957) techniques of neutralization is explored. For the current study, neutralization theory was subsumed under social learning theory. This is a common practice in the literature, as techniques of neutralization have often been used as a measure of the definitions concept in social learning theory.

Qualitative studies have often been instrumental in the further development of neutralization theory. It is often through qualitative studies that new techniques are discovered (Klockars, 1974). In addition, qualitative studies allow for a more detailed examination of neutralizing definitions presented in the respondents own words. More and McMullan (2009) conducted in-depth interviews with 44 university students who identified as being file sharers. The primary focus of the study was on examining the neutralization techniques used by digital pirates. The authors used a semi-structured questioning approach. The participants were asked questions related to the legality of file sharing, their level of participation in the behavior, and other questions related to the behavior of file sharing. In addition, participants were asked if they would ever shoplift from a retail store. A final structured question asked participants why they participated in file sharing after discovering the activity was illegal. The questions were asked in this manner so the authors could see if neutralization techniques emerged without leading the respondents.

All participants in the study responded that they were aware that piracy was illegal, and 96% said they would never shoplift. Regarding neutralization techniques, the participants provided evidence of using six of the ten techniques pre-identified from the literature by the authors. Perhaps most interesting, 100% of the respondents vocalized a neutralization technique as their primary response for why they continue to participate in piracy even after knowing it is illegal. This demonstrates that neutralizing definitions are perhaps the main method digital pirates use to account for their behavior. The study found the greatest support for the denial of injury, the denial of the victim, and the claim of normalcy.

Past studies have demonstrated the extent to which neutralization theory can be applied to numerous behaviors. Hinduja (2007) examined digital piracy utilizing Sykes and Matza's techniques of neutralization as a framework. For this study, a self-report measure was given to students measuring levels of neutralization acceptance as well as a measure of past copyright infringement. The neutralization scale provided the following partial statement "I would be more likely to download/ upload commercial full version software" (p. 191) followed by various "if" statements representing techniques of neutralization. The participants rated their agreement with each "if" statement. These answers were then used to construct a neutralization scale. Overall, Hinduja (2007) found weak support for the applicability of neutralization theory as an explanatory factor of copyright infringement. However, this may be due to methodological problems with the study. It is possible that the statement prefixing the neutralization scale was too broad, because it could be interpreted as applying to legal as well as illegal behavior. For this reason, the theory may be more applicable than Hinduja (2007) observed.

A second cross-sectional study conducted by Ingram and Hinduja (2008) also found that participation in digital piracy was affected by neutralization acceptance. The dependent variable for the study asked participants how often they had pirated music. Response categories were created to represent no piracy participation (0), low participation (1-10), medium participation (11-100), moderate participation (101-1000), and high participation (over 1000). The study tested four neutralization techniques: denial of responsibility, condemnation of condemners, appeal to higher loyalties, and denial of injury/ denial of victim. The results of a multinomial logistic regression indicated that denial of responsibility, denial of injury/ denial of victim, and appeals to higher loyalty were significant predictors of moderate digital music piracy. The measures representing appeal to higher loyalty were also significant predictors of high levels of digital piracy participation (Ingram & Hinduja, 2008). The results of this study were supportive of neutralization theory; however Ingram and Hinduja's study only included measures representing Sykes and Matza's (1957) five original techniques of neutralization. As previously discussed multiple new techniques were added since Sykes and Matza's development of the theory, such as the metaphor of the ledger, when possible studies should include these new techniques.

A recent longitudinal study by Higgins, Wolfe, and Marcum (2008) examined digital piracy and its link to neutralization techniques. Their study used a short-term longitudinal design consisting of four waves over a four-week period. For the first wave of their study Higgins, Wolfe, and Marcum (2008) measured gender and low self control, and for all four waves intentions and digital piracy were measured. The results of the study showed support for neutralization theory by demonstrating that participants used such techniques to absolve themselves from the criminality of the behavior. Also of interest, the results showed that the initial levels and changes in criminal behavior paralleled the initial level and changes in neutralization. From this, the authors concluded that neutralization theory could be considered a theory of dissonance.

Demographics and Digital Piracy / Control Variables

Most studies of digital piracy only utilize a moderate number of control variables. The two most common control variables are gender followed by age (Hinduja, 2006; Higgins & Makin, 2004; Skinner & Fream, 1997; Morris & Higgins, 2009, 2010; Higgins, Wilson, & Fell, 2007). Hinduja (2006) found that younger college students were more likely to pirate. However, the majority of studies have found that age is not a good predictor of digital piracy (Higgins & Makin, 2004a, 2005a). This could be due to low levels of variance in sample ages in most studies, because most samples utilize college students. This would likely be a problem with the current study, thus age was not included as a control variable.

Early studies regarding digital piracy nearly universally demonstrate that males pirate more than females (Hollinger, 1993; Skinner & Fream, 1997). More recent studies have been mixed. Two recent studies found gender to be insignificant in determining a person's *propensity* for software piracy (Higgins & Makin 2004). However, the majority of studies have indicated that males *participate* in digital piracy at a higher rate than females (Gunter, 2009: Hinduja, 2001, 2003; Higgins, Wilson, & Fell, 2005).

Technical ability may be another important factor in predicting digital piracy. Two studies that have tested the effect of technical ability have found it to be a statistically insignificant predictor of computer crime (Higgins & Wilson, 2006; Higgins & Makin; 2004). However, according to Gunter (2009) both of these studies utilized measures of technical ability that did not capture the reality of what can be considered a high level of technological sophistication today. Additionally, other studies have demonstrated that higher technical ability is associated with digital piracy (Higgins & Ingram, 2009; Hinduja, 2001; Hinduja; 2003; Gunter, 2009). Hinduja and Ingram, (2009) tested internet proficiency by asking respondents about their experiences conducting 10 online activities, such as building a web page, and setting up mail server preferences. These variables were combined into a scale representing internet proficiency. Their results indicated that a higher level of internet proficiency is associated with increased digital piracy. Their study also indicated that faster internet connectivity was associated with higher piracy rates.

Hinduja and Ingram (2009) also included a group of questions designed to measure the activities the respondent frequently participated in online. For this measure, respondents were asked to indicate the reasons they used the internet from a list of possibilities, such as email, research, shopping, and gaming. The results were combined into a five-point scale, with participations in a higher number of online activities corresponding to a higher score. Results for this portion of their study indicated that those individuals who used the internet for a larger variety of tasks were more likely to participate in digital piracy. In addition to measuring internet proficiency and variety Hinduja and Ingram also included a question designed to measure the respondents home internet speed. Internet speed was measured as a dichotomous variable, with 1 representing high speed internet and a 0 representing low speed internet. They found that individuals with high speed internet connections were more likely to participate in digital piracy.

Income and employment status have also been used as statistical controls, however these two variables are usually not found to be significant (Hinduja, 2003; Gunter, 2009; Hinduja & Ingram, 2009; Higgins, Fell, & Wilson, 2007; Morris & Higgins, 2009). Despite the failure of many studies to find significance with income or employment, qualitative studies have found that digital pirates often attribute a lack of being able to pay for a product as their primary reason for downloading a product illegally. Thus, income and employment may be important for instances of digital piracy in which the product being pirated was expensive, such as software piracy. For this dissertation, was not included because it was decided that it would likely not have enough variability given the population being studied. For that reason, only employment was examined for the current study.

Conclusion of Literature Review

The current study expanded the literature on digital piracy in many ways. First, it examined four different types of piracy: software, movies, music, and computer games. Few studies had included more than one form of digital piracy, and to the researcher's knowledge computer game piracy was not examined as an individual variable prior to this study.

Next, this dissertation also expanded the understanding of social learning theory in many ways. Taken as a whole, past studies have found support for all four of the main components of social learning theory when examining digital piracy. Despite positive findings, there have been few full tests of social learning variables on digital piracy. In the past, only one study has included all four social learning variables to test digital piracy (Skinner & Fream, 1997). Thus, the current study was only the second study to test a full model of social learning theory on digital piracy while also including elements from neutralization and deterrence theory for definition and differential reinforcement variables. Since Skinner and Fream's study, digital piracy has changed significantly. For example, digital piracy has become easier allowing less technologically sophisticated individuals the opportunity to pirate freely (Holt & Copes, 2010). For this reasons, a full test of social learning theory was warranted once again. In addition, Skinner and Fream's (1997) study only included gender as a control variable, while the current study inlcuded multiple control variables.

Third, a review of the existing literature demonstrated that the understanding of the influence of social learning variables on digital piracy is incomplete, largely ignoring the potential effects of online peer influences. The current study expanded on the past literature by examining both offline and online sources of social learning.

Research Questions and Hypotheses

Given the previous literature, the following research questions and hypotheses were tested in the current study.

Q1. What is the relationship between online and offline sources of social learning variables (i.e., differential association, imitation, differential reinforcement, and definitions) and digital piracy after controlling for demographic characteristics?

H_a (1): Variables representing on and offline sources of differential association are positively related to individual participation in digital piracy.

H_a (2): Variables representing on and offline sources of imitation are positively related to individual participation in digital piracy.

H_a (3): Variables representing positive and neutralizing definitions are positively related to individual participation in digital piracy.

H_a (4): Variables representing positive reinforcement in response to pirating behaviors are positively related to individual participation in digital piracy.

H_a (5): Variables representing punishment are inversely related to individual participation in digital piracy.

Q2. What is the relationship between the various control variables and digital piracy?

H_a (6): Males are more likely to participate in all forms of digital piracy compared to females.

H_a (7): Internet and computer proficiency is positively related to participation in all forms of digital piracy.

H_a (8): Individuals with high speed internet connections are less likely to participate in all forms of digital piracy compared to individuals without high speed connections.

H_a (9): Individuals who are employed are less likely to participate in all forms of digital piracy.

CHAPTER III

METHODS

A quantitative cross sectional design was used to test the above stated hypotheses. Data was collected from a sample of college students at two universities. To collect the data, a survey was used. The primary goal of the study was to examine the relationship between variables representing social learning theory and digital piracy. This chapter presents the methods and data collection strategy for this study, including a discussion of the research design, sampling, survey methodology, strengths and limitations of the design, the steps taken to insure human subject protection, and the analysis plan.

Site Selection and Sample

The unit of analysis for this study was college students enrolled at two eastern universities for the fall 2011 semester. Both graduate and undergraduate students were included in the study. In the fall of 2010, university one had 15,126 students, with 57% of the students being female and 43% being male. University one had 12,827 undergraduate students and 2,299 graduate students. In the fall of 2010 the second university had 4,709 students; including 4362 undergraduate and 347 graduate students. In addition, it had 2674 (56%) female and 2035 (44%) male students. The sample for the proposed study consisted of undergraduate and graduate students from both universities. This study was open to both male and female respondents who were 18 years old or older at the time of the study.

College students are not the ideal population to study for many types of crime, since the population may differ significantly from criminal populations. However, college students often have a greater level of access to high-speed internet compared to the general population (Jones, 2002), making it easier for them to commit digital piracy. In addition, college students exhibit a high level of technological literacy (Kaminski, Seel, & Cullen, 2003). Due to their high level of access to high-speed internet and familiarity with technology it is not surprising that past studies have demonstrated that college students commit high levels of computer crime. This is especially true for digital piracy, making university students a suitable population for the study of digital piracy (Cronan, Foltz, & Jones, 2006; Rogers, Seigfried and Tidke. 2006).

To determine the needed sample size, the computer program GPOWER (Erdfelder, Faul, & Buchner, 1996) was utilized. The alpha level for the study was set at .05, and the most sophisticated statistical technique used was originally going to be ordinary least squares multiple regression. Based on the above criterion, when a medium effect size is expected (.15) and thirty two independent variables, a minimum sample of 193 participants was needed. However, due to the low response rate common with internet-based surveys, a larger number of respondents were requested from both universities. At both universities a random sample of 1000 students were asked to complete an on-line survey.

To obtain the sampling frame for the first college population, a randomly generated list of 1,000 current students and their email addresses was requested from a research lab after IRB approval had been obtained. A random sample of 1,000 current students and their email addresses was also requested from the second university. The emails at the second university were provided by the Information Systems department after IRB approval was obtained. Once the sampling frame was obtained from both universities, the email addresses of the sample were placed into two panels in the web based survey software, Qualtrics: one for each university. Once the panels were created, emails containing a link to the on-line survey were sent inviting the students to participate in the study.

This first random sample yielded only 150 returned surveys. Based on the power analysis a minimum of 197 was required. Thus, a second random sample was needed. Subsequently, 1,000 students were selected from the student bodies of each universities and a second wave of surveys were sent. In total, 4,000 students were invited to participate in the study. In all, 356 students responded to the survey, 213 from university one and 143 from university two. This represented a response rate of 10.65% from university one and 7.15% from university two, with a combined response rate of 8.9%. Low response rates are common with internet-based surveys (see, for example, Sax, Gilmartin, and Bryant, 2003) and introduce the possibility of non-response bias. This issue is discussed in greater detail in the conclusions chapter IV. Each of the 356 cases was examined for incomplete data. Fifty-two cases were removed due to incomplete data or outliers, making the final sample size 304. Each of the removed cases were either extreme outliers (e.g. one respondent who indicated they had pirated over a million times in each category over the past month), or did not complete a substantial portion of the survey (e.g. stopped halfway). The removal of these cases resulted in a final response rate of 304 out of 4,000 (7.6%).

Research Design

As previously stated, the current study utilized a cross sectional survey design. According to Menard (2002b) "[I]f the research question or hypothesis can be addressed satisfactorily with cross sectional data, there is little or no point in trying to use longitudinal research to answer the research question or test the hypothesis" (p.78). A cross sectional design was sufficient for the proposed study, because the study does not seek to address causation. Rather, the current study examined the correlation relationship between the dependent and independent variables under study. Thus, all of the study's hypotheses are adequately answered with a cross sectional design.

Additionally, cross sectional research is generally cheaper and less time consuming than longitudinal research, which made a cross sectional design preferable for the proposed study.

Survey Design

In this section, the variables utilized in the survey are discussed. First, the dependent variables are discussed, followed by the independent variables that include social learning theory, demographics, and control variables.

Dependent Variable

The dependent variables for this study included eight separate measures of digital piracy. For this study, digital piracy was conceptualized as the unlawful copying of digital products (software, digital audio files, digital video files, and PC games) without the owner’s consent, and without compensation to the owner. This conceptualization is similar to the definition of piracy used by Gopal, Sander, Bhattacharjee, Agrawal, & Wagner (2004).

In the past, studies focusing on digital piracy have generally measured digital piracy as either a self-report measure of past involvement in digital piracy (involvement) or as a scenario based measure designed to capture a person’s willingness to participate in digital piracy (willingness) (Morris, & Higgins, 2009; 2010; Gunter, 2009). The current study measured both involvement and willingness for four different types of digital piracy (digital piracy, software, movie, music, and PC game) for a total of eight dependent variables.

Each involvement question had two parts. First, respondents were asked if they have participated in each form of digital piracy (music, video, software, and PC game) over the last year, with a binary answer choice (no, yes). For example, the question for music piracy asked, “Have you downloaded a music file without the owner’s permission within the last year?” If a respondent answered “yes” a follow up question was provided. For the follow up question respondents were asked to indicate the number of times they have participated in each of the four piracy types over the one-year period prior to the administration of the survey [e.g., “If yes, how many music files have you downloaded without the owner’s permission within the last month?”]. Splitting the question into two parts made the question applicable to all respondents, and allowed for the desired information to still be obtained. For the analysis the two parts of the involvement question were combined to make one continuous variable. This allowed each involvement variable to be treated as a ratio level variable.

For the willingness measures, four vignettes were provided. Each vignette provided the respondent with a scenario specific to each of the four types of digital piracy examined. The movie and music vignettes were adapted from those used by Morris and Higgins (2010). The movie piracy vignette states,

> A popular movie has just been released in theaters nationwide. All your friends have seen the movie and told you that it is great and that you have to see it! Unfortunately, every time that you try to go see the movie, you cannot because the tickets are always sold out. However, a friend tells you about a Web site that has posted an underground copy of the entire movie. The site will only allow visitors to download the movie before it can be viewed. You really want to see the movie.

The software and pc game vignettes were original to the current study. For example, the pc game piracy vignette stated, “A popular computer game has just been released nationwide. All of your friends have played the game and told you it is great and you should get it! While discussing your intentions to buy the game a friend tells you that an unauthorized copy of the entire game can be obtained online for free.” At the end of each vignette, the respondent was asked to indicate how likely they would participate in the behavior described in the vignette. Respondents provided their answer on a visual analog scale, anchored with the responses very likely and very unlikely. Values on the scale range from 0-100, and respondents selected their response using a sliding bar. The use of a visual analog scale allowed the four willingness variables to be treated as ratio level data (Reips & Funke, 2008), meaning they could be analyzed using ordinary least squares regression.

Independent Variables

The current study originally had thirty-two independent variables. Twenty seven of these variables were designed to measure the four components of social learning theory. The remaining five variables measured demographic characteristics that past studies had indicated may be important predictors of digital piracy.

Social Learning Variables. The four components of social learning theory are differential association, definitions, imitation, and differential reinforcement. After an exhaustive search failed to uncover alternatives it appears that Skinner and Fream's (1997) study was the only study of digital piracy prior to the current study to test a full model of social learning theory. For the most part, other studies of digital piracy only examined differential association and definitions. The current study included measures for all four components of social learning theory. These are discussed in turn below.

Differential Association. According to Akers (2009), and as a re-thinking of Sutherland (1947), differential association refers to direct and indirect interactions with people and groups an individual is exposed to throughout their life. The current study examines the link between multiple sources of differential association and digital piracy. In the past, digital piracy studies have often examined the impact of differential association by measuring the number of friends an individual has that participate in digital piracy (Skinner & Fream, 1997; Gunter, 2009). Three questions in the proposed study followed this format. Respondents were asked how many of their best friends, friends they hang out with the most, and friends they have known the longest participate in digital piracy. Pasts research regarding social learning theory has used this framework to measure the intensity (best friends), frequency (friends they hang out with the most), and priority (friends they have known the longest) of deviant peer association. Four response categories were provided based on previous examinations of differential association in the literature (Akers, 1979; Akers, et. al. 1983). The response categories for the current study included none (coded as a 0), less than half (coded as a 1), half (coded as 2), more than half (coded as a 3), and all (coded as a 4). Based on past research indicating a high level of intercorrelation between the three measures, the responses for the three questions were combined into a composite score representing association with "real life" pirating peers (Aker, 1979; Akers et al, 1983; Skinner & Fream, 1997; Gunter, 2009). The scaled score ranged from 0 to 9, with higher values representing greater association with real life digital pirates.

Although many studies have examined the effect of associating with digital pirating peers, few have examined *online* peer influences. To date, only one quantitative study of digital piracy has included measures of online sources of differential association (Hinduja & Ingram, 2009). The current study included four measures of online differential association as applied to digital piracy. Respondents were first asked, "Do you associate with others online through any of the following means (chat, message boards, social networking, or multiplayer online games)". The response categories included yes and no. If respondents selected no they automatically skipped the three questions regarding online differential association. If they responded "yes", they were provided three additional questions about their association with online peers. The first of these measures was adapted from Hinduja's and Ingram's (2009) study. For this measure respondents were asked to indicate their level of agreement with the following statement, "I associate with others online who exchange pirated copies of digital goods (music, movies, software, and games) with me". For this measure respondents were provided four response categories (Strongly Disagree, Disagree, Agree, and Strongly Agree).

The other three measures of online differential association were developed specifically for the current study. These three measures were based on past studies that measured differential association as the perceived approval or disapproval peers place on a deviant act (Akers, 2009; Akers et al., 1979; Agnew, 1991). In addition, these three measures were developed to measure intensity, frequency, and priority of online peer association. All three of these variables measured the respondent's perceptions of how those they associate with online view digital piracy. The first stated, "The people who I have associated with online the longest view digital piracy in a positive light". The second stated, "The people who I associate with online the most view digital piracy in a positive light". The third stated, "The people I associate with online who I consider to be close friends with me view digital piracy in a positive light". Once again respondents were asked to indicate their level of agreement from strongly disagree to strongly agree. The four online differential association variables will be scaled into a composite score representing online peer influences. The internal consistency of the combined online peer influence variable will be analyzed. The scaled score will range from 0 to 12, with higher values representing greater association with online digital pirates.

Imitation. Imitation refers to an individual engaging in a behavior after witnessing someone else participate in the behavior (Akers, 2009). Prior to the current study, the only study to examine imitation with regards to digital piracy was the early study conducted by Skinner and

Fream (1997). To test imitation Skinner and Fream asked respondents how much they had learned about piracy from a number of sources including, family, teachers, books and magazines, television and movies, and computer bulletin boards. Responses ranged from “learned nothing” to “learned everything”. The imitation measures for the current study were based on those used by Skinner and Fream. However, the current study included multiple sources of modeling not covered by Skinner and Fream. These new sources of modeling were necessary due to changes in technology from the time when Skinner and Feam conducted their study. In the current study, respondents were asked how much they have learned about digital piracy from eight sources. The sources of modeling included: real life peers, online peers, books or magazines, television or movies, message boards, streaming online videos, Wiki’s, and directional web pages. Respondents were provided a 100 point visual analog scale anchored with the responses “learned nothing” (0) and “learned everything” (100). Respondents selected their answer with a sliding bar. The use of visual analog scales allowed each imitation variable to be treated as ratio level data (Reips & Funke, 2008). Which allowed each imitation variable to be entered separately in the OLS multiple regression models.

Differential Reinforcement. Differential reinforcement refers to the effects of rewards and punishments on current and future behavior. Few studies have examined the impact of variables representing differential reinforcement on digital piracy. When past studies included measures of differential reinforcement they were usually variables representing the impact of certainty and severity of punishment (Skinner & Fream, 1997). Based on the items created by Skinner and Fream (1997), the current study measured certainty of punishment as the respondent’s perceived likelihood of detection of participation in digital piracy. Four response categories were provided (extremely unlikely, unlikely, likely, and extremely likely). The effects of severity of punishment were measured by asking respondents what the penalty would be if they were caught participating in digital piracy. Response categories were based on those used by Gunter (2009), with five possible choices (nothing, small fine, loss of internet access, heavy fines/lawsuit, and jail/ prison). For the analysis these categories were combined to create a dichotomous variable representing severe (heavy fines/lawsuit, and jail/ prison) and non-severe (nothing, small fine, loss of internet access) punishment. Severe punishment was coded as a 1 and non-severe punishment as a 0.

Punishment is not the only negative consequence associated with participation in digital piracy. Prior studies demonstrated that digital pirates were concerned with receiving viruses (Holt & Copes; 2010; Wolfe, Higgins, & Marcum, 2008). Thus, receiving a virus or the threat of receiving a virus may be an important representation of a negative consequence (punishment) for piracy. The current study asked respondents if they had ever received a virus from downloading pirated materials, with a simple dichotomous response (yes, no). Respondents were also asked what they felt were the chances of receiving a virus due to participation in digital piracy. Response categories ranged from "very unlikely" to "very likely".

As described in the literature review, past studies of digital piracy had focused almost exclusively on the influence of negative forms of reinforcement. The current study expanded on the past literature by including multiple measures representing positive reinforcement. The current study included three newly created measures of positive reinforcement, based on positive incentives found to be important to pirates by Holt and Copes (2010). The first new measure was based on the potential to save money (economic benefit). This question stem for this measure stated, "Participation in digital piracy would help me because I could save money". The second focused on positive feelings associated with digital piracy (positive feelings). The question stem for the positive feelings measure stated, “I would feel good after downloading pirated copies of music, movies, software, or games online without paying”. The final positive incentive to pirate identified by Holt and Copes is the ability to access media in a convenient manner (convenience). This measure stated, “participation in digital piracy would positively affect me because I could download digital goods when I want to”. Four response categories were provided for each positive reinforcement variable (strongly disagree, disagree, agree, and strongly agree). The internal consistency of the three positive reinforcement variables was checked. If the variables hung together they were combined into a single measure in the final analyses. If not the three variables were entered into the regression models as separate variables.

Definitions. The current study included measures for definitions favorable and unfavorable to digital piracy. Two measures of positive definitions were adapted from a study by Morris and Higgins (2010), originally created by Rahim et al. (2001). The two definitions stated that using copied movies or music for entertainment is “ok” (Morris & Higgins, 2010). For example, one of the definitions adapted from the study by Morris and Higgins states, “I think it is okay to use copied music for entertainment.” In addition, a new measure representing a positive definition for digital piracy was created for this study. The stem of the question states, “I feel that all digital goods should be provided free for everyone”. This question represented the view found to be held by some hackers and digital pirates that the free exchange of information and digital goods over the internet is a virtue (Holt and Copes, 2009). The current study also included one measure of an unfavorable definition to digital piracy, asking respondents how much they agree with the statement “I feel that downloading or uploading copyrighted material without the owner’s permission is never okay”. The responses to all three definitions utilized a Likert item with four response categories (strongly agree, agree, disagree, and strongly disagree). All four definitions were combined into a Likert scale, with the definition unfavorable to digital piracy being reverse coded.

The study also included multiple measures for neutralizing definitions. According to Akers, “neutralizing definitions favor violating the law or other norms not because they are positively desirable but because they justify or excuse them” (2009, 79). Many of the neutralizing techniques used in the current study were adapted from the work of Hinduja (2007), and Morris and Higgins (2010) (See Appendix C). To measure neutralization acceptance a subscale was created for each of the neutralization techniques examined. The neutralization techniques included were the denial of responsibility, denial of injury, denial of a victim, condemning the condemners, an appeal to higher loyalties, the defense of necessity, the metaphor of the ledger, the claim of normalcy, and the claim of entitlement. In addition, two new techniques were created that apply specifically to instances of digital piracy (i.e., claim of future patronage, and DRM defiance).

According to Maruna and Copes (2005), studies utilizing neutralization techniques should make the techniques crime specific. For this reason, two new techniques were created for this study specific to digital piracy. The two new techniques were “the claim of future patronage” and “DRM defiance” (See Appendix A). With the claim of future patronage it is expected that digital pirates rationalize that they will eventually buy what they pirate. In this way they minimize the harm of their behavior. Two questions were created to measure the claim of future patronage. The first measure for this technique stated, “If I like a product that I pirate I will go buy the product, therefore my pirating actually helps the company”. And the second stated, “I will pay for the majority of the things I pirate when I graduate and make more money than I do now”. With the DRM defiance neutralization technique, digital pirates rationalize that piracy is desirable because it allows them to circumvent draconian DRM protections. Two questions were included to measure DRM defiance. The first stated, “pirated copies of products are often superior because copyright restrictions are removed allowing more freedom of use”. The second questions testing DRM defiance stated, “when people pirate digital goods, companies are getting what they deserve for using copyright protection that harms paying customers”.

When applied to digital piracy some of the techniques of neutralization such as the denial of injury and denial of a victim, as well as the techniques the defense of necessity and appeal to higher loyalties, are conceptually similar. For this reason, these techniques were combined for the purposes of this study.

For all neutralization measures, respondents were asked to indicate their agreement with each statement using Likert responses. The response categories included strongly disagree, disagree, agree, and strongly agree. For each technique of neutralization, the Likert items representing the technique were combined into a Likert scale. The denial of injury/ denial of victim subscale and the defense of necessity/ appeal to higher loyalties subscale were each comprised of four questions, while the remaining subscales (denial of responsibility, condemning the condemners, metaphor of the ledger, claim of entitlement, claim of normalcy, claim of future patronage, and DRM defiance) were each comprised of two questions.

Demographic and Control Variables

Multiple control variables were included in the current study (i.e., 6). Each of these was a demographic measure that previous literature had identified as relevant to the study of digital piracy. The first demographic question will ask participants their sex. This question included two response categories (male, female). The second demographic question asked the participant if they are employed, with three response categories included (i.e., part time, full time, and not employed).

Three more variables are included, which are intended to measure various factors related to computer use. The first asked respondents to report their internet speed at the address they currently live at while attending school, with three response categories (no internet at home, low speed, and high speed). The final two control variables were based on measures used by Hinduja and Ingram (2008), measuring internet variety and proficiency. The internet variety measure explored the participant’s main reasons for using the internet. Respondents were provided with a list of thirteen online activities, and asked to check each of the listed activities they have participated in online over the last month (email, chat/IRC, research, file transfer, using newsgroups, product and travel information, online stock trading, online shopping, online auctions, online games, online banking, news, sports, weather, collect info on hobbies, and web design). The internet proficiency measure examined the respondent’s level of technological ability. For this measure, respondents were asked to check each online activity they had experience with. Ten activities were listed (changed my browser's "startup" or "home" page, made a purchase online for more than $100, participated in an online game, participated in an online auction, changed my "cookie" preferences, participated in an online chat or discussion, listened to a radio broadcast or music clip online, made a telephone call online, created a web page, set up my incoming and outgoing mail server preferences). For both measures, the answers were summed, with higher values representing higher levels of internet variety and proficiency.

Survey Administration

A self-report survey was used to collect the data for this study. Using a survey was the best approach for this study for multiple reasons. First, digital piracy is a behavior that often goes undetected and is rarely prosecuted so, there is little official data. It is likely that any official data that does exist lacks the information required to test most criminological theories including social learning theory. For this reason, a self-report survey was the best method for ascertaining participation in digital piracy. Second, the use of surveys provided the opportunity to reach a large, geographically diverse sample (in this case, students at two universities). This is especially true because the survey was administered online. Third, the use of a self-report survey allowed for the data for this study to be collected quickly. By using the web based survey software Qualtrics, the data collection and entry for the current study only took six weeks.

A pretest of the survey used for this study was conducted using a paper version of the survey. For the pretest eighteen students from university one were provided with a copy of the survey and asked to provide feedback regarding the wording of the survey questions. To goal of this pretest was to test the face validity of the survey instrument. The suggestions and comments from the students were examined and changes were made to the survey where warranted.

The survey was and administered using the web based survey software Qualtrics. After the requested student e-mail addresses were received from both universities two panels were created in Qualtrics, one for each university. Panels are databases within the Qualtrics software that conveniently store sample information. The creation of two separate panels allowed the emails to be personalized to each institution. Each wave of the survey remained open for a three week period, for a total of six weeks.

An initial email was sent to the sample of students midway through the Fall 2011 semester. It was sent at 7:00 am on a Monday. According to Dillman et. al. (2009) there is some evidence that sending the survey out early in the morning can increase response rates. This may be because respondents are able to respond to the email request before their daily responsibilities take precedence (Dillman et. al., 2009). The initial email described the nature of the study, highlighting why their response were important, and provided a link to the survey.

According to Dillman et. al. (2009) the use of multiple contacts with respondents is the most effective way to improve e-mail administered survey response rates. For this reason, reminder emails were sent to sample members who had not yet completed the survey. This was easily accomplished in Qualtrics, which allowed reminder emails to be sent to sample members who have not responded yet. Both follow up emails were sent at 7:00 a.m., the follow-ups were sent one and two weeks after the initial email. Dillman et. al. (2009) suggests varying the message across each email reminder. Reminders are less effective if they use the same wording over and over. For this study, two follow-up emails were sent to participants with the content of each email varied (see Appendix A). The first follow-up email reminded potential respondents about the survey, and once again stressed the importance of their participation. The second follow-up once again stressed the importance of the study. In addition, the second follow-up email notified the potential respondents that time was running out to take the survey. Recall that the first wave of emails only yielded 150 responses. For this reason, the process was repeated with a second sample.

Once students select the survey link in any of the emails they received they were directed to an informed consent page (See Appendix B) for the study. The informed consent page discussed the purpose of the study, and informed the students of the voluntary and anonymous nature of the study. If students agreed to participate in the study they were asked to click on a box labeled “I Agree”. This directed the students to the first page of the survey. Once respondents took the survey their responses were saved in the researchers account on Qualtrics, where the results of the study were easily retrieved after the data collection process was complete.

Utilizing an online survey mode holds multiple advantages compared to other survey modes, such as mail surveys. First, one of the major advantages to this method is that it is much less expensive than a mail survey. When including postage for multiple contacts as well as token incentives, mail surveys can become very expensive. Second, the amount of time it takes to collect data is shortened. Once the emails of the desired sample were obtained, the administration of the survey was largely automated. As previously stated the data collection process for this study took a total of three weeks for each sample using an online mode. For this study, survey results were downloaded into the statistical analysis software SPSS. This saved valuable time that would normally have been spent performing data entry.

Along with numerous benefits, there are some problems associated with internet-based surveys. According to Dillman, Smyth, and Christian (2009), there are significant coverage gaps in internet access within the general population. In addition, there is often a problem obtaining an adequate sample frame for internet populations. However, these issues were not a problem with the population used for this study. This was not a problem because at both universities students were provided with a university email account. The invitations for the study were sent to the students' university accounts.

The largest problem with using an internet-based survey administered through email is low response rate. Internet surveys often have a lower response rate when compared to other forms of survey administration (Shih, & Fan, 2009; Cook, Heath, & Thompson, 2000). A low response rate can introduce non-response error. According to Dillman et al. (2009), "Nonresponse error occurs when the people selected for the survey who do not respond are different from those who do respond in a way that is important to the study" (p. 17). To minimize non response error for the current study multiple strategies were utilized, following the suggestions of Dillman, Smyth, and Christian (2009).

First, Dillman et. al. (2009) suggests personalizing all contacts with respondents to the greatest extent possible as doing so helps create a connection between the surveyor and the respondent. Unfortunately it was not possible to address each email recipient by name due to time and technical restraints with Qualtrics. More specifically it was not possible to personally address by name each email and send the survey request to all members in a panel at one time. However, one benefit of Qualtrics is that the survey solicitation appears to have been sent to only one individual rather than as a bulk email. This feature increases the level of personalization as bulk emails can make respondents feel less important, which lowers their chances of taking the survey.

It is also important to carefully time all contacts with recipients (Dillman, et. al, 2009). As previously indicated, the emails for the current study were sent early in the morning on a Monday, and each follow-up email will be sent on a subsequent week during the same time. In addition, each email should be made as short as possible. For the current study, the body of each email was limited to three short Paragraphs (See Appendix A).

Another way to enhance response rate is to carefully tailor the "from" and "subject" lines of the email (Dillman et. al, 2009). For this dissertation, the "from" line of the email included the researcher's full name. The subject line stated "Student Digital Piracy Survey and Chance to win Amazon Gift Card". As a final measure to increase response rate, the participants in the study were given a chance to win one $100 Amazon gift card. Although past studies generally demonstrate that lotteries have no effect on response rate (Brennan, Rae, & Parackal, 1999), other studies have demonstrated slight increases in response rates (Bosnjak & Tuten, 2003; Porter and Whitcomb, 2003). Porter and Whitcomb (2003) found that the inclusion of a drawing for a $100 gift card produced a survey response rate 2.3% higher than a control group with no incentive, which was a statistically significant difference.

Reliability and Validity

For any item to be considered a good measure, it must be both reliable and valid. Reliability refers to the extent to which a measurement yields the same results on repeated tests. While, validity refers to the extent to which a measurement accurately represents the construct it is supposed to measure (Thornberry and Krohn, 2000).

To test reliability for this study, the internal consistency method was used. This means the internal consistency of the scale variables utilized in the study were examined. This test was used to determine if the measures present in each scale are highly intercorrelated and thus, measuring the same thing. To accomplish this, a Cronbach's alpha test was conducted for each scale in the survey, and an inter-item correlation of .7 or higher was sought (Carmines, & Zeller, 1979). Scores lower than .7 indicated that the items are not measuring the same thing. Only one variable was not internally consistent (claim of future patronage). For this reason it was split into two separate variables. This issue is discussed in greater detail in chapter IV of this dissertation.

Validity was assessed in two ways. First the questionnaire's face validity was assessed. The purpose of face validity is to see if the questionnaire makes sense at face value. For this study, such a test was particularly important for assessing the social learning variables. It was imperative that each social learning variable be appraised to make sure it represented the social learning component it was intended to represent. To test this, the researcher asked colleagues who are familiar with the subject matter to review the survey and provide feedback. In addition, as previously discussed the survey was given to eighteen students, and feedback was solicited.

The construct validity of the instrument was also assessed. According to Carmines and Zeller, "…construct validity is concerned with the extent to which a particular measure relates to other measures consistent with theoretically derived hypotheses concerning the concepts (or constructs) that are being measured" (1979, p. 23). For this study the demographic and social learning variables were examined to see if the related to digital piracy in expected ways. For example past research has demonstrated that males participate in higher levels of digital piracy than females. In addition, real life peer association often has the strongest effect on digital piracy out of all the social learning variables. For this dissertation, some unexpected results occurred. For example in the willingness to engage in music piracy regression males were found to be less likely to pirate than females. However, the majority of the findings demonstrated the expected relationships between variables.

Human Subject Protection

Before this study commences IRB approval was sought and obtained, and any changes recommended to enhance human subject protection by the IRB were adhered to. The current study had a minimal number of human subject protection issues. However, there were some human subject protection issues that should be discussed.

First, participants must give informed consent when participating in a study. For the current study, an informed consent form was provided to the participants on the first page of the online survey. Participants were provided with information regarding the purpose of the study, notification of IRB approval, and the contact information for the researcher. After the presentation of the consent form, participants were asked to click on a button stating "I Agree", if they choose to participate in the study. It was made clear that participants were giving their informed consent to participate in the study when they click on button.

Second, some college students who make up the sampling frame may have been under the age of 18. These students were not included in the current study. To ensure that students under the age of 18 were not included in the study the research lab at university one and the sampling frame gatekeepers at university two were asked to not include individuals under the age of 18 in the samples they provided. In addition, respondents were asked to not participate in the study if they were under the age of 18 in the introduction email and informed consent page.

Third, there is some concern with the study because participants were asked about their past participation in digital piracy, which is a crime. For this reason, great care will be taken to insure that responses were anonymous. It was easy to make responses anonymous using Qualtrics, because email information was by default saved separately from survey results. Thus, it was not possible to link responses back to an individual survey taker. As an added measure of protection all digital data for this study was placed in password protected folders. In addition, all physical data was kept in a filing cabinet with a lock. Only the author of this study will have access to this information. Thus, participation in the study posed no more than minimal risk to the respondents.

CHAPTER IV

ANALYSIS

The purpose of this chapter is to provide the results from the statistical analyses conducted for this study. The descriptive statistics representing the control, independent, and dependent variables are presented first. These are followed by the results for the tests of the assumptions for the statistical methodology chosen. Based on the results of the tests for normality and multicollinearity some changes were made regarding the analyses and models used for this study. More specifically a change in statistical analysis from OLS to logistic regression was made for some of the dependent variables, and one variable was removed from the regression models. These changes are discussed in further detail in a later section of this chapter.

Descriptive Statistics

This section presents the descriptive statistics for the study. First, the descriptive characteristics of the demographic variables are presented. This is followed by the descriptive statistics for the independent and dependent variables. Categorical variables were recoded in the event that one of the categories had less than 15% in one of the categories.

Demographics

Table 1 presents the frequencies and percentages for the following four variables: sex, class rank, employment status, and internet connection.

Table 1

Descriptive Statistics for the Demographic Variables

Variable	Frequency	Percent
Current Class Rank		
Freshman	74	24.4
Sophomore	57	18.8
Junior	49	16.2

Senior	83	27.4
Graduate Student	40	13.3
Employment Status		
Not Employed	111	36.5
Part Time	151	49.7
Full Time	42	13.8
Sex		
Female	207	68.1
Male	97	31.9
Home Internet Connection		
No Internet at Home	4	1.3
Cable	97	31.9
DSL	70	23.0
Wi-Fi	129	42.4
Dial-up	4	1.3

The majority of respondents in this study were female (68.1%). This was consistent with past research that demonstrated females were more likely to respond to surveys, both on and offline (Porter, and Whitcomb, 2005; Moore, and Tanari, 2002). In addition, this was consistent with the populations of the two universities, as both universities had a higher female to male ratio. At university one 57% of the student body populations was female and 43% male. Similarly, at university two 56% of the student body population was female and 44% male. Despite the two universities having higher proportions of female students compared to males, the female response rate was still disproportionately high for this study. This may suggest a problem with non-response bias as males are under-represented in the sample. This may have ramifications for the current study as the majority of studies have demonstrated that men participate in digital piracy more than females (Gunter, 2009: Hinduja, 2001, 2003; Higgins, Wilson, & Fell, 2005).

In regards to the distribution of the class rank variable for this study, the largest category was senior (27.4%) followed by freshman (24.4%), sophomore (18.8%), juniors (16.2%) and graduate students (13.3%). Due to the lack of variability in the graduate student category, it was collapsed into the senior category. For the OLS and logistic regressions, the class rank variable was dummy coded with freshman being the reference category.

The majority of respondents in the study were employed part time (49.7%), followed by not employed (36.5%), and employed full time (13.8%). The employment variable was recoded into two categories due to the lack of variability in the full time employment category. The variable was recoded as not employed (coded as a 0) and employed (coded as a 1), with the full time and part time employment categories being combined.

For the variable "home internet connection", respondents were asked to indicate the type of internet connection used at their current residence. The survey identified and provided five internet speeds. They were as follows: no internet at home, dial up, DSL, Wi-Fi, and cable. The purpose of this question was to control for internet speeds at home, since piracy is more accessible to those with fast internet connection due to quicker download speeds. For this reason, the variable was originally going to be coded as a dichotomous variable, with high and low speeds internet as the two categories. However, due to very low representation in the categories no internet (1.3%) and dial-up (1.3%), the two categories that would have comprised the low speed internet category, the decision was made to remove the variable form the analyses. Several factors may account for the small representation of individuals with slow internet speeds in the sample. First, it is possible that these results represent an increase in the availability of fast speed internet in recent years. Second, it may be possible that individuals with slower internet speeds would be less likely to take the survey in an online format, as the survey process itself would be more cumbersome and time consuming. If this second factor is the cause, it may add to the problem of non-response bias with online surveys.

Computer Use and Proficiency Control Variables

Respondents were also asked multiple questions designed to capture their monthly internet use and computer proficiency, with the intent that each set of questions be combined into a scale. Recall that the questions making up these two scales were adapted from the work of Hinduja and Ingram (2008). For weekly internet use, respondents were asked thirteen “yes” (1) or “no” (0) questions representing common internet activities. The frequencies for each individual question are provided in Table 2.

Table 2

Descriptive Statistics for Monthly Internet Use

	No	Yes
Email/ Chat	6 (2.0%)	398 (98%)
Research for School	27 (8.9%)	277 (91.1%)
File Transfer	153 (50.3%)	151 (49.7%)
Use Newsgroup	273 (89.8%)	31 (10.2%)
Product or Travel Information	156 (51.3%)	148 (48.7%)
Online Stock Trade	293 (96.4%)	11 (3.6%)
Online Shopping	63 (20.7%)	241 (79.3%)
Online Auctions	259 (85.2%)	45 (14.8%)
Online Games	178 (58.6%)	126 (41.4%)
Online Banking	98 (32.2%)	206 (67.8%)
Collect Info on News, Sports or Weather	69 (22.7%)	235 (77.3%)
Collect Info Related to Personal Hobbies	81 (26.6%)	223 (73.4%)
Web Design	280 (92.1%)	24 (7.9%)

For the two questions “email/chat use” and “research for school”, over 90% of the respondents selected “yes”. Thus, these two items represented the most common internet activities across this sample. Activities with very low participation included web design (7.9%), use of newsgroups (10.2%), online auctions (14.8%), and online stock trade (3.6%). The remaining activities (i.e., collect info related to personal hobbies, collect info related to sports or weather, file transfer, product or travel information, online gaming, and online banking) generally had over 40% weekly participation.

For the computer proficiency variables, respondents were asked ten “yes” (1) or “no” (0) questions representing participation in computer activities with varying levels of technical knowhow required. For the most part, the computer proficiency variables were more evenly distributed than the internet use variables, with 40% to 75% of the sample having engaged in each activity at least once in their lifetime. Table 3 provides the frequencies for each individual question.

Table 3

Descriptive Statistics for Computer Proficiency Measures

	No	Yes
Changed Browser’s Homepage	64 (20.1%)	240 (78.9%)
Made Online Purchase (Over $100)	81 (26.6%)	223 (73.4%)
Participated in Online Game	107 (35.2%)	197 (64.8%)
Participated Online Auction	177 (58.2%)	127 (41.8%)
Changed Cookie Preference	154 (50.7%)	150 (49.3%)
Participated Online Message Board	126 (41.4%)	178 (58.6%)
Listened To Radio Broadcast Online	87 (28.6%)	217 (71.4%)
Made Online Phone Call	171 (56.3%)	133 (43.8%)

Created a Web Page	174 (57.2%)	130 (42.8%)
Set up Mail Server Preference	155 (51.0%)	149 (49.0%)

The four most common activities were changing a browser's homepage (78.9%), made online purchase (73.4%), listened to a radio broadcast online (71.4%), and participated in an online game. The least engaged in activities were participated in an online auction (41.8%), created a web page (42.8%), and made an online phone call (43.8%).

As previously stated both the internet use and computer proficiency measures were combined into distinct scales. To make the internet use scale, the results from the thirteen questions were summed. This created a scale with a possible range of 0 to 13, with 13 representing a very high level of internet use and 1 a very low level. The actual range was 1 to 13. The same was done with the ten computer proficiency measures making a scale with a possible range of 0 to 10, with an actual range of 0 to 10. For this scale, a 0 represents the lowest possible level of computer proficiency and 10 the highest. The descriptive statistics for both of the scale variables are provided in Table 4. The average internet use score was 6.62 (SD 2.08), and the average computer proficiency score was 5.737 (SD 2.69).

Table 4

Descriptive Statistics for Scaled Computer Pro and Monthly Internet

	N	Mean	SD	Minimum	Maximum
Internet Use	304	6.62	2.08	1	13
Computer Proficiency	304	5.737	2.69	0	10

Dependent Variables

The dependent variables for this study included measures for four distinct types of digital piracy: music, movie, game, and software. Each type of digital piracy was measured two ways, for an original total of eight dependent variables. First, respondents were asked to report their past piracy participation over the last month in each category. This represented each participant's past involvement in piracy (involvement). For the second measure, a scenario was provided for each type of piracy, and respondents were asked to indicate the likelihood that they would participate in piracy in that specific situation. The scenario variables were designed to determine each respondent's willingness to engage in digital piracy (willingness).

For each of the four *involvement* piracy measures, respondents were first asked to indicate if they had participated in each type of digital piracy over the last month with a binary "yes" or "no" response. They were then asked to indicate the number of times they engaged in each type of piracy over the last month, so that a ratio level variable of actual piracy could be created. The majority of respondents provided a numeric value for their answer. However, sixteen responses were not in numeric form (e.g. a few, more than 5). For this reason, non-numeric responses were either recoded or removed from the analysis entirely[1].

Table 5 provides the descriptive statistics for each of the four involvement measures at the ratio level. As Table 5 demonstrates music piracy had the highest mean as well as the largest standard deviation (M = 13.65, SD = 61.66) of all the piracy variables. All of the other variables had means under one indicating very low levels of movie, game, and software piracy in the last month.

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[1] Two responses were completely removed because the respondents stated they were unsure how much they had pirated, making it impossible to approximate a numeric answer. Four of the responses stated that the respondent had pirated more than a specific number (ex. more than 5). These responses were recoded as one number higher from the given numeric value. Three respondents gave an approximation (ex. around 5). These responses were recoded as the numeric value given. Three responses were a range of numbers (ex. 1-6). In such cases the responses was recoded to the center value of the range given. One response simply stated "a few". This response was change to three. Finally, one respondent wrote that they had pirated several discs worth of music. This response was recoded as sixty.

Table 5

Descriptive Statistics Involvement in Piracy Ratio Level

	N	Mean	SD	Min	Max
Music Piracy	303	13.65	61.66	0	600
Movie Piracy	303	0.42	1.84	0	20
Game Piracy	303	0.08	0.49	0	5
Software Piracy	303	0.15	0.87	0	12
Combined (Movie, Game, Software)	303	0.64	2.79	0	32
Total Piracy	303	16.62	62.31	0	605

Note: For this analysis, one case was removed due to outliers. This outlier was removed because it was over three times the next highest value.

After examining the means, standard deviations, and the ranges for each variable it was clear that the four ratio level involvement variables were highly skewed. This indicated problems with normality for each of these variables. Although normally distributed variables are not an assumption of OLS regression, the lack of normality is often a good indication that a violation of an assumption may be present, such as non-normally distributed error terms. This was the case, for each of these variables. For this reason, logistic regression was used to analyze these variables using the binary (yes, no) involvement variables presented in Table 6. This issue is further explored in the regression assumptions section later in this chapter.

In addition to the four binary involvement variables, a combined (movie, game, and software piracy) variable is presented in table 6. This new variables was created due to a lack of involvement in the pirating categories for the movie, game, and software piracy variables. Each of these variables had very low levels of piracy participation, with only 4.6% of the sample having participated in gaming piracy over the last month, 9.5% movie piracy, and 7.9% software piracy. The reasoning behind the creation of this variable is further discussed in the regression assumptions section of this chapter.

Table 6

Frequencies for Involvement in Piracy Binary Response

	No	Yes	Total
Music Piracy Over Last Month	224 (73.7%)	80 (26.3%)	304 (100%)
Movie Piracy Over Last Month	275 (90.5%)	29 (9.5%)	304 (100%)
Game Piracy Over Last Month	288 (94.7%)	14 (4.6%)	304 (100%)
Software Piracy Over Last Month	280 (92.1%)	24 (7.9%)	304 (100%)
Combined (Movie, Game, Software)	261(85.9%)	43 (14.1%)	304 (100%)

For the *willingness* digital piracy measures, respondents were provided with a scenario related to each type of digital piracy examined in the study (music, movie, game, and software). These variables can be viewed as capturing an individual's willingness to engage in piracy rather than their actual past participation in piracy. Based on each scenario respondents were asked to indicate how likely they would be to participate in digital piracy if they were placed in the situation. Responses were measured on a 0 to 100 sliding scale, with a 0 representing extremely unlikely and a 100 representing extremely likely. The descriptive statistics for the scenario based piracy measures are provided in Table 7.

Table 7

Descriptive Statistics Scenario Based Piracy

	N	Mean	SD	Min	Max
Music Piracy	304	27.12	33.42	0	100
Movie Piracy	304	20.62	29.46	0	100
Game Piracy	304	11.08	22.55	0	100
Software Piracy	304	34.14	37.05	0	100

The actual ranges of all four variables were from 0 to 100. Software piracy had the highest mean score (M = 34.14, SD = 37.05), followed by music piracy (M = 27.12, SD = 33.42), movie piracy (M = 20.62, SD = 29.46), and gaming piracy (M = 11.08, SD = 22.55). The results indicated that individuals are most willing to engage in software followed by music piracy. These results are slightly different from those found for actual piracy involvement, which may indicate that those who do not normally pirate would possibly do so under the right circumstances. Willingness to engage in the other three forms of piracy parallels the actual piracy rates; with music being the highest followed by movie and game piracy. Like the actual piracy variables, the willingness variables were skewed. The data was skewed toward the left with the majority of respondents demonstrating a low willingness to participate in digital piracy. This problem is most pronounced for the gaming and movie piracy variables, both of which had a large number of outliers. The consequences of these issues are further discussed in the regression assumption section of this chapter.

Independent Variables

In this section, the descriptive statistics of the independent variables are presented. First, the differential association variables are presented. The imitation, differential reinforcement, and definitions/ neutralization variables follow.

Differential Association

In total seven questions were used to capture the concept of differential association. The questions were designed to measure offline (three questions) as well as online (four questions) differential association. The frequencies for the offline differential association variables are provided in Table 8 below.

Table 8

Frequencies Offline Differential Association

Variable	Frequency	Percent
Intensity		
None	52	17.2
Less Than Half	122	40.4
Half	51	16.8
More Than Half	68	22.4
All	10	3.3
Frequency		
None	72	23.8
Less Than Half	117	38.6
Half	52	17.2
More Than Half	55	18.2
All	7	2.3
Duration		
None	68	22.5
Less Than Half	120	39.7
Half	50	16.6
More Than Half	52	17.2
All	12	4.0

The three offline questions measured each respondent's intensity, frequency, and duration of involvement with peers who participate in digital piracy. As can be seen in Table 8, the majority of respondents for each variable indicated that less than half of their friends participate in digital piracy, while only 2.3 to 4.0% indicated that all of their friends participate in digital piracy. However, a significant portion of respondents also indicated that either half or more than half of their friends participated in digital piracy. For example, 16.8% of the respondents stated that half of their friends participated in piracy for the intensity variable, and 22.4% stated more than half of their friends participate in digital piracy. This indicates that a sizable portion of the sample view their friends as digital pirates.

For the online differential association variables, the respondents were first asked if there was anyone who they considered a peer that they only associated with online through chat, message boards, social networking, or multiplayer online games. A small percentage of the sample (N = 34, 11.2%) did not have any exclusively online peers and as such, were excluded from answering the four online peer association variables in the survey. To keep these individuals in the regression analyses, their responses were coded as the lowest value for the online differential association scale (i.e., 0).

The frequencies for the four online differential association variables as well as the association with online friends in general variable are provided in Table 9.

Table 9

Frequencies Online Differential Association

Variable	Frequency	Percent
Engagement in Online Peer Associations		
Yes	269	88.8
No	34	11.2
General Online Association with Digital Pirates		
Strongly Disagree	133	49.4
Disagree	97	36.1
Agree	35	11.5
Strongly Agree	4	1.3
Intensity		
Strongly Disagree	76	28.5
Disagree	108	40.4
Agree	71	26.6
Strongly Agree	12	4.5
Frequency		
Strongly Disagree	68	25.5
Disagree	121	45.3
Agree	68	25.5
Strongly Agree	10	4.7
Duration		
Strongly Disagree	69	25.7
Disagree	116	43.4
Agree	72	26.9
Strongly Agree	11	4.1

The first question of the four online differential association variables was designed to measures whether a respondent generally associated with others online who participate in digital piracy by indicating their level of agreement with the statement “I associate with people online who exchange pirated copies of digital goods (music, movies, software, and games) with me”. While the remaining three were designed to measure the intensity, frequency, and duration of online association with pirating peers. For example, the duration variable asked respondents to indicate their level of agreement with the statement “the people who I have associated with online the longest view digital piracy in a positive light”. The majority of respondents strongly disagreed (49.4%) or disagreed (31.6%) with the first question. However, on average 25% agreed and 5% strongly agreed with the intensity, frequency, and duration questions. This indicates that the majority of respondents do not exchange files directly with online peers, but are more likely to have online peers who view digital piracy as okay.

The three offline differential association variables were summed to create an offline differential association scale with a range of 4 to 16. The four online differential association variables were summed to create an online differential association scale with a range of 0 to 12. The descriptive statistics for the offline and online differential association scales are provided below in Table 10.

Table 10

Descriptive Statistics for Differential Association Scales

	N	Mean	SD	Min	Max
Offline Differential Association Scale	302	4.32	3.11	0	12
Online Differential Association Scale	304	7.41	2.89	4	16

Higher values for both scales represent greater association with pirating peers. As can be seen in the table both scales have fairly low means. The offline differential association scale has a mean of 4.32 (SD 3.11), and the online differential association scale has a mean of 7.41 (SD 2.89). Both scales were found to be internally consistent based on Cronbach’s alpha tests.

According to Devellis (2003) in order for an alpha value to be good it should be above .7. Offline differential association had an alpha of .860 and online differential association had an alpha of .875, meaning both scales were internally consistent. The ranges of the scales differ due to the measurement of the variables in each scale.

Imitation

Eight imitation variables were included in this study, representing the amount learned about digital piracy from a variety of offline and online sources. Respondents were asked how much they learned about the techniques needed to commit digital piracy from eight imitation sources (i.e., offline friends, online friends, books/magazines, television/ movies, message boards, online videos, wikis, and directional web pages). Each variable was measured with a sliding scale from 0 to 100 with higher scores representing greater levels of information gained from a particular source. Table 11 provides the descriptive information for each imitation variable.

Table 11

Descriptive Statistics for Imitation Variables (Sources of Imitation)

Variable	N	Mean	SD	Minimum	Maximum
Offline Friends	304	36.35	34.56	0	100
Online Friends	304	18.00	25.31	0	100
Books/ Magazines	304	17.12	23.14	0	94
Television/ Movies	304	22.81	27.53	0	100
Message Boards	304	14.11	24.67	0	100
Online Videos	304	16.62	25.62	0	100
Wikis	304	7.72	18.55	0	91
Directional Web Pages	304	13.90	22.69	0	100

As Table 11 indicates offline friends were the largest source of learning regarding digital piracy with a mean of 36.35 (SD = 34.56). The variable with the second highest mean was Television/ Movies (M = 22.81, SD = 27.53), followed by online friends (M= 18, SD = 25. 312), books and magazines (M = 17.12, SD = 23.142), online videos (M = 16.62. SD = 25.62), message boards (M = 14.11, SD = 24.67), directional web pages (M = 13.9, SD = 22.69), and wikis (M = 7.72, SD = 18.55).

Differential Reinforcement

Based on past research (Skinner & Fream, 1997; Gunter, 2009; Holt & Copes; 2010; Wolfe, Higgins, & Marcum, 2008), the current study included four measures of negative differential reinforcement: severity of punishment, certainty of punishment, perceived likelihood of obtaining a virus, and past virus exposure from pirated materials. Table 12 provides the descriptive statistics for the four negative reinforcement variables.

Table 12

Frequencies Negative Differential Reinforcement Variables

Variable	Frequency	Percent
Severity of Punishment		
No Punishment	15	5.0
Small Fine	93	30.8
Internet Cancelation	11	3.6
Large Fine or Lawsuit	142	47.0
Jail/ Prison	39	12.9
University Sanction	2	0.7
Certainty of Punishment		
Very Unlikely	90	29.6
Unlikely	141	46.4
Likely	64	21.1
Very Likely	9	3.0
Chance of Obtaining Virus		
Very Unlikely	12	4.0
Unlikely	40	13.2
Likely	142	47.0
Very Likely	108	35.8
Virus Received		

No	223	73.6
Yes	80	26.3

For the severity of punishment variable, respondents were most likely to perceive the punishment for piracy as a large fine or lawsuit (47%), followed by a small fine (30.8%). Each of the four other variables represented less than 15% of the sample. For this reason, the severity of punishment variable was recoded into a dichotomous variable, with a category representing severe punishment (coded as 1), and a category representing non-severe punishment (coded as 0). The severe punishment category combined the prison/ jail and large fine or lawsuit categories, while the non-severe punishment category combined the no punishment, internet cancelation, university sanction, and small fine categories.

For the certainty of punishment variable, respondents were asked what they felt was the likelihood of being caught participating in digital piracy with four response categories ranging from strongly disagree to strongly agree. The majority of respondents felt that it was either unlikely (46.4%) or very unlikely (29.6%) that they would ever be caught pirating. Few respondents felt that the chances were likely (21.1%), and almost none felt that the chances were very likely (3%). Due to the low level of cases in the very likely response category the decision was made to collapse the certainty of punishment variable into a dichotomous variable representing likely (coded as 1), and unlikely chances (coded as 0) of being caught pirating.

Respondents were also asked if they had ever received a virus from pirated material. The majority of the sample indicated that they had not received a virus from pirating (73.6%). However, 26.3% indicated that they had. Respondents were also asked to indicate the general likelihood of receiving a virus from pirating with responses ranging from very unlikely to very likely. The majority of respondents indicated that the chances of receiving a virus were either very likely (35.8%), or likely (47%). Only 13.2% said the chances were unlikely and 4% chose very unlikely. Thus, it was clear that most respondents view pirating as a high risk behavior in regards to computer viruses. Like the certainty of punishment variable, the chance of obtaining a virus variable was collapsed into a dichotomous variable due to lack of cases in the very unlikely and unlikely categories. Once again, likely (coded as 1), and unlikely (coded as 0) categories were created. The frequencies of the recoded negative differential association variables are provided in Table 13.

Table 13

Frequencies Negative Differential Reinforcement Variables Recode

Variable	Frequency	Percent
Severity of Punishment		
Non-Severe Punishment	121	40.1
Severe Punishment	181	59.9
Certainty of Punishment		
Unlikely	231	76.0
Likely	73	24.0
Chance of Obtaining Virus		
Unlikely	52	17.2
Likely	250	82.8

Three positive forms of differential reinforcement were also tested including economic benefit, convenience, and positive feelings of pirating. For each of these variables respondents were asked to indicate how much they agreed with a given statement using a Likert scale. For example, with the economic benefit variable respondents were asked how much they agreed with a statement that digital piracy is okay because it allows them to save money. Table 14 provides the frequencies for each variable.

Table 14

Frequencies Positive Differential Reinforcement Variables

Variable	Frequency	Percent
Economic Benefit		
Strongly Disagree	48	15.8

Disagree	76	25.1
Agree	126	41.6
Strongly Agree	53	17.5
Convenience		
Strongly Disagree	60	19.7
Disagree	118	38.9
Agree	108	35.6
Strongly Agree	17	5.6
Positive Feelings		
Strongly Disagree	90	29.8
Disagree	140	46.4
Agree	66	21.9
Strongly Agree	6	2.0

The three positive reinforcement variables were combined into a scale representing the overall effect of positive reinforcement. The summations of these variables created a scale with a possible range from three to twelve, with a higher value representing high positive reinforcement. A Cronbach's alpha test was conducted on the positive reinforcement scale; the test produced an alpha of .829. Although there is not agreed upon cutoff for a good alpha score, Devellis (2003), suggests that a score between .80 and .90 is a very good score. The mean for the positive scale was 6.85 (SD 2.21).

Definitions/ Neutralizations

The survey that was administered included positive, negative, and neutralizing definitions toward digital piracy. The survey included three questions related to positive definitions, one question for negative definition, and twenty-two questions for neutralization definitions. For each question respondents were asked to indicate their level of agreement using a Likert scale. Table 15 provides the frequencies for the three positive definitions and one negative definition. For two of the positive definitions (digital goods should be free, and movie piracy is okay) the majority of the sample rejected the statements, with over 60% of the sample disagreeing or strongly disagreeing the two definitions. Despite the majority of respondents rejecting these two definitions, many more agreed with them indicating some acceptance for positive definition related to digital piracy. For the positive definition stating that movie piracy is okay and the negative definition stating piracy is never okay, agreement was almost a 50/50 split. Such an even split for the negative definition may indicate that individuals are willing to make excuses for piracy in certain circumstances, as many individuals do not completely condemn piracy.

Table 15

Frequencies Definition Variables

Variable	Frequency	Percent
Positive Definitions		
Digital Goods Should be Free		
Strongly Disagree	57	18.9
Disagree	132	43.7
Agree	90	29.8
Strongly Agree	23	7.6
Music Piracy is Okay		
Strongly Disagree	56	18.5
Disagree	98	32.5
Agree	128	42.4
Strongly Agree	20	6.6
Movie Piracy Okay		
Strongly Disagree	65	21.7
Disagree	146	48.7
Agree	77	25.7
Strongly Agree	12	4.0
Negative Definition		
Piracy Never Okay		
Strongly Disagree	28	9.3
Disagree	104	34.6
Agree	116	38.5
Strongly Agree	53	17.6

The four definitions variables were combined into a definitions scale for the OLS and logistic regression analyses. Before combining the four variables, the negative definitions variable was reverse coded. A Cronbach's alpha was conducted resulting in an acceptable alpha value of .736. The descriptive statistics for the definitions scale are provided in Table 17.

Twenty-two questions representing neutralizing statements were included in the survey. These twenty-two questions were combined into nine distinct scales representing techniques of neutralization. The frequencies for each of these twenty two questions are provided in Appendix D (Tables 18 – 26) grouped by neutralization technique (denial of injury/ victim, defense of necessity/ appeal to higher loyalties, denial of responsibility, condemning the condemners, metaphor of ledger, claim of entitlement, claim of normalcy, claim of future patronage, DRM defiance). A Cronbach's alpha was conducted on the variables making up each individual neutralization scale in order to test their internal consistency. The alpha value and descriptive statistics for each neutralization scale variable are displayed in Table 16.

Table 16

Descriptive Statistics for Neutralization Scales

Variable	N	Mean	SD	Min	Max	Alpha
Definitions Scale	295	9.09	2.53	4.00	16.00	.736
Denial of Injury/ Victim	299	8.13	2.53	4.00	16.00	.811
Defense of Necessity/ Appeal to Higher Loyalties	290	8.86	2.94	4.00	16.00	.755
Denial of Responsibility	296	5.37	1.64	2.00	8.00	.714
Condemning the Condemners	297	4.25	1.49	2.00	8.00	.723
Metaphor of Ledger	299	4.05	1.38	2.00	8.00	.671
Claim of Entitlement	300	3.79	1.39	2.00	8.00	.911
Claim of Normalcy	299	4.03	1.46	2.00	8.00	.868
Claim of Future Patronage	299	4.42	1.45	2.00	8.00	.620
DRM Defiance	298	4.07	1.43	2.00	8.00	.742

As a general rule of thumb, an alpha value above .7 is desirable. Two of the scales had alphas lower than this cut off; the two scales were the metaphor of the ledger (.671) and the claim of future patronage (.620). According to Devellis (2003), a score between .60 and .65 is undesirable, and a score between .65 and .70 is only minimally acceptable. Based on this standard, there may be a problem with the claim of future patronage scale.

Due to the low alpha score, the two variables for the future patronage scale were entered into each regression as two separate variables. The frequencies for these two variables are provided in table 18. As can be seen in table 17, approximately two thirds of the sample disagreed with the statement "I will pay for the majority of the things I pirate when I graduate and make more money than I do now". In a similar trend, two thirds of respondents disagreed with the statement "If I like a product that I pirate, I will go buy the product".

Table 17

Frequencies for Separate Future Patronage Questions

Variable	Frequency	Percent
Buy After Graduation		
Disagree	186	62.2
Agree	113	37.8
If Like Buy		
Disagree	200	66.2
Agree	102	33.8

Regression Assumptions

Before conducting the OLS regression analyses it was necessary to test to make sure the data being used did not violate any of the assumptions of OLS regression. Multiple assumption diagnostics were conducted. The results for three of these tests are discussed here.

As previously stated, the statistical analysis for the involvement variables was changed to logistic regression because the variables did not meet all of the assumptions of OLS regression.

After conducting the regression diagnostics, it was clear that each involvement variable violated the normality of the residuals assumption of OLS regression. In small samples, this can create problems with the accuracy of the statistical significance for the regression coefficients (Menard, 2002). Thus, violation of this assumption can negatively affect hypothesis testing. These variables also had problems with outliers. However, simply removing the outlier cases did not appear to be a good solution as many outliers grouped together suggesting a class of high-level pirates. For this reason, the analysis of these four variables were conducted in logistic regression using the binary (yes, no) involvement variables.

Logistic regression allows the researcher to determine the relationship between a dichotomous dependent variable and multiple independent variables. Thus, logistic regression was an appropriate substitution for OLS regression for the four involvement dependent variables. However, switching the analysis of these four variables did not completely eliminate all problems. Three of the variables did not meet all of the assumptions of logistic regression due to low variance in the dependent variable, again due to the answers being heavily skewed towards no piracy. More specifically, the movie, game, and software involvement variables each had a problem with zero cells. Zero cells are a problem in which one or more values of a categorical independent variable are invariant with a category of the dependent variable (Menard, 2002). This is a problem that may also lead to biased estimates. To overcome these problems a new dependent variable was created. The movie, game, and software involvement variables were collapsed into a new non-music piracy variable. After running cross tabulations it was found that zero cells were not a problem for the new variables. As a final note although zero cells were not a problem for the non-music piracy variable, the estimates may still be biased because only 14.1% of the sample had committed movie, gaming, or software piracy over the last month.

Therefore, the results from the non-music piracy logistic regression analysis should be interpreted with caution.

The second problem was related to the distributions for the willingness to pirate dependent variables. As previously noted each of these variables was negatively skewed, and the gaming and software piracy variables had problems with outliers. The skewness of these variables does not inherently violate any of the assumptions of OLS regression. The presence of outliers can distort the OLS regression estimates. Despite this problem, the decision was made to keep the outliers for these two variables in the analysis to not lose the information they provide. For this reason, the estimates for the gaming and software piracy variables should be interpreted with caution.

The third problem with the data concerns high multicollinearity. Although the data satisfied the regression assumption of no perfect multicollinearity, problems can also arise from high multicollinearity. According to Berry (1993), high multicollinearity results in the inflation of the standard errors for partial slope estimates for variables with high collinearity. Meaning, high collinearity between variables can lead to biased estimates for the independent variables. Two techniques were used to test for the presence of high multicollinearity. First, all the independent variables were correlated. There is no agreed upon cut-off value in regards to what level of correlation may indicate a problem with multicollinearity. However, according to Lewis-Beck (1980) as long as the correlations are below .80, multicollinearity is not a problem. None of the independent variables were correlated above .80. However, the neutralization technique defense of necessity/ appeal to higher loyalties was highly correlated with several variables above .70.

For the second technique, the variance inflation factors (VIFs) for the variables used in the study were examined. Generally, if a variable has a VIF higher than four there is a possibility that high multicollinearity is a problem. Only one variable had a VIF higher than four, the neutralization technique defense of necessity/ appeal to higher loyalties. Multicollinearity can be addressed by combining highly correlated items into a new variable. However, because the variable in question was highly correlated with multiple variables (i.e., condemning the condemners, denial of injury/victim, DRM defiance, and the definition scale) the decision was made to simply remove it from the analysis. Thus, the neutralization variable defense of necessity/ appeal to higher loyalties was removed from both the OLS and logistic regression models.

OLS Regression

As previously stated the statistical technique used to test the relationship between the independent variables and the four willingness dependent variables was OLS regression. Regression was the most appropriate statistical analysis for these four variables because they were measured at the ratio level. In addition, incorporating multiple independent variables into a multiple regression offers many advantages. According to Lewis-Beck (1980), multiple regression provides a more complete explanation of the dependent variable. In addition, the effect of each independent variable is more accurate, due to the control of the other independent variables in the model.

The regression analyses were conducted in the statistical analysis program SPSS. The previously discussed demographic variables along with variables representing the four main components of social learning theory were entered into each regression in order to predict willingness to participate in four types of digital piracy.

The regression equation is as follow:

$$\hat{Y} = a + B_1X_1 + B_2X_2 + \ldots + B_kX_k + \hat{e}_i$$

Where:

$\hat{Y}$ = the predicted value of the dependent variable, digital piracy (participation or willingness)

a = the y-intercept when $X = 0$; or, the constant

B = the slope of the regression line

X_1 = Offline differential association

X_2 = Online differential association

X_3= definitions

X_4= neutralization (1, denial of responsibility)

X_5 = neutralization (2, denial of injury/ denial of victim)

X_6= neutralization (3, Condemning the Condemners)

X_7= neutralization (4, Metaphor of the ledger)

X_8= neutralization (5, Claim of Entitlement)

X_9= neutralization (6, Claim of Normalcy)

X_{10}= neutralization (7, Claim of Future Patronage)

X_{11} = neutralization (8, DRM Defiance)

X_{12} = differential reinforcement (1, Severity of Punishment)

X_{13} = differential reinforcement (2, Certainty of Punishment)

X_{14} = differential reinforcement (3, Chances of Virus)

X_{15} = differential reinforcement (4, Ever received Virus)

X_{16} = differential reinforcement (5 Tangible Benefits)

X_{17} = differential reinforcement (6, Feelings)

X_{18} = imitation (online Friends)

X_{19} = imitation (offline Friends)

X_{29} = imitation (Books)

X_{21}= imitation (TV/ Movies)

X_{22} = imitation (Message Boards)

X_{23} = imitation (Streaming Videos)

X_{24} = imitation (Wikis)

X_{25}= imitation (Directional Webpage)

X_{26} = internet activity

X_{27} = computer proficiency

X_{28} = sex

X_{29} = employment status

X_{30} = class rank

$\hat{e}_i$ = the predicted error term

For each regression five models were created. This provided an alternative from beta weights for assessing the importance of each set of independent variables. First the differential association variables (X_1 - X_2) were entered into the regression, followed by the neutralization and definitions variables (X_3 - X_{11}). Next, the differential reinforcement variables (X_{12} - X_{17}) were entered into the regression, followed by the imitation variables (X_{18}– X_{25}). Lastly, the demographic variables were included (X_{26} – X_{30}).

For each regression model the R^2, F value and p value were reported. For each significant predictor in the model the b value, significance level, and beta weight were reported. The full results of each of the four regression analyses are provided in Appendix F (tables 27 – 30). To maximize the sample size being used for each regression, missing cases were dealt with pairwise, under the assumption that the missing cases were randomly missing. This decision was made after removing cases from the data that did not appear random. The decision was made to deal with missing cases pairwise because it generally excludes less variables form the analysis.

Music Piracy Willingness

For the first regression conducted the dependent variable was willingness to engage in music piracy. In total, five models of independent variables were analyzed. The first of the five models included the offline and online differential association variables. Both variables were statistically significant. The full results of all five models can be found in Table 27 (Appendix F). In addition, these two variables explained 23.5% of the variance in the model. Both variables were positively associated with digital piracy. Out of the two variables offline differential association was more influential (Beta = .359, b = 3.860) than online (Beta = .190, b = 2.188).

For the second model, the definitions and neutralization scales were added to the regression. Both offline and online differential association remained significant, and were positively associated with willingness to engage in music piracy. The only new significant variable was the neutralization technique the claim of normalcy, which was positively associated with digital piracy. The R squared increased to .327, meaning the addition of the neutralization and definitions scales increased the variance explained in the model to 32.7%. The most influential variable in this model was claim of normalcy (Beta= 2.77, b = 6.311) followed by offline differential association (Beta = 3.59, b = 2.707), and online differential association (Beta = 1.35, b = 1.555).

For the third model, the differential reinforcement variables were entered into the regression. The addition of these variables increased the variance explained in the model to

39.4%. Four variables were significant. The most influential variable was "positive reinforcement" (Beta = 0.335, b = 5.033). The second most influential variable was the claim of normalcy (Beta = 0.217, b = 4.954) followed by offline differential association (Beta = 0.184, b = 1.977), and the receiving a virus from piracy in the past (Beta = 0.106, 8.035). All of the significant variables were positively related with willingness to engage in music piracy. This was the expected relationship for all of the variables except for the variable receiving a virus in the past. It was expected that receiving a virus in the past would decrease an individual's willingness to engage in piracy. However, it was found that receiving a virus in the past actually increased a person's willingness to engage in piracy. Online differential association lost significance with the addition of the reinforcement variables.

The imitation variables were added for the fourth model, increasing the variance explained in the model to 43.9%. For this wave, the variable receiving a virus from piracy in the past lost significance. Once again the most influential variable was positive reinforcement (Beta= 0.357, b = 5.358), followed by the claim of normalcy (Beta = 0.216, b = 4.925), and offline differential association (Beta = 1.67, b = 1.799). This was followed by the only new significant variable, "learned from message boards" (Beta = 0.148, b = 0.201). Once again, all of the significant variables were positively associated with willingness to engage in music piracy.

For the final model, the control variables were added to the regression, which increased the variance explained to 45.7%. Once again, offline differential association, claim of normalcy, positive reinforcement, and learned from message boards were statistically significant. In addition, the newly entered variable "sex" was statistically significant. Based on the betas values, the positive reinforcement variable was most influential (Beta = 0.344). Based on the unstandardized coefficient, a one unit increase on the positive reinforcement scale is associated with a 5.163 unit increase in willingness to engage in music piracy under the given situation. The second, most influential variable was the neutralization technique claim of normalcy (Beta = 0.195), indicating that a one unit increase on the claim of normalcy scale was associated with a 4.451 increase in willingness to engage in music piracy. The third, most influential variable was offline differential association (Beta = 0.180). For this variable, a one unit increase on the offline pirating peer association scale was associated with an increase in willingness to participate in music piracy of 1.929 units. The fourth most influential variable was sex (Beta = 0.133). For this sample, males had an average willingness to pirate music score 9.539 points lower than females. This finding was unexpected because the majority of past research demonstrated that males participate in digital piracy more than females (Hollinger, 1993; Skinner & Fream, 1997). The least influential variable was the imitation variable "learned from message boards" (Beta = 0.157). The results for this variable indicate that a one unit increase on the learned about piracy form message boards scale is associated with a .213 increase in willingness to engage in piracy.

Movie Piracy Willingness

Table 28 (Appendix F) provides the complete results for all five models of the OLS regression examining willingness to engage in movie piracy. For the first model on and offline differential association were entered into the regression. The R square for the first wave was .140, meaning on and offline differential association accounted for 14% of the variance in the model. Both variables were significant and positively related to digital piracy. Interestingly, online differential association had a larger impact (Beta = 2.33, b = 2.266) than offline differential association (Beta = 2.08, b = 1.965).

For the second model, the definition and neutralization scales were entered into the regression. With the addition of the new variables, the variance explained increased to 27.6%. In addition, offline differential association lost significance. In total, three variables were significant, each significant variable was positively associated with digital piracy. The most influential variable was the neutralization technique claim of normalcy (Beta = 0.311, b = 6.249). The second most influential variable was the definitions scale (Beta = 0.306, b = 3.565), followed by offline differential association (Beta = 0.155, b = 1.575).

For the third model the differential reinforcement variables were entered into the regression, increasing the variance explained in the model to 31.7%. With the addition of the reinforcement variables online differential association lost significance. However, three variables were statistically significant. Each significant variable was positively associated with digital piracy. The most influential of the three variables was positive reinforcement (Beta = 0.291, b = 3.850) followed by the definitions scale (Beta = 0.267, b = 3.103), and the claim of normalcy (Beta = 0.258, b = 5.191).

In model four, the imitation variables were added to the regression. With the addition of the new variables the variance explained in the model increased to 35.7%. No new variables were significant. However, positive reinforcement, the claim of normalcy, and the definitions scale all remained significant. Once again, each variable was positively related to willingness to engage in movie piracy. The most influential of the three variables was positive reinforcement (Beta = 0.303, b = 4.015), followed by the claim of normalcy (Beta = 5.242, b = .261), and the definitions scale (Beta = 0.258, b = 3.002).

For the final model, the control variables were entered into the regression. With the addition of the control variables the variance explained in the model increased to 37.4%. The significant variable with the highest Beta was once again positive reinforcement (Beta = 0.318). The results indicated that a one unit increase on the positive reinforcement scale was associated with a 4.205 unit increase on the willingness to engage in movie piracy scale. The second most influential variable was the definitions scale with a Beta of 0.252. The results for this variable indicated a 2.930 unit increase in willingness to engage in movie piracy for every one unit increase one the definitions scale. The final significant variable was the neutralization technique claim of normalcy (Beta = 0.247). The results demonstrated that for every one unit increase on the claim of normalcy scale willingness to engage in movie piracy increased 4.960 units.

Game Piracy Willingness

The full results of the five models for the willingness to commit gaming piracy regression are provided in Table 29 (Appendix F). For the first model in the willingness to engage in gaming piracy regression both offline and online differential association were significant. These two variables explained 12% of the variance explained in the model.

In the second model, the definition and neutralization scales were added to the regression. The most influential of the two variables was offline differential association with a Beta of 0.261 (b = 1.893), while the Beta for online differential association was 0.131 (b = 1.002). The addition of the new variables, the variance explained increased to 27.4%. Offline differential association remained significant but online did not. In addition, two of the newly entered variables were significant. Based on beta values the most influential variable in the model was the neutralization technique metaphor of the ledger (Beta = -0.349, b = -5.673). Unexpectedly metaphor of the ledger was negatively associated with digital piracy. The second most influential variable was the neutralization technique DRM defiance (Beta = 0.324, b = 5.114), followed by offline differential association (Beta = 0.148, b = 1.073). Both DRM defiance and differential association were positively related to digital piracy as expected.

In model three, the differential reinforcement variables were added to the regression. With the added variables, the variance explained in the model increased to 31.3%. Offline differential association lost statistical significance. However, four other variables were statistically significant. Once again, the neutralization technique metaphor of the ledger was the most influential variable in the model (Beta = -0.369, b = -6.001), and was negatively related toward digital piracy. This was not the expected relationship for this variable. The remaining three significant variables were each positively related to digital piracy. The most influential of the three was the neutralization technique DRM defiance (Beta -0.266, b = 4.192), followed by positive reinforcement (Beta = 0.233, b = 2.263), and the neutralization technique condemning of the condemners (Beta = 1.93 b = 2.904).

For the fourth model, the imitation variables were entered into the regression, increasing the variance explained in the model to 36.2%. With the addition of the new variables the neutralization technique condemning of the condemners lost statistical significance. However, the other significant variables from wave three remained significant, with the addition of the imitation variable “learned from message boards”. Once again, the most influential variable in the model was the metaphor of the ledger (Beta = -0.312, b = -5.076), followed by DRM defiance (Beta = 0.270, b = 4.256), and positive reinforcement (Beta = 0.243, b = 2.466). The imitation variable “learned from message boards” was the least influential (Beta = 0.152, b = .139). Once again the metaphor of the ledger had an unexpected relationship with gaming piracy.

For the fifth model, the control variables were entered into the regression. All of the previously significant variables remained significant, and the variance explained increased to 38.1%. Only one new variable was significant for the fifth wave, the junior category of the class rank dummy variable. In the full model, the most influential variable in the model was the neutralization technique the metaphor of the ledger (Beta = 0.293), indicating that a one unit increase on the metaphor of the ledger scale is associated with a 4.756 decrease in willingness to engage in computer game piracy. Once again, this was an unexpected relationship. Thus, for each wave of the analysis the neutralization technique metaphor of the ledger had the opposite relationship with willingness to engage in game piracy than was expected. The second most influential variable was the neutralization technique DRM defiance (Beta = 0.285). The results for this variable showed that there is a 4.501 unit increase in willingness to engage in computer game piracy for every one-unit increase on the DRM defiance scale. The third most influential variable was positive reinforcement (Beta = 0.285), with a one unit increase on the positive reinforcement scale being associated with a 2.438 unit increase in willingness to engage in computer game piracy. The fourth most influential variable was the imitation variable "learned from message boards" (Beta = 0.139). For the learned about piracy from message boards imitation variable a one unit increase on the imitation scale was associated with a .127 unit increase in willingness to engage in computer game piracy. The least influential variable was the junior category of the dummy coded class rank variable (Beta = 0.131). The results from this variable can be viewed as a comparison between juniors and the reference category freshmen. It was found that juniors scored 8.007 points higher on the willingness to engage in computer game piracy scale compared to freshmen.

Software Piracy Willingness

The results of the software piracy regression models are provided in Table 30 (Appendix F). For the first model in the willingness to engage in software piracy regression, offline differential association was significant (Beta = 0.215, b = 3.850), but online was not. With just the differential association variables, the variance explained was 15.6%.

For the second model, the definition and neutralization scales were entered into the regression. The addition of these variables increased the variance explained to 25.6%. Three variables were significant, and each of the three was positively related with digital piracy. The most influential of the three was the definitions scale (Beta = 0.263, b = 3.848), followed by offline differential association (Beta = .215, b = 2.565), and the neutralization technique denial of responsibility (Beta = 0.168, b = 3.797).

Once again, the differential reinforcement variables were entered into the regression for the third model. The addition of the reinforcement variables increased the variance explained in the model to 32.2%. The three variables significant in model two remained significant, with the addition of positive reinforcement. Each significant variable was positively associated with digital piracy. The most influential of the four variables was positive reinforcement (beta = 0.378, b = 6.297), followed by the definitions scale (Beta = .209, b = 3.065), the neutralization technique denial of responsibility (Beta = 0.165, b = 3.716), and offline differential association (Beta = 0.163, b = 1.946).

In model four, the imitation variables were added to the analysis. This led to an increase in the variance explained in the model to 35.3%. The four significant variables from the previous model remained significant, in addition to two of the newly entered imitation variables. Each variable was positively related to digital piracy. Once again, the most influential variable in the model was positive reinforcement (Beta = 0.352, b =5.857), followed by the definitions scale (Beta = .199, b = 2.920), the neutralization technique denial of responsibility (Beta = 0.156, b = 3.527), and offline differential association (Beta = 0.149, b = 1.774). Offline differential association is followed in influence by the imitation variables “learned from online friends” (Beta = 0.113, b = .122), and “learned from message boards” (Beta = 0.103, b = .227).

For the final model, the control variables were entered into the model. The addition of the control variables increased the variance explained in the model to 37.4%. Seven variables were significant in the final model. The most influential variable in the model was once again positive reinforcement (Beta = 0.351). The results indicated that a one-unit increase on the positive reinforcement scale was associated with a 5.849 unit increase in willingness to engage in software piracy. Unexpectedly, the second most influential variable was the neutralization technique denial of injury/ victim (Beta = 0.215). The results for this variable indicated, a one unit increase on the neutralization variable denial of injury/ victim was a associated with a 3.143 unit decrease in willingness to engage in software piracy. This finding was unexpected for two reasons; the variable was not significant in previous waves, and the direction of the relationship between the "denial of injury/victim" and software piracy was the appositive of what was expected.

The remaining significant variables were each positively related to digital piracy. The third most influential variable was the definitions scale (Beta = 0.204). A one unit increase in the definitions scale was associated with a 2.980 unit increase in willingness to engage in software piracy. The fourth most influential variable was the denial of responsibility (Beta = 0.155). For this variable, a one unit increase on the denial of responsibility scale was associated with a 3.509 unit increase in willingness to engage in software piracy. The fifth most influential variable was offline differential association (Beta = 0.138). The results for this variable indicated that a one unit increase on the offline differential association scale was associated with a 1.651 unit increase in willingness to engage in software piracy. The next most influential variable was the imitation variable "learned from message boards" (Beta = 0.146). For this variable a one unit increase on the learned from message boards scale was associated with a .220 unit increase in willingness to engage in software piracy. The final significant variable in the model was the imitation variable “learned from online friends” (Beta = 0.119), with a one unit increase on the learned from offline friends scale being associated with a .127 unit increase in willingness to engage in software piracy.

Logistic Regression

As previously discussed, the analyses for the actual piracy dependent variables were conducted using logistic regression rather than OLS regression. This was done because the interval level data was heavily skewed toward non-participation in piracy, which led to multiple problems meeting the assumptions of OLS regression. For the analysis, the same independent variables as those used in the OLS regression were utilized. In addition, the variables were placed into the model in the same order as they were for the OLS regressions.

For each logistic regression analysis model the Cox & Snell R^2, and Nagelkerkie R^2 were reported. Both of these techniques are considered pseudo R^2, thus the interpretation of these variables is different than R-square used in OLS regression. R-square is interpreted as the variance explained in the dependent variable by the independent variables in the model. However, the Cox & Snell R^2, and Nagelkerkie R^2 are interpreted as the proportionate reduction in error in predicting the category of a dependent variable based on the independent variables. Both of these measures are best used to compare different models of the same data set (Menard, 2000a). For the current study the Cox & Snell R^2, and Nagelkerkie R^2 were used to compare the models in a logistic regression as new independent variable were entered into the model. For each significant predictor in the model the B value, significance level, and Exp (B) are reported. The results of each of the four regression analyses are provided in Appendix G (tables 31 – 32).

The interpretation of logistic regression is different from that of OLS regression in that it is much less straight forward. However, an appropriate interpretation can be calculated with the following equation: (Exp (B) – 1) * 100. This calculation gives the percentage increase or decrease of the odds of a unit change in the independent variable (Pampel, 2000).

Music Piracy Involvement

The full results of the following analyses are provided in Table 31 (Appendix G). For the first model of the involvement in music piracy logistic regression the differential association variables were entered into the model. Out of the two variables offline differential association was significant, but online was not. The Cox & Snell R^2 for the first wave was .262, meaning that for this sample; there is a 26.2% percent proportionate reduction in error when the differential association variables are included in the model compared to when they are not.

For the second model, the definitions and neutralization scales were entered into the logistic regression. The addition of these variables increased the Cox & Snell R-square to .342. For this model three variables were statistically significant. The first significant variable was offline differential association, which was positively related to digital piracy. The second, was the neutralization technique condemning of the condemners. This variable was negatively related to digital piracy, which was not the expected relationship for this variable. The final significant variable was the definitions scale. The scale was positively related to digital piracy.

For the third wave, the differential reinforcement variables were added to the model. Both offline differential association and the neutralization technique condemning of the condemners remained significant. However, the definitions scale did not remain significant. Out of the newly entered variables, only the negative reinforcement variable, chance of obtaining a virus, was significant. With the addition of the reinforcement variables the Cox & Snell R Square increased to .368. Both offline differential association and change of obtaining a virus were positively related to digital piracy, and condemning of the condemners was negatively related to it. All of the variables exhibited the expected relationship with digital piracy except for the neutralization variable condemning of the condemners.

For the fourth model, the imitations variables were added to the regression. The Cox & Snell R Square increased to .391. All of the variables significant in wave three remained significant in model four, and no new variables were significant. In addition, each variables relationship with digital piracy remained the same.

In the final wave, the control variables were entered into the model. Offline differential association, condemning of the condemners, and certainty of punishment remained significant. In addition, employment status and the imitation variable "learned about piracy from movies/TV" were significant. The Cox & Snell R Square increased to .406, indicating that with all the variables in the model there is a 40.6% percent proportionate reduction in error compared to when they are not. Recall that the following equation: (Exp (B) – 1) * 100, is used to transform the odds ratio into a more interpretable form. Applying this equation to the offline friends variable the equation becomes (1.397 – 1) * 100. The result of this equation can be interpreted as follows: for each one unit increase in the offline differential association scale the odds of participating in music piracy increases by 39.7% for this sample. For the variable condemning of the condemners, the transformed odds ratio indicated that for every one unit increase on the condemning the condemners scale the odds of participating in music piracy decreases by 49.7%. This was not the expected relationship for this variable.

For the imitation variable learned from TV/ movies a one unit increase on the TV/movies scale was associated with the odds of participating in music piracy decreasing by 2.6%. This was the opposite relationship from what was expected. For the change of obtaining a virus variable, a one unit increase on the change of obtaining a virus scale was associated with a decrease in the odds of committing music piracy by 73.1%. The final significant variable was employment status. Interpretation for this variable is slightly different because both the dependent and independent variables are categorical. The odds of participating in music piracy are 156% higher for those who are employed compared to the unemployed.

Software, Game, and Movie Piracy Involvement

Table 32 (Appendix G) provides the full results for the five waves of the combined movie, software, and gaming piracy logistic regression model. As previously stated the results from this regression should be interpreted with caution, as there was a lack of variation in the dependent variable. For the first wave the Cox and Snell R Square was .106, meaning that the inclusion of the two differential association variables resulted in a proportionate reduction in error of 10.6%. For this wave, both offline and online differential association were statistically significant and positively related to digital piracy. However, neither variable was significant in the remaining waves.

In the second wave, the definition and neutralizations scales were entered into the model. The Cox and Snell R Square for wave two was .236. Five of the newly entered variables were significant in wave two. The first significant variable was the neutralization variable condemning of the condemners, which was negatively related to digital piracy. This was an unexpected outcome. The remaining significant variable in wave two were each positively related to digital piracy as expected, including the neutralization technique claim of normalcy, DRM defiance, the definitions scale, and the variable “will buy if like”.

For the third wave, the differential reinforcement variables were added to the model. The Cox and Snell R Square increased to .257. Each of the significant variables from wave three remained significant, and the direction of each variables relationship with piracy remained the same. In addition, the variables chances of virus and the neutralization technique metaphor of the ledger were significant. Both of these variables were negatively related to digital piracy. The relationship between the metaphor of the ledger was the opposite of what was expected. However, this variable was only significant for this wave.

In wave four, the imitation variables were entered into the model. The Cox and Snell R square increased to .290. Each of the significant variables from wave four other than the metaphor of the ledger remained significant. Once again, each variables relationship with piracy remained unchanged. In addition to the previously significant variables, two new variables were significant in wave four. These two newly significant variables were the imitation variable learned from message boards, and the neutralization technique denial of injury/ victim. The denial of injury/ victim variable was negatively related to digital piracy, which was not the expected direction.

For the final wave, the control variables were entered into the model. Eleven variables were significant. These variables included; definitions, denial of injury/victim, condemning of the condemners, claim of normalcy, will buy if liked, DRM defiance, positive reinforcement, learned about piracy from books/magazines, learned about piracy from directional web pages, internet use, and sex. The Cox and Snell R-square for the full model was .364, meaning that there was a proportionate reduction in error of 36.1% after all the variables were included in the model.

For the definitions variable a one unit increase on the definitions scale was associated with the odds of committing piracy increasing by 98.4%. Looking at the significant neutralization variables, a one unit increase on the claim of normalcy scale was associated with the odds of participating in digital piracy increasing by 193.6%, and a one unit increase on the DRM defiance scale was associated with the odds of committing piracy increase by 103%. For the variable "will buy if liked" the odds of participating in piracy was 430.1% higher for respondents who agreed with the statement "If I like a product that I pirate I will go buy the product" compared to those who did not agree with the statement. The other two significant neutralization variables both had a negative relationship with digital piracy. For the variable denial of injury/ victim a one unit increase on the denial of injury/victim scale was associated with the odds of participating in the last month decreasing by 47.6%. The condemning the condemners variable also demonstrated an inverse relationship, with each one unit increase on the scale being associated with the odds of participating in piracy decreasing by 72.8%. The results for these two variables were unexpected.

The imitation variable learned about piracy from books also demonstrated an inverse relationship with the odds of an individual pirating, with a one-unit increase on the scale associated with a decrease in the odds of committing piracy by 4.6%. This was also an unexpected relationship. On the other hand, the imitation variable learned from directional web pages was positively related to piracy, with a one unit increase on the scale being associated with a 3.3% increase in the odds of committing piracy. For the internet use scale, a one unit increase on the scale was associated with the odds of participating in movie, software, or game piracy increasing by 133.4%. For the variable sex, the odds of a male participating in movie, software, or game piracy was 485% higher than the odds of females participating.

Research Questions and Hypotheses

Research Question 1

The first research question investigated in this study was, "what is the relationship between online and offline sources of social learning variables (differential association, imitation, differential reinforcement, and definitions) and digital piracy after controlling for demographic characteristics"? To answer this research question multiple hypotheses were provided addressing the relationship between the various differential association variables and participation in digital piracy. The results of the OLS and logistic regressions provide the answers for this research question.

The first hypothesis stated, "variables representing on and offline sources of differential association are positively related to individual participation in digital piracy". Offline differential association was significant in at least one of the waves for every OLS and logistic regression model. Moreover, it was significant at wave five in two of the OLS models, as well as one of the logistic regression models. In every model, it was positively associated with piracy participation. Based, on these results the hypothesis as it pertains to offline differential association was partially supported. The results for online differential association were not as robust. Although the variable was significant in at least one wave for three of the OLS models and one of the logistic models, the variable lost significance with the addition of more variables to the models. When online differential association was significant, it was positively related to digital piracy. Based on these results, the hypothesis was partially supported. It should also be noted that the differential association variables were often some of the most influential variables in the model based on Beta values. In addition, they also explained a large portion of the variance in the model.

The second hypothesis stated, “variables representing on and offline sources of imitation are positively related to individual participation in digital piracy”. Out of the eight imitation variables, four were significant. Learning about digital piracy from books was negatively associated with digital piracy in the movie, game, and software piracy logistic regression analysis. Likewise, learning about digital piracy from TV/ movies was negatively related to digital piracy in the fifth wave of the logistic regression for music piracy. However, message boards as a source of imitation was significant in multiple models, and “learned from online friends” was significant in the willingness to commit software piracy regression. In addition, both variables were positively related to digital piracy, demonstrating that online friends and online message boards may serve as an important source of imitation for digital piracy. Based on these results, this hypothesis was partially supported.

The third hypothesis stated, “variables representing positive and neutralizing definitions are positively related to individual participation in digital piracy”. The positive definition variable was positively related to digital piracy in the willingness to engage in movie piracy OLS regression, willingness to engage in software piracy OLS regression, and both logistic regressions. Thus, this portion of the hypothesis was supported.

Support for the neutralization portion of this hypothesis is less clear. For example, several of these variables demonstrated an unanticipated inverse relationship with piracy. The metaphor of the ledger variable was negatively related to gaming piracy in the willingness to commit gaming piracy OLS regression, and one wave of the combined (movie, game, and software piracy) logistic regression. These results indicate that the more an individual agrees with statements representing the metaphor of the ledger, the less likely they are to pirate games. The denial of injury/ victim variable had a negative relationship with piracy in the software piracy

OLS regression, and the combined (movie, game, and software piracy) logistic regression. Finally, the variable condemning of the condemners was negatively associated with digital piracy in both of the logistic regression models. Clearly, these results did not support the hypothesis.

Conversely, several other neutralization variables demonstrated a positive relationship with piracy, indicating that as agreement with these neutralization techniques increased so did piracy. The claim of normalcy was positively related to piracy in the music OLS regression, movie OLS regression, as well as the combined (movie, game, and software piracy) logistic regression. DRM defiance was positively related to piracy in the willingness to commit gaming piracy OLS regression, and the combined (movie, game, and software piracy) logistic regression. The denial of injury was positively related to software piracy and the condemning the condemners variable was actually positively related to piracy in the willingness to commit software piracy OLS regression. Finally, the variable "will buy if liked" was positively related to digital piracy in the combined (movie, game, and software piracy) model. Thus, it appears that the hypothesis was at least partially supported.

The forth hypothesis was, "variables representing positive reinforcement in response to pirating behaviors are positively related to individual participation in digital piracy". This hypothesis was supported. For all four OLS regressions and one wave of the combined (movie, game, and software piracy) logistic regression, the positive reinforcement variable was positively related to digital piracy. In addition, it was the most influential variable in two of the full OLS regression models. Thus, this hypothesis was supported.

The fifth hypothesis stated, "variables representing punishment are inversely related to individual participation in digital piracy". Four variables examined the impact of punishment or negative reinforcement on piracy. The two traditional measures of punishment (certainty, and severity) were not significant in any of the models, indicating that the threat of formal punishment has little impact on piracy for this sample. However, the variable representing the threat of obtaining a virus was negatively related to digital piracy in both of the involvement models, indicating that individuals who view the changes of obtaining a virus as high are less likely to pirate. Unexpectedly, the variable representing receiving a virus in the past was positively associated with digital piracy in one model. Based on these results, this hypothesis was partially supported.

Research Question 2

The second research question investigated for this study was, “what is the relationship between the various control variables and digital piracy”? The first hypothesis related to this research question stated, “males are more likely to participate in all forms of digital piracy compared to females”. The results were mixed. For the willingness to engage in music piracy regression, females were more likely to participate in music piracy compared to males. However, for the involvement in non-music piracy logistic regression, males were more likely to pirate, indicating that the relationship between piracy and gender may differ depending on the type of piracy. Alternatively, this may demonstrate a difference between willingness to engage in piracy and actual piracy committed.

The second hypothesis related to this research question stated, “Internet and computer proficiency is positively related to participation in all forms of digital piracy”. This hypothesis was partially supported. Although computer proficiency was not significant in any of the models, internet use was significant in one of the models, indicating that higher internet use was positively associated with piracy.

The third, hypothesis related to this research question stated, “individuals with high speed internet connections are less likely to participate in all forms of digital piracy compared to individuals without high speed connections”. It was not possible to answer this hypothesis with the data for this study, due to the limited variance in internet speed between respondents.

The final hypothesis related to this research question stated, “individuals who are employed are less likely to participate in all forms of digital piracy”. This hypothesis was not supported. Interestingly the results for wave five of the involvement in music piracy logistic regression demonstrated a higher likelihood of piracy by those who are employed. However, the sample for this study was a fully student sample. It is possible that the results were opposite from what was expected because many students receive financial support from sources other than employment.

Summary

This chapter presented the results of this dissertation, which primarily sought to determine the relationship between social learning and digital piracy. Overall, the results demonstrated the expected relationship between the four social learning variables and digital piracy. At least one variable representing each social learning component was significant across the OLS and logistic regression analyses. However, the four components varied in importance. Differential association and definition/ neutralizations were the components with the strongest influence on digital piracy, and the most significant variables across the models. Aspects of differential reinforcement were supported in multiple models, although positive reinforcement had a larger impact than negative. Out of the social learning components, imitation was the least supported, with only one out of eight variables being positively related to piracy. Finally, different social learning variables were significant in regards to different digital piracy models.

This suggests that the social learning factors differentially effect piracy participation based on type of piracy.

Although the majority of the results supported social learning theory, there were also some unexpected results. First, multiple neutralization components were found to be negatively associated with digital piracy. There are multiple possible reasons for these findings, which will be discussed in detail in the next chapter. Second, the demographic and control variables produced some unanticipated results. More specifically, females showed a higher willingness to pirate in one of the music OLS regression model. In addition, participants who stated that they were employed had a higher probability of participating in the piracy music logistic regression model. A detailed interpretation of these findings is presented in the next chapter, as well as a discussion of the strengths and weaknesses of this study, and remarks on potential avenues for future research.

CHAPTER V

DISCUSSION AND CONCLUSION

Many studies have examined the problem of digital piracy, and tested the applicability of criminological theories to it (Skinner and Fream, 1997; Hinduja, 2001; 2007; Morris and Higgins, 2009; 2010; Gunter, 2009; Higgins, Fell, & Wilson, 2006). The current study expanded on this past research in many areas. The main purpose of this study was to conduct a more complete test of the effects of social learning theory on digital piracy, with a focus on online interactions. In this chapter, the results of the analyses outlined in the previous chapter are discussed in greater detail. This chapter first covers the strengths and limitations of the study. In addition, this chapter highlights the important findings from the analyses and evaluates their meaning. Finally, suggestions for future research are provided.

Strengths and Limitations of the Current Study

Limitations

There were a number of limitations to the current study that warrant discussion. Perhaps the largest limitation of this study was the very low response rate (8.9%). Even though multiple measures were taken to increase response rates (i.e., offering an incentive, sending survey invitations early, and personalizing the emails to each institution), they appeared to have little effect. For this reason, online survey administration seems to be a double edged sword. On the one hand, the current study provided the first truly random sample for a study examining digital piracy. However, with a response rate so low it was likely no better than the many convenience samples used in past research.

The biggest problem with such a low response rate was that it increased the chances of non-response error. Non-response error could potentially happen in any sample; however the risk is higher when response rates are low. Non-response error occurs when those who do not respond to the survey are significantly different in some meaningful way from the individuals who do participate (Dillman, 2009). For example, if the only people who took the survey were strongly in favor of piracy and answered the survey because the topic was interesting to them, non-response error could have been an issue. It is fairly difficult to assess non-response error. The impact of non-response error on the current study was likely minimized to some extent because the sample matched the demographics of the population under study somewhat closely. This was encouraging because having low response rates does not necessarily mean non-response error is present, when the characteristics of the respondents match those of non-respondents (Sax, Gilmartin, and Bryant, 2003). Nevertheless, the results from the current study should be interpreted with caution.

A second limitation was related to the sample size for this dissertation. As previously mentioned, the sample size for this study was 304 after removing individuals with large amounts of missing cases. This was a sufficient number of respondents for conducting the analyses used in the study. However, for the regression analyses, the sample size was often lower than this due to random missing cases. The cases entered into the OLS regression models was 289, and 269 for the logistic models. While this was more than enough cases for the OLS models, it is less than ideal for wave five of the logistic regression model based on the conservative estimate of 10 cases per variable (Harrell et al, 1984). Thus, the results for waves five, and potentially four, were suspect for the logistic regression models. This may have resulted in variables not achieving significance that should have because the sample size was too small. For this reason, variables significant at the .10 level were indicated on Tables 32 and 33 (Appendix F). One variable that was close to achieving significance in models four and five of the involvement in music piracy logistic regression was the imitation variable “learned from directional webpage”. It was possible that this variable did not achieve significance due to the low response rate.

Third, only college students were sampled for this study. Thus, generalizations could not be made to non-college students. A fourth limitation relates to the way the criminal involvement of peers was measured. For the present study, the criminal involvement of peers was measured by asking the respondent to report how many of their friends participate in the behavior being studied. This form of measurement may not accurately capture the criminality of a respondent’s friends, and has been criticized as capturing the individual’s own criminality rather than their friends (Gottfredson and Hirschi, 1990). However, this is likely not a large problem as multiple studies have demonstrated that a respondent’s perception of their friends’ behavior is not the same as their own (Menard and Elliot, 1990; Warr, 1993, and Thornberry et al, 1994).

A fifth limitation concerns the way the involvement dependent variables were measured. The involvement in piracy variables measured each respondent’s participation in digital piracy over the past month. Based on the results of this study, it was clear that one month was not a long enough interval of time to collect participation data on the less frequent forms of piracy. Due to problems stemming from the low levels of piracy, the analysis for these variables was changed to logistic regression, and movie, gaming, and software piracy were collapsed into one variable. These changes limited the comparisons that could have been made between the willingness and involvement dependent variables. To avoid this problem, future studies should consider a one year interval when examining past piracy.

Strengths

The current study had multiple strengths. First, it was a more complete test of social learning theory on digital piracy than previous studies. Most past studies that have tested the influence of social learning theory on digital piracy have only included measures for differential association and definitions. The only other study to test all four components of social learning theory on digital piracy was Skinner and Fream's (1997) study examining software piracy. A great deal has changed in regards to piracy and computer use in general over the last fourteen years, meaning a fresh test of the full theory was needed. All in all, the current study tested eight imitation variables, six differential reinforcement variables, one general definitions variable, eight neutralization variables, and two differential association variables. Many of these variables had never or had only rarely been tested in past research. Thus, this study contributed to the advancement of social learning theory in multiple areas. For example, to the knowledge of the researcher this was the first study on digital piracy to include positive as well as negative differential reinforcement variables.

A second strength for this study was the creation and testing of two new neutralization techniques. Both DRM defiance and the claim of future patronage were created for this study, and both variables provided important insights and new directions of study related to digital piracy. Thus, the utilization of these variables has provided a greater understanding of digital piracy and neutralization theory. Both of these techniques follow the advice of Murana and Copes (2005) that neutralization techniques should be crime specific. The results from these two variables, particularly DRM defiance, suggested that specially created neutralization techniques that are tailored to a behavior can be important predictors of crime. Thus, future studies of the techniques of neutralization should consider crime specific neutralizations as well as the more traditional general definitions.

Third, this study contributed to the literature on the effect of online sources of social learning on criminality. The way people interact has changed a great deal in recent years. Online forms of communication have continually evolved and developed. The studies on the subject have demonstrated that online sources of social learning can have an effect on behavior (Holt and Copes, 2010, Hinduja and Ingram, 2009); although, as the current study demonstrated, the effect of online sources of social learning may not be as strong or clear as offline sources. Thus, it is clear that future criminological studies need to take the influence of online social interaction seriously and further research should be conducted in this crucial developing area. This dissertation demonstrated that online differential association and imitation from message boards are both related to digital piracy. This is a good start for this area of research. However, there is still much that needs to be examined in future studies.

The final major strength of this study is that it examined four distinct types of digital piracy separately. In addition, each type of piracy was measured two separate ways. This allowed for a more comprehensive examination of digital piracy and hints that the factors that influence digital piracy differ to some extent between piracy types. In addition, this was the first study to examine gaming piracy, which provided many interesting results.

Discussion of Findings

The findings from this study provided many insights, but also offered new questions in regards to digital piracy and social learning theory. Overall, the results from this study supported the claim that social learning theory can be used to explain digital piracy. This was consistent with past multivariate tests of social learning theory on digital piracy (Morris & Higgins, 2009; Gunter, 2009; Higgins, Fell & Wilson, 2006; 2007). In this section a few of the more noteworthy findings for this study are discussed.

Piracy Prevalence for the Sample

Some of the interesting findings for this study did not coincide with any of the hypotheses that were tested. To begin, the levels of piracy found in this study were noticeably lower than those from previous studies (Morris and Higgins, 2009; Hinduja, 2007; Ingram and Hinduja, 2008). For example, Morris and Higgins (2009) reported a *one year* music piracy prevalence of 57.4% looking at piracy. In addition, they found the one year piracy prevalence for video piracy to be 26.9%, and software piracy to be 24.5%, for a total piracy prevalence of 60.2%. For the current study the music piracy *one month* prevalence was 26.3%, while the movie and software piracy rates were 9.5 and 7.9% respectively. In addition, the total piracy prevalence for the current study was 29.9%. This difference appears to be a byproduct of how the piracy variables were measured. Based on the low piracy prevalence rates for this study it is recommended that future studies examine longer periods of time, such as six to twelve months. Accordingly, this difference does not appear to be entirely inconsistent with past research (Morris and Higgins, 2009; 2010; Gunter, 2009). On the contrary, in past research music piracy was consistently the most prevalent form of piracy, followed by movie piracy, then software piracy. The current study is the first to examine gaming piracy as a separate dependent variable, which had the lowest prevalence rate of all four variables in the study (i.e., 4.6%).

There are multiple possible reasons for why research has consistently found music piracy to be the most prevalent form of piracy. First, the files downloaded are often much smaller and take considerable less time to download. In addition, the technical ability needed is arguably lower as the files are easily transferred between devices, and the quality of the pirated product is often comparable to that of a retail product. This is not always the case for pirated movies, software, and games. Software and game piracy, for example, often require a higher level of technical know-how to circumvent DRM protections. In addition, software is often provided by the university in some capacity; thus, need for pirated software may be reduced for this sample. In short, this creates fewer incentives to download pirated movies, games, and software.

Differential Association and Imitation

One of the main focuses of this study was to test the importance of social learning on digital piracy, particularly online social learning. This issue was explored with the differential association and imitation variables. One of the most supported findings for differential association theory in past research was the positive link between criminal peers and individual criminality (Warr, 2002). This was largely the case for the current study with regards to offline sources of differential association. However, the results for the online sources of social learning were not as clear and warrant deeper discussion.

To the knowledge of the researcher, only one previous study had quantitatively examined the influence of online differential association on digital piracy (Hinduja and Ingram, 2009) prior to this study. In that study, online peers were a significant predictor of music piracy even after eight control variables were entered into the analysis. For the current study, online peer association was a significant predictor of digital piracy in multiple models, including: music willingness, movie willingness, game willingness, and involvement in the combined movie, game, and software piracy. In each model, online peer association lost statistical significance as more variables were entered into the model, often losing significance at wave two or three. Comparatively, the offline differential association variable often remained significant through all five waves of a model. However, this does not necessarily signify that it should be excluded from future research; quite the contrary. It is clear the variable has some importance in explaining digital piracy, and it is possible its importance will grow in coming years as people continue to interact in new and innovative ways online.

Based on these results it appears online differential association is not as strong of a predictor of digital piracy as offline differential association. There are a couple of possible explanations for this finding. First, according to Akers (2009), differential association has the strongest effect on behavior when the association is occurring in intimate personal groups such as the family or close friends. It is possible that at this time online differential association can be viewed more as a secondary group similar to neighbors, teachers, and the media. Online interactions differ significantly from offline interactions in that it is possible for individuals to obtain information from online sources in a relatively passive manner. In other words the intensity of their interactions may be weaker, which would explain the variables weaker effect on digital piracy. A second possible explanation is that the majority of respondents simply interact more with offline friends. This makes sense for a college population, since students often live in close proximity and are surrounded by their friends often. Recall that differential association usually has a stronger effect on a behavior if the frequency of association is higher (Akers, 2009; Sutherland, 1947). If this is the case, it is not unexpected that offline differential association had a stronger effect than online differential association.

A third potential explanation for the weak finding for this variable is the social structure of the population being studied. The majority of college students receive ample opportunity to associate with a large pool of people who are technologically savvy while attending college. Thus, there may be less need for online sources of social learning for this population. However, online differential association may prove more important in a non-college student sample with less access to a large pool of offline peers.

Another potential explanation for the weak findings is that the measurement of the online differential association variable was too broad. For the current study, online differential association was broadly measured to include all online social interaction (e.g. social networking, online gaming, message boards). It is possible, that certain forms of online peer interaction are more conducive to online social learning than others. In addition, this could have led to overlap between the online and offline variables. For this reason, future examinations of online social learning should take care not to make their variables too broad which may diminish the effects. One way this could be accomplished is by measuring more specific subcategories of online interaction. For the current study, this was accomplished to some extent with the imitation variables. The results from the imitation variables do demonstrate a difference in the importance of online social learning variables. Recall that for this study imitation was conceptualized as a source used for learning the techniques to commit digital piracy. This was based on the study by Skinner and Fream (1997), which was the only prior study to examine imitation variables in relation to digital piracy. Although multiple online sources of imitation were significant in at least one regression analysis, online message boards was significant in multiple. This is likely due to the higher level of social interaction possible on online message boards where techniques to commit digital piracy as well as rationalization in favor of piracy are easily shared and retrieved at any time (Etzioni and Etzioni, 1999). Thus, message boards may be important because they have a greater potential to expose individuals to definitions in favor of piracy, and provide opportunities for receiving positive reinforcement. These results add further support to the statement that online sources of social learning can affect digital piracy participation.

Examining the online differential association and imitation variables together it appears that online sources of social learning can have an impact on digital piracy, however the impact varies across different sources of online interaction. Future studies should explore this issue in greater detail in order to pinpoint the most influential sources of online social learning. As a final note, it is possible that the conceptualization of online imitation and differential association needs to be refined in future studies to move our understanding of online sources of social learning on criminal behavior forward. This may require combining the differential association and imitation variables as there is some overlap between the two in the current study.

Definitions

In this section the results for the neutralizing definitions are discussed. Two findings were especially noteworthy. The first was the results for the newly created neutralization variables. The second was the mixed relationship found between piracy and the various neutralization techniques. Each of these findings are discussed in this section, starting with a discussion of the mixed results.

Neutralizing definitions represent justifications used for diminishing the guilt of delinquent or criminal acts (Akers, 2009). Thus, it was expected that neutralizing definitions would be positively related to criminality. Based on the results of this study it was clear that many of the variables were supportive of neutralization theory (i.e., claim of normalcy, DRM defiance, denial of responsibility). However, others were not (i.e., the metaphor of the ledger, condemning of the condemners). Thus, the overall results for the impact of neutralization techniques were mixed for this study. Such mixed results have been common in past neutralization literature (Murana and Copes, 2005). The question is whether these mixed results are due to flaws within social learning theory or due to measurement and methodological issues.

There are a few theoretical issues that may account for the mixed findings. First, it is possible that some digital pirates do not view their behavior as wrong. Neutralization techniques allow for criminality by diminishing the guilt associated with a criminal act. If an individual does not view a behavior as wrong, neutralization techniques may be of little use for them. This could potentially be controlled for by including more variables measuring general acceptance of piracy. Second, specific neutralization techniques may not be applicable to all crimes equally. According to Minor (1981), not all neutralizations apply equally across all circumstances. In other words, certain neutralization techniques may not apply as well to digital piracy as they do other crimes. For example, the metaphor of the ledger was originally developed in a study of a professional fence. The notion of justifying actions based on mental calculation of positive and negative actions over a lifetime may make more sense for a fence than a digital pirate.

Some of the mixed results may also be due to methodological issues related to threats to internal validity out of the control of the researcher. For example, large scale events taking place at the time of the study could have shaped the views of participants (i.e., a history threat). This could explain the strange results for variables such as the neutralization technique condemning of the condemners. As this study was taking place the Occupy Wall Street movement was beginning to capture a large amount of public attention. The movement is credited with placing corporate greed and many other social issues in the public spotlight. It is evident that Occupy Wall Street had an effect when examining trends in newspaper reporting. For example, stories related to greed and inequality were covered much more than normal while this study was being conducted. This has largely been attributed to the Occupy Wall Street movement (Dreier, 2011). It is possible these events influenced the results of this study by creating higher levels of disapproval and distrust for big companies in non-pirating individuals. This could have had an influence on the neutralization variable condemning of the condemners and the denial of injury/victim.

The second noteworthy finding was the results for the two new neutralization techniques created for this study. The first was the claim of future patronage. The creation of this technique was based on qualitative statements made by digital pirates' in prior studies stating they would eventually pay for pirated products (Hold and Copes, 2010). Recall, that the claim of future patronage was not measured as a scale due to a low alpha value. Instead it was split into two separate variables with only one being significant (i.e., "will buy if like"). This variable should be expanded upon in future studies. However, the second future patronage variable (i.e., "buy after graduation") should be dropped from study as it does not seem to represent a neutralization used to justify digital piracy. The results for the "will buy if like" variable demonstrate that some digital pirates may view digital piracy as a way of sampling different digital products. If this practice is widespread it may demonstrate that piracy can actually be benefitual to companies to some extent, as it could potentially lead to increased sales. However, it is also possible that this technique of neutralization represents an empty rationalization, and few pirates actually follow through and buy the product. Based on this, future studies should determine if an individual has participated in piracy, and then ask a follow up question to see if any participants who pirate actually do eventually buy the products they pirate.

The second new technique was DRM defiance. This variable was based on past findings from studies outside of criminology which found that DRM can have a negative effect on legitimate customers (Sinha, Machada, and Sellman, 2010; Milligan, Han, and Burestein, 2003). The variable had the strongest impact on gaming piracy. A possible reason for this is that the gaming industry has some of the most restrictive DRM out of the four industries examined. Thus, it makes sense that gaming is the area it has the largest impact. Based on these results it is clear that DRM defiance is a potentially important new neutralization technique when examining gaming piracy specifically. The results suggest that DRM can actually be counter-productive, and may potentially increase piracy rather than decrease it because it provides pirates a compelling rationalization for their behavior. From a policy stand point companies should consider the net harm of DRM to legitimate customers before implementing it, and avoid the risk of creating new pirates. This point is heightened by the research that shows DRM is often cracked fairly quickly (Haber, Horne, Pato, Sander, & Tarjan, 2003), meaning it at times does very little to actually stop piracy. This variable should be included in future studies that choose to examine gaming piracy, and may even be significant for other types of piracy.

Differential Reinforcement

In this section, the results for the differential reinforcement variables are discussed. Recall that differential reinforcement refers to the influence of a reward or punishment on future behavior (Akers, 2009). The punishment variables in the current study had a limited impact on digital piracy with the exception of “the threat of obtaining a virus” variable, which was inversely related to digital piracy. The limited impact of punishment was particularly apparent in regards to legal sanctions, a finding that is consistent with much of the past research (Skinner and Fream, Gunter, 2009; Cooper and Harrison, 2001). One potential reason for this is that the threat of legal punishment was perceived as low by the majority of participants in this study. This can be contrasted to the threat of obtaining a virus from piracy, which the majority respondents saw as a likely event. Receiving a virus is a more realistic negative consequence of digital piracy. Thus, it is no surprise that it was an important variable while legal sanctions were not.

In contrast to the overall weak impact of the punishment variables for this study, positive reinforcement often had the strongest effect out of all of the variables in the model. From a theoretical perspective the strong relationship between digital piracy and positive reinforcement is promising, these results demonstrate that the perceived outcome of piracy can affect a person's decision to pirate. There are a few possible explanations why the results for the positive reinforcement variables had a stronger effect than the punishment variables. First, differential reinforcement theoretically encompasses the probability of past, present, and anticipated rewards or punishment for a given behavior while the current study mainly focused on anticipated rewards and punishments. The only exception to this was the variable “ever received a virus”. Since the variables for this study focused on anticipated rewards and punishment, the probability of those rewards and punishments occurring could have had an effect on the results. The positive reinforcement variables were all related to outcomes that would almost always be a benefit of piracy (e.g. saving money), while many of the punishment variables examined events that only had a slight possibility of occurring. Thus, the difference between punishment and reinforcement may be due to the way the variables were measured. Based on these results it is recommended that future studies examine the impact of positive reinforcement on digital piracy in greater detail, and should include more sources of reinforcement and punishment, and consider examining the relationship between differential reinforcement and digital piracy longitudinally.

Second, these results may simply demonstrate that positive reinforcement has a stronger effect on behavior than punishment. This may indicate that behaviors are more easily reinforced with positive reinforcement rather than punishment. This is consistent with literature on operant conditioning, on which Akers conceptualization of reinforcement and punishment is partially based. Such findings have been widely documented in the study of non-criminal behavior, such as research on controlling student behavior (Charles, 1999). If positive reinforcement is more effective than punishment for digital piracy policies to combat digital piracy should take this possibility into account. For example, companies should utilize strategies that compete with the factors that positively reinforce digital piracy. More specifically, companies should make digital products convenient to obtain legitimately through digital distribution. If legitimate copies are just as easy to obtain as a pirated copy it may reduce the allure of piracy.

Based on these results companies should consider limiting the use of punishment as a way to stop digital piracy. If punishment is used it needs to be more certain to have any effect, as it is possible that punishment had little effect in this study because the majority of respondents viewed the certainty of punishment as low. However, making punishment for digital piracy more certain is not an easy task. Although it is possible to track digital pirates in some cases the tracking process can have problems because it tracks IP addresses. IP addresses are not necessarily a good source for identifying individual pirates because they are often shared and easily compromised.

Directions for Future Research

The current study provides many insights for future areas of inquiry related to digital piracy. Many potential directions for future research were already discussed throughout this chapter, such as expanding the research on online sources of social learning. In this section five addition suggestions for future research are provided.

First, future studies of digital piracy should continue to measure the different subcategories of piracy separately, because the reasons for pirating may differ between piracy categories. A student downloading a program needed in a class has different motivation for piracy than one who downloads a song for fun. For this reason, many social learning variables may have differential effects depending on the type of piracy being examined, as this study has demonstrated. In addition, further study should be conducted on the gaming subcategory of piracy. The current study was the first to examine gaming piracy as its own category. Although, gaming piracy had the lowest prevalence, the results from the analysis of the gaming piracy model were very interesting. For this reason, future studies should continue to explore this subcategory of piracy by continuing to include it as a separate variable in future studies. In addition, future studies should examine piracy in the gaming community specifically. Doing so would likely yield a higher prevalence of gaming piracy. This could be achieved by sampling individuals who participate in online gaming communities through gaming community message boards.

Second, the sample for the current study consisted solely of college students. This is a common problem with digital piracy research. College students are a suitable population for the study of digital piracy due to their easy access to technology and high levels of technical knowhow (Jones, 2002; Kaminski, Seel, and Cullen, 2003). However, to date, only a sliver of the digital piracy research has examined non-college student populations. As society in general becomes more technologically sophisticated, it is possible that piracy will become a larger problem within the general population. Therefore, studies should begin to examine digital piracy in the general population. In addition, piracy studies should be expanded to include middle and high school students. Most juveniles today possess a high level of technological ability. Knowing that high speed internet is becoming more prevalent, many juveniles today have the same tools as most college students for committing digital piracy. There are many new insights that could be gained from the study of these non-college student populations, such as the extent of digital piracy in the general community, and the applicability of social learning theory in a non-college student sample. For this reason, researchers need to move past the convenient samples of the past for the literature on digital piracy to move forward.

Third, regarding methodology future studies should consider the use of longitudinal and qualitative methods to further study digital piracy, such as the differential association variables. A common criticism of social learning theory is that the relationship between criminal friends and self-criminality does not support the learning of crime from peers. Instead, it simply demonstrates that criminals will seek out like minded individuals to include in their peer group (Gottfredson and Hirschi, 1990). The use of a longitudinal design could potentially shed some light on this problem with regards to digital piracy. For example, future studies could examine a cohort of students over their first four years of college and examine changes in peer association and self-reported digital piracy. Qualitative studies would also increase the understanding of digital piracy, by providing a more focused examination of the problem and how it relates to social learning theory. For example, future researchers could conduct participant observation studies and online interviews with digital pirates within online communities.

Finally, future studies should consider grouping pirates into categories based on their propensity for piracy so that the nuanced differences between the occasional pirate and the hardcore pirate can be more fully established. It is reasonable to consider that social learning affects different classes of pirates differently because it affects who they associate with. For example, hardcore digital pirates may hold neutralizations different from less committed pirates who may not identify themselves as a pirate. Analyses for such a variable could easily be accomplished using multinomial logistic regression. If distinctions exist between categories of pirates, it could explain some of the unexpected findings from the current study.

Conclusion

In conclusion, digital piracy is a growing issue in the United States and worldwide. This is an important issue, and how it is dealt with can have huge implications for society as a whole.

This is apparent when examining the potential implications of the Stop Online Piracy Act (SOPA), a bill that was introduced in Congress as this study was being conducted. This bill was designed to stop digital piracy however, critics point out that the bill's wording is very broad and has the potential to damage legitimate businesses, censor portions of the internet if not handled properly, and reduce the overall security of the internet (Limley, Levine, and Post, 2011). It is evident from these developments that governmental responses to digital piracy can potentially have a large impact on all of society and not just digital pirates. This increased social significance of digital piracy highlights the importance of this study and others that shine a light on the possible causes of digital piracy. As we come to better understand what factors contribute to digital piracy we can better respond to the problem while reducing the amount of collateral damage to society.

The results of this study demonstrated the importance of social learning theory as an explanatory factor for digital piracy. From a policy perspective the current study offered some insights on how to deal with digital piracy. Based on the results of this study changing definitions toward piracy could potentially lower piracy. In addition, based on the differential reinforcement findings, companies may do better reducing piracy by offering legitimate products through more convenient methods such as digital distribution. Lastly, the results may indicate that the use of DRM can be counterproductive and alternative strategies should be developed. At this time these solutions are only speculative, as more studies need to be conducted to verify and expand on the results from this study.

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APPENDIX A

Initial Email University One

Dear (University Name) Student,

You have been invited to participate in a survey regarding digital piracy. This survey is part of my dissertation project. Your completion of the survey would really help me with the project. You are eligible to participate because you are a student at (University Name). Your participation in this study is important leading to a better understanding of why students do and do not participate in digital piracy.

If you decide to take part in the study, you will be directed to a separate page where you will be presented with an informed consent form. This form will go over the study in more detail. Your answers to the survey are completely anonymous and cannot be linked back to you in any way.

If you are willing to participate in this study, please click on the link provided at the bottom of this email. The survey should take no more than 15 to 20 minutes to complete. Once you have completed the survey, you will have the choice of being entered into a drawing to receive a $100 Amazon gift card.

I greatly appreciate your participation in this study! Thank you for your time. If you have any questions or comments feel free to contact me or my dissertation chair, my contact information is provided below.

Sincerely,

Joshua Smallridge, Doctoral Candidate .
(Contact Information Provided Here)

to the Survey:
Survey Link

Or copy and paste the URL below into your internet browser:
Survey URL

Initial Email University Two

Dear (University Name) Student,

You have been invited to participate in a survey regarding digital piracy. This survey is part of my dissertation project. Your completion of the survey would really help me with the project. You are eligible to participate because you are a student at (University Name). Your participation in this study is important leading to a better understanding of why students do and do not participate in digital piracy.

If you decide to take part in the study, you will be directed to a separate page where you will be presented with an informed consent form. This form will go over the study in more detail. Your answers to the survey are completely anonymous and cannot be linked back to you in any way.

If you are willing to participate in this study, please click on the link provided at the bottom of this email. The survey should take no more than 15 to 20 minutes to complete. Once you have completed the survey, you will have the choice of being entered into a drawing to receive a $100 Amazon gift card.

I greatly appreciate your participation in this study! Thank you for your time. If you have any questions or comments feel free to contact me or my dissertation chair, my contact information is provided below.

Sincerely,

Sincerely,

Joshua Smallridge,
(Contact Information Provided Here)

Follow this link to the Survey:
Survey Link

Or copy and paste the URL below into your internet browser:
Survey URL

Follow-up Email # 1 University One

Dear (University Name) student,

Last week I sent you an email asking you to respond to a brief survey on digital piracy I'm doing as part of my dissertation research. I was hoping you could take 15- 20 minutes of your time to complete the survey. Doing so would help me greatly. Any information you provide in the survey is completely anonymous and cannot be linked to you in any way.

Your responses to this survey are important! For this reason, I encourage you to take a few minutes and complete the survey.

Please click on the link below to go to the survey website, where you will be able to take the survey. Once you have completed the survey, you will have the choice of being entered into a drawing to receive a $100 Amazon gift card.

Thank you for your time.

Many thanks,

Joshua Smallridge, Doctoral Candidate

(Contact Information Provided Here)

Follow this link to the Survey:
Survey Link

Or copy and paste the URL below into your internet browser:
Survey URL

Follow-up Email # 1 University Two

Dear (University Name) Student,

Last week I sent you an email asking you to respond to a brief survey on digital piracy I'm doing as part of my dissertation research. I was hoping you could take 15- 20 minutes of your time to complete the survey. Doing so would help me greatly. Any information you provide in the survey is completely anonymous and cannot be linked to you in any way.

Your responses to this survey are important! For this reason, I encourage you to take a few minutes and complete the survey.

Please click on the link below to go to the survey website, where you will be able to take the survey. Once you have completed the survey, you will have the choice of being entered into a drawing to receive a $100 Amazon gift card.

Thank you for your time.

Many thanks,

Sincerely,

Joshua Smallridge,
(Contact Information Provided Here)

Follow this link to the Survey:
Survey Link

Or copy and paste the URL below into your internet browser:
Survey URL

Follow-up Email # 2 University One

Dear (University Name) Student,

I am hoping that you may be able to give about 15 minutes of your time to help me collect important information regarding digital piracy by completing a short survey.

If you decide to take part in the study, you will have the choice to be entered into a drawing for a $100 Amazon gift card. I encourage you to complete the survey. I will be ending the study next week, so I wanted to email everyone who has yet to complete the survey to make sure everyone has a chance to participate.

If you are willing to participate in this study, please click on the link provided at the bottom of this email.

Thank you in advance for completing the survey, your input is very important.

Sincerely,

Joshua Smallridge, Doctoral Candidate
(Contact Information Provided Here)

Follow this link to the Survey:
Survey Link

Or copy and paste the URL below into your internet browser:
Survey URL

Follow-up Email # 2 University Two

Dear (University Name) Student,

I am hoping that you may be able to give about 15 minutes of your time to help me collect important information regarding digital piracy by completing a short survey.

If you decide to take part in the study, you will have the choice to be entered into a drawing for a $100 Amazon gift card. I encourage you to complete the survey. I will be ending the study next week, so I wanted to email everyone who has yet to complete the survey to make sure everyone has a chance to participate.

If you are willing to participate in this study, please click on the link provided at the bottom of this email.

Thank you in advance for completing the survey, your input is very important.

Sincerely,

Joshua Smallridge, Doctoral Candidate
(Contact Information Provided Here)

Follow this link to the Survey Follow this link to the Survey:
Survey Link

Or copy and paste the URL below into your internet browser:
Survey URL

APPENDIX B

Informed Consent Page

You are invited to participate in a research project by completing this survey. The following information is provided to help you to make an informed decision about participating in this survey. If you have any questions, please do not hesitate to ask. You are eligible to participate because you are a student enrolled during the current semester at (University Names)

The purpose of this study is to determine why students do and do not participate in digital piracy. Participation in this study will require approximately fifteen minutes of your time. There are no known risks associated with this research.

Your participation in this study is entirely voluntary. You may withdraw from the study at anytime by simply closing your browser. If you participate your responses to the survey questions will be completely anonymous. The information obtained in this study will help us better understand the reasons why individuals participate in digital piracy.

If you are willing to participate in this study, please click on box stating “I Agree” at the bottom of this page. Once you complete the survey you will have the option of being entered into a drawing for a $100 Amazon gift card. Choosing to be entered into this drawing will not be connected to your survey response.

Thank you for your time,

Joshua Smallridge, Doctoral Candidate
Indiana University of Pennsylvania
Department of Criminology
Wilson Hall, Room 200
Indiana, PA 15705
Email: rznq@iup.edu
Phone: (304) 502-2767

Jennifer Roberts, Ph.D.
Indiana University of Pennsylvania
Department of Criminology
Wilson Hall, Room 205
Indiana, PA 15705
Email: jroberts@iup.edu
Phone: 724-357-5933

This project has been approved by the Indiana University of Pennsylvania Institutional Review Board for the Protection of Human Subjects (Phone: 724/357-7730).

I Agree

APPENDIX C

Neutralization Indicators

Denial of Responsibility

1. 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.
2. The university should be responsible for providing access to software or other digital media; this way people would not have to download it illegitimately.

Denial of Injury

3. Artists make so much money from concerts, videos, sponsors, and other sources, they aren't really hurt by illegal downloading.
4. It is ok to download copyrighted materials without the owner’s permission because most big companies have so much money copyright infringement by individuals doesn’t really hurt them.

Denial of a Victim

5. Illegitimate downloading is a victimless crime.
6. It is okay to download copyrighted materials without the owner’s permission because many big companies are unethical and try to rip of consumers, so they deserve what they get.

Condemning the Condemners

7. Music, gaming, and software companies often steal ideas and materials from other companies, so they are getting what they deserve when people pirate from them.
8. It's really not college students’ fault that they download digital goods rather than paying for it; prices are just too high these days.

An Appeal to Higher Loyalties

9. It feel it would be ok to download copyrighted materials without the owner’s permission if a family member, friend, or significant other really needed me to do so.

Defense of Necessity

10. If I had to pay for all the music and software that I listen to or use, I *wouldn’t* be able to afford tuition, books, and other regular expenses.
11. 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.
12. College students who download necessary software because they can't afford it should not be held liable for doing such things.

Metaphor of the ledger.

13. It is ok to download copyrighted materials without the owner's permission because downloading a few things without permission isn't that big of a deal when you consider all the good that I have done in my life.
14. Doing something questionable once in a while is a lot less serious than someone who regularly breaks the rules.

Claim of Entitlement

15. It is ok for me to download copyrighted materials from time to time, because I deserve something for free sometimes.
16. I work hard; therefore, sometimes I deserve to download something for free.

Claim of Normalcy

17. I feel digital piracy is ok, since everyone else downloads copyrighted material.
18. Other people are benefiting from digital piracy, and so why shouldn't I?

Claim of Future Patronage

19. If I like a product that I pirate I will go buy the product.
20. I will pay for the majority of the things I pirate when I graduate and make more money than I do now.

DRM Defiance

21. Pirated copies are often superior because copyright restrictions are removed allowing more freedom of use.

22. Companies get what they deserve when college students pirate digital goods because copyright protections restrict paying customers.

Note: Items 1, 2, 3, 5, 7, 8, 9, 10, 11, and 12 were adapted from Morris and Higgins (2010). Items 14, 15, 16, 17, and 18 were adapted from the work of HInduja (2007).

APPENDIX D
SURVEY INSTRUMENT

A common definition of digital piracy is the unlawful copying or downloading of digital products (software, digital audio files, digital video files, and PC games) without the owner's consent, and without compensation to the owner.

1.) Have you downloaded a music file without the owner's permission within the last month?

a. Yes
b. No

If yes… How many music files have you downloaded without the owner's permission within the last month.

☐ # of music files

2.) Have you downloaded a movie without the owner's permission within the last month?

c. Yes
d. No

If yes… How many movies have you downloaded without the owner's permission within the last month.

☐ # of movies

3.) Have you downloaded a computer game without the owner's permission within the last month?

e. Yes
f. No

If yes… How many computer games have you downloaded without the owner's permission within the last month.

☐ # of computer games

4.) Have you downloaded commercial software (i.e. Photoshop, Microsoft office, exc) without the owner's permission within the last month?

g. Yes
h. No

If yes… How many times have you downloaded commercial software without the owner's permission within the last month?

☐ # of software

For each of the following questions please select the best answer.

5.) How likely is it that you would be caught if you downloaded a pirated copy of a movie, pc game, software program or song?

☐ Extremely Unlikely
☐ Unlikely
☐ Likely
☐ Extremely Likely

6.) If you were caught downloading pirated copy of a movie, pc game, software program or song what do you think the punishment would be if any?

☐ Nothing
☐ A Small Fine
☐ Cancelation of Internet Connection
☐ A large fine/ Lawsuit
☐ Jail or Prison Time
☐ University Sanctions

7.) How likely is it that you would receive a virus from downloading a pirated copy of a movie, pc game, software program or song?

☐ Extremely Unlikely
☐ Unlikely
☐ Likely
☐ Extremely Likely

8.) Have you ever received a virus from downloading pirated copies of a movie, pc game, software program or song?

☐ Yes.
☐ No

For the following four questions you will be presented with four scenarios. Please read each scenario and answer the corresponding question.

9.) A popular movie has just been released in theaters nationwide. All your friends have seen the movie and told you that it is great and that you have to see it! Unfortunately, every time that you try to go see the movie, you cannot because the tickets are always sold out. However, a friend tells you about a Web site that has posted an underground copy of the entire movie. The site will only allow visitors to download the movie before it can be viewed. You really want to see the movie.

How likely would it be for you to download a copy of the movie from the website if you were in this situation?

Answer the question by moving the slider to the point on the bar representing how likely you would participate in the above behavior, ranging from extremely unlikely (0) to extremely likely (100).

(0) Extremely Unlikely Extremely Likely (100)

10.) A popular CD has just been released to music stores nationwide. All your friends have heard the CD and told you that it is great and that you have to get it! While discussing your intention to buy the CD a friend tells you about an on-line Web site that has posted an underground copy of the entire CD. The site will only allow visitors to download the CD before visitors can listen to it. You really want the CD.

How likely is it that you would attempt to download the CD from the website under these circumstances?

Answer the question by moving the slider to the point on the bar representing how likely you would participate in the above behavior, ranging from extremely unlikely (0) to extremely likely (100).

(0) Extremely Unlikely Extremely Likely (100)

11.) You are taking a class that requires the use of a particular computer program. The class is important to your success in your major. Unfortunately, the program is expensive. However, a friend tells you that an unauthorized copy can be obtained on-line for free.

How likely is it that you would attempt to download an unauthorized copy of the computer program under these circumstances?

Answer the question by moving the slider to the point on the bar representing how likely you would participate in the above behavior, ranging from extremely unlikely (0) to extremely likely (100).

(0) Extremely Unlikely Extremely Likely (100)

12.) A popular computer game has just been released nationwide. All of your friends have played the game and told you it is great and you should get it! While discussing your intentions to buy the game a friend tells you that an unauthorized copy of the entire game can be obtained online for free.

How likely is it that you would attempt to download an unauthorized copy of the computer game under these circumstances?

Answer the question by moving the slider to the point on the bar representing how likely you would participate in the above behavior, ranging from extremely unlikely (0) to extremely likely (100).

(0) Extremely Unlikely Extremely Likely (100)

For the following questions, select the answer category that best represents your response.

13.) How many of your **best friends** participate in digital piracy?

☐ None
☐ Less Than Half
☐ More than Half
☐ All

14.) How many of the **friends you spend the most time with** participate in digital piracy?

☐ None
☐ Less Than Half
☐ More than Half
☐ All

15.) How many of your **friends you have known the longest** participate in digital piracy?

☐ None
☐ Less Than Half
☐ More than Half
☐ All

16.) Do you associate with people online through any of the following means (chat, message boards, social networking, or multiplayer online games) who you only communicate with online?

☐ Yes
☐ No

If no… skip to question 20.

How much do you agree or disagree with each of the following statements regarding your friends who you only associate with online?

17). I associate with people online who exchange pirated copies of digital goods (music, movies, software, and games) with me.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

18.) The people who I associate with online the most view digital piracy in a positive light.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

19.) The people who I have associated with online the longest view digital piracy in a positive light.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

20.) The people I associate with online who I consider to be close friends with me view digital piracy in a positive light.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

In this section, you will be asked how much you learned about the techniques used to participate in digital piracy from a variety of sources. For each question move the slider on the line to the point that represents how much you learned from that source. Ranging from learned nothing (0) to learned everything (100).

21.) How much have you learned about digital piracy from <u>each</u> of the following sources?

21A. **Offline** Friends

(0) Learned Nothing Learned Everything (100)

21B. **Online** Friends

(0) Learned Nothing Learned Everything (100)

21C. Books and Magazines

(0) Learned Nothing Learned Everything (100)

21D. Television and Movies

(0) Learned Nothing Learned Everything (100)

21E. Message Boards

(0) Learned Nothing Learned Everything (100)

21F. Streaming Online Videos

(0) Learned Nothing Learned Everything (100)

21G. Wikis

(0) Learned Nothing Learned Everything (100)

21H. Directional Web Pages (FAQS, ect).

(0) Learned Nothing Learned Everything (100)

Please indicate your level of agreement or disagreement with each of the following statements:

22.) I would feel good after downloading pirated copies of music, movies, software, or games online without paying.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

23.) Participation in digital piracy would positively affect me because I could download digital goods when I want to.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

24.) Participation in digital piracy would help me because I could save money.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

25.) I feel that all digital goods should be provided free for everyone.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

26.) I think it is okay to use copied music for entertainment.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

27.) I think it is okay to use copied movies for entertainment.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

28.) I think it is okay to use copied software because the community at large is eventually helped.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

29.) I think it is okay to use copied software if it improves my knowledge.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

30.) I feel that downloading or uploading copyrighted material without the owner's permission is *never* okay.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

31.) 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.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

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

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

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

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

34.) It is ok to download copyrighted materials without the owner’s permission because most big companies have so much money copyright infringement by individuals *doesn’t* really hurt them.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

35.) Illegitimate downloading is a victimless crime.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

36.) It is ok to download copyrighted materials without the owner’s permission because many big companies are unethical and try to rip of consumers, so they deserve what they get.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

37. Music, gaming, and software companies often steal ideas and materials from other companies, so they are getting what they deserve when people pirate from them.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

38.) It's really *not* college students’ fault that they download digital goods rather than paying for it; prices are just too high these days.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

39.) I feel it would be ok to download copyrighted materials without the owner’s permission if a family member, friend, or significant other really needed me to do so.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

40.) If I had to pay for all the music and software that I listen to or use, I *wouldn’t* be able to afford tuition, books, and other regular expenses.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

41.) It is ok to participate in digital piracy if someone needs a program for their job or their class work.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

42.) College Students who download necessary software because they *can't* afford it should *not* be held liable for doing such things.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

43. It is ok to pirate digital goods, because doing so *isn’t* that big of a deal when you consider all the good that I have done in my life.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

44. Doing something questionable once in a while is a lot less serious than someone who regularly breaks the rules.

☐ Strongly Disagree
☐ Disagree
☐ Agree
☐ Strongly Agree

45. It is ok for me to download copyrighted materials from time to time, because I deserve something for free sometimes.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

46. I work hard. Therefore, sometimes I deserve to download something for free.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

47. I feel digital piracy is ok, since everyone else downloads copyrighted material.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

48. Other people are benefiting from digital piracy, so why shouldn't I?

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

49. If I like a product that I pirate, I will go buy the product.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

50. I will pay for the majority of the things I pirate when I graduate and make more money than I do now.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

51. Pirated copies are often superior because copyright restrictions are removed allowing more freedom of use.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

52. Companies get what they deserve when college students pirate digital goods because copyright protections restrict paying customers.

- ☐ Strongly Disagree
- ☐ Disagree
- ☐ Agree
- ☐ Strongly Agree

For the following questions please select the best answer to each question.

53.) What is your gender?

- ☐ Male
- ☐ Female

54) What is your current class standing?

- ☐ Freshman (0-29 hours)
- ☐ Sophomore (30-59 hours)
- ☐ Junior (60-89 hours)
- ☐ Senior (Over 90 hours)
- ☐ Graduate Student

55.) Are you currently employed?

- ☐ No
- ☐ Part Time
- ☐ Full Time

56.) How fast is your internet connection at where you currently live?

- ☐ No Internet at Home
- ☐ Cable
- ☐ DSL
- ☐ WIFI
- ☐ Dial-up

57.) From the following list place a check beside <u>each</u> of the behaviors that you have used the internet for in the last month.

___Email, Chat/IRC

___Research for school work

___File Transfer

___Use Newsgroups

___Product and Travel Information

___Online Stock Trading

___Online Shopping

___Online Auctions

___Online Games

___Online Banking

___To collect information related to news, sports, or the weather

___To collect information related to personal interests and hobbies

___Web Design

58.) From the following list place a check beside <u>each</u> of the following behaviors that you have <u>ever</u> participated in online.

___changed my browser's "startup" or "home" page

___made a purchase online for more than $100

___participated in an online game

___participated in an online auction

___changed my "cookie" preferences

___participated in an online chat or discussion (not including email, ICQ, or AOL Instant Messenger, or similar instant messaging programs)

___listened to a radio broadcast or music clip online

___made a telephone call online

___created a web page

___set up my incoming and outgoing mail server preferences

APPENDIX E
Neutralization Frequency Tables

Table 18

Frequencies Neutralization Variables Denial of Injury/ Victim

Question	Frequency	Percent
Q1. Artists make so much money from concerts, videos, sponsors, and other sources, they aren't really hurt by illegal downloading.		
Strongly Disagree	76	25.2
Disagree	128	42.4
Agree	79	26.2
Strongly Agree	19	6.3
Q2. It is ok to download copyrighted materials without the owner's permission because most big companies have so much money copyright infringement by individuals doesn't really hurt them.		
Strongly Disagree	84	27.7
Disagree	154	50.8
Agree	49	16.2
Strongly Agree	16	5.3
Q3. I feel that digital piracy is a victimless crime.		
Strongly Disagree	72	23.8
Disagree	159	52.6
Agree	62	20.5
Strongly Agree	9	3.0
Q4. It is ok to download copyrighted materials without the owner's permission because many big companies are unethical and try to rip of consumers, so they deserve what they get.		
Strongly Disagree	75	24.9
Disagree	163	54.2
Agree	52	17.3
Strongly Agree	11	3.7

Table 19

Frequencies Neutralization Denial of Responsibility

Variable	Frequency	Percent
Q1. 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.		
Strongly Disagree	28	9.2
Disagree	58	19.5
Agree	137	46.0
Strongly Agree	75	25.2
Q2. The university should be responsible for providing access to software or other digital media; this way people would not have to download it illegitimately.		
Strongly Disagree	51	17.1
Disagree	96	32.2
Agree	102	34.2
Strongly Agree	49	16.4

Table 20

Frequencies Neutralization Defense of Necessity/Appeal

Variable	Frequency	Percent
Q1. I feel it would be ok to download copyrighted materials without the owner's permission if a family member, friend, or significant other really needed me to do so		
Strongly Disagree	76	25.6
Disagree	132	44.4
Agree	77	25.9
Strongly Agree	12	4.0
Q2. If I had to pay for all the music and software that I listen to or use, I *wouldn't* be able to afford tuition, books, and other regular expenses.		
Strongly Disagree	69	23.1
Disagree	109	36.5
Agree	82	27.4
Strongly Agree	39	13.0
Q3. 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.		
Strongly Disagree	65	21.7
Disagree	131	43.7
Agree	82	27.3
Strongly Agree	22	7.3
Q4. College students who download necessary software because they can't afford it should not be held liable for doing such things.		
Strongly Disagree	60	20.1
Disagree	123	41.1
Agree	27	29.8
Strongly Agree	27	9.0

Table 21

Frequencies Neutralization Condemning the Condemners

Variable	Frequency	Percent
Q1. Music, gaming, and software companies often steal ideas and materials from other companies, so they are getting what they deserve when people pirate from them.		
Strongly Disagree	72	24.2
Disagree	171	57.4
Agree	49	16.4
Strongly Agree	6	2.0
Q2. It's really not college students' fault that they download digital goods rather than paying for it; prices are just too high these days.		
Strongly Disagree	72	23.8
Disagree	108	35.8
Agree	83	27.5
Strongly Agree	39	12.9

Table 22

Frequencies Neutralization Metaphor of the ledger

Variable	Frequency	Percent
Q1. It is ok to download copyrighted materials without the owner's permission because downloading a few things without permission isn't that big of a deal when you consider all the good that I have done in my life.		
Strongly Disagree	102	33.6
Disagree	147	49.0
Agree	46	15.3
Strongly Agree	5	1.7
Q2. Doing something questionable once in a while is a lot less serious than someone who regularly breaks the rules.		
Strongly Disagree	68	22.4
Disagree	121	39.8
Agree	95	31.3
Strongly Agree	18	5.9

Table 23
Frequencies Neutralization Claim of Entitlement

Variable	Frequency	Percent
It is ok for me to download copyrighted materials from time to time, because I deserve something for free sometimes.		
Strongly Disagree	85	28.1
Disagree	160	53.0
Agree	51	16.9
Strongly Agree	6	2.0
I work hard; therefore, sometimes I deserve to download something for free.		
Strongly Disagree	83	27.6
Disagree	153	50.8
Agree	60	19.9
Strongly Agree	5	1.7

Table 24

Frequencies Neutralization Claim of Normalcy

Variable	Frequency	Percent
Q1. I feel digital piracy is ok, since everyone else downloads copyrighted material		
Strongly Disagree	81	26.9
Disagree	146	48.5
Agree	67	22.3
Strongly Agree	7	2.3
Q2. Other people are benefiting from digital piracy, and so why shouldn't I?		
Strongly Disagree	78	25.9
Disagree	144	47.8
Agree	69	22.9
Strongly Agree	10	3.3

Table 25

Frequencies Neutralization Claim of Future Patronage

Variable	Frequency	Percent
Q1. If I like a product that I pirate I will go buy the product		
Strongly Disagree	65	21.5
Disagree	135	44.7
Agree	82	27.2
Strongly Agree	20	6.6
Q2. I will pay for the majority of the things I pirate when I graduate and make more money than I do now.		
Strongly Disagree	64	21.4
Disagree	122	40.8
Agree	93	27.2
Strongly Agree	5	6.6

Table 26

Frequencies Neutralization DRM Defiance

Variable	Frequency	Percent
Q1. Pirated copies are often superior because copyright restrictions are removed allowing more freedom of use.		
Strongly Disagree	83	27.7
Disagree	137	45.7
Agree	65	21.7
Strongly Agree	15	5.0
Q2. Companies get what they deserve when college students pirate digital goods because copyright protections restrict paying customers.		
Strongly Disagree	73	24.3
Disagree	154	51.3
Agree	61	20.3
Strongly Agree	12	4.0

APPENDIX F

OLS Regression Tables

Table 27: Music Piracy Willingness OLS Regression

Variable	Model 1 b (Beta)	Model 2 b (Beta)	Model 3 b (Beta)	Model 4 b (Beta)	Model 5 b (Beta)
Differential Association					
Offline	3.860 (.359)*	2.707 (.252)*	1.977 (.184)*	1.799 (.167)*	1.929 (.180)*
Online	2.188 (.190)*	1.555 (.135)*	.841	.590	.701
Definitions/ Neutralizations					
Definitions Scale		1.316	.655	.454	.299
Denial of Injury/ Victim		-1.536	-2.182	-1.939	-1.843
Denial of Responsibility		-1.013	-.896	-.684	-.861
Condemning		.974	1.316	.211	1.274
Metaphor of Ledger		-2.529	-3.521	-2.659	-3.080
Entitlement		2.027	1.607	1.346	.816
Normalcy		6.311 (.277)*	4.954 (.217)*	4.925 (.216)*	4.451 (.195)*
Buy after Graduation		5.730	3.395	2.206	1.547
Will Buy if Like		-3.710	-3.081	-3.716	-.2.618
DRM Defiance		1.291	-.112	-.570	-.352
Differential Reinforcement					
Severity Punishment			2.022	3.204	2.281
Certainty Punishment			.788	-.634	-.961
Chances of Virus			-8.037	-6.795	-7.952
Ever received Virus			8.035 (.106)*	5.728	5.918
Positive Reinforcement			5.033 (.335)*	5.358 (.357)*	5.163 (.344)*
Imitation					
Learned- Online Friends				.003	.017
Learned- Offline Friends				-.004	.008
Learned – Books				.145	.153
Learned – TV/ Movies				-.115	-.118
Learned - Message Boards				.201 (.148)*	.213 (.108)*
Learned - Streaming Video				.149	.141
Learned - Wiki				-.161	-.163
Learned - Directional webpage				.103	.116
Controls					
Internet Use Scale					-.516
Computer Proficiency Scale					.786
Sex					-9.539 (-.133)*
Employment Status					-.972
Class Rank					
Sophomore					-.045
Junior					-2.936
Senior/ Grad					-3.866
Model R^2 (Adjusted R^2)	.235 (.230)	.327 (.298)	.394 (.356)	.439 (.386)	.457 (.389)
F Value	44.041	12.221	10.412	8.273	6.749
P Value	.000	.000	.000	.000	.000

*Sig at *p*=.05 level

Table 28: Movie Piracy Willingness OLS Regression

Variable	Model 1 b (Beta)	Model 2 b (Beta)	Model 3 b (Beta)	Model 4 b (Beta)	Model 5 b (Beta)
Differential Association					
Offline	1.965 (.208)*	.593	.188	-.038	-.021
Online	2.266 (.233)*	1.575 (.155)*	1.119	.961	.851
Definitions/ Neutralizations					
Definitions Scale		3.563 (.306)*	3.103 (.267)*	3.002 (.258)*	2.930 (.252)*
Denial of Injury/ Victim		-.975	-1.659	-1.631	-1.838
Denial of Responsibility		-2.087	-2.128	-2.069	-1.995
Condemning		-.702	-.582	-1.198	-.320
Metaphor of Ledger		-2.480	-2.930	-2.357	-2.936
Entitlement		-1.416	-1.552	-2.151	-2.341
Normalcy		6.249 (.311)*	5.191 (.258)*	5.242 (.261)*	4.960 (.247)*
Buy after Graduation		.819	-.537	-1.414	-1.742
Will Buy if Like		-4.656	-4.058	-3.948	-3.304
DRM Defiance		2.961	1.835	2.205	2.109
Differential Reinforcement					
Severity Punishment			-2.717	-1.693	-2.350
Certainty Punishment			-2.272	-3.718	-3.970
Chances of Virus			-2.027	-1.483	-2.022
Ever received Virus			1.007	-.399	-.839
Positive Reinforcement			3.850 (.291)*	4.015 (.303)*	4.205 (.318)*
Imitation					
Learned- Online Friends				.056	.071
Learned- Offline Friends				-.042	-.039
Learned – Books				.168	.160
Learned – TV/ Movies				-.016	-.029
Learned - Message Boards				.102	.124
Learned - Streaming Video				.124	.120
Learned - Wiki				-.075	-.074
Learned - Directional webpage				-.010	-.012
Controls					
Internet Use Scale					1.383
Computer Proficiency Scale					-.926
Sex					-5.429
Employment Status					.786
Class Rank					
Sophomore					-3.824
Junior					.742
Senior/ Grad					-.868
Model R^2 (Adjusted R^2)	.140 (.134)	.276 (.244)	.317 (.274)	.357 (.296)	.374 (.296)
F Value	23.403	8.779	7.429	5.868	4.805
P Value	.000	.000	.000	.000	.000

*Sig at p=.05 level

Table: 29: Gaming Piracy Willingness OLS Regression

Variable	Model 1 b (Beta)	Model 2 b (Beta)	Model 3 b (Beta)	Model 4 b (Beta)	Model 5 b (Beta)
Differential Association					
Offline	1.893 (.261)*	1.073 (.148)*	.762	.746	.612
Online	1.002 (.131)*	.243	-.174	-.308	-.403
Definitions/ Neutralizations					
Definitions Scale		1.020	.713	.609	.672
Denial of Injury/ Victim		.037	-.192	-.191	-.370
Denial of Responsibility		-1.079	-1.038	-1.044	-1.253
Condemning		2.647	2.904 (.193)*	2.300	2.527
Metaphor of Ledger		-5.673 (-.349)*	-6.001 (-.369)*	-5.076 (-.312)*	-4.756 (-.293)*
Entitlement		-.693	-.876	-1.143	-1.199
Normalcy		2.745	2.176	1.896	2.004
Buy after Graduation		3.562	2.866	2.767	2.469
Will Buy if Like		-4.691	-4.430	-4.550	-5.009
DRM Defiance		5.114 (.324)*	4.192 (.266)*	4.256 (.270)*	4.501 (.285)*
Differential Reinforcement					
Severity Punishment			-1.612	-1.606	-1.319
Certainty Punishment			3.716	2.939	3.025
Chances of Virus			-5.094	-4.169	-4.318
Ever received Virus			5.066	3.927	3.729
Positive Reinforcement			2.263 (.223)*	2.466 (.243)*	2.438 (.240)*
Imitation					
Learned- Online Friends				.022	.016
Learned- Offline Friends				-.61	-.074
Learned – Books				.111	.101
Learned – TV/ Movies				-.009	.013
Learned - Message Boards				.139 (.152)*	.127 (.139)
Learned - Streaming Video				.048	.052
Learned - Wiki				-.140	-.116
Learned - Directional webpage				.117	.115
Controls					
Internet Use Scale					.452
Computer Proficiency Scale					.267
Sex					.364
Employment Status					-1.463
Class Rank					
Sophomore					-.889
Junior					7.435 (.121)*
Senior/ Grad					3.141
Model R^2 (Adjusted R^2)	.120 (.114)	.274 (.242)	.313 (.270)	.362 (.302)	.381 (.304)
F Value	19.659	8.700	7.218	6.000	4.947
P Value	.000	.000	.000	.000	.000

*Sig at *p*=.05 level

Table 30: Software Piracy Willingness OLS Regression

Variable	Model 1 b (Beta)	Model 2 b (Beta)	Model 3 b (Beta)	Model 4 b (Beta)	Model 5 b (Beta)
Differential Association					
Offline	3.850 (.215)*	2.565 (.215)*	1.946 (.163)*	1.774 (.149)*	.1.651 (.138)**
Online	1.484	.297	-.500	-.881	-1.090
Definitions/ Neutralizations					
Definitions Scale		3.848 (.263)*	3.065 (.209)*	2.920 (.199)*	2.980 (.204)*
Denial of Injury/ Victim		-1.081	-.2.066	-2.612	-3.143 (-.215)*
Denial of Responsibility		3.797 (.168)*	3.716 (.165)*	3.527 (.156)*	3.509 (.155)*
Condemning		-.137	-.136	-.754	-.115
Metaphor of Ledger		-3.049	-3.715	-2.324	-2.253
Entitlement		-.222	-.408	.462	.438
Normalcy		1.961	.324	.648	1.044
Buy after Graduation		-.264	-2.115	-.530	-.851
Will Buy if Like		-3.805	-2.760	-3.207	-4.393
DRM Defiance		2.813	2.760	.936	.882
Differential Reinforcement					
Severity Punishment			-5.659	-6.251	-5.925
Certainty Punishment			1.302	2.290	1.000
Chances of Virus			-2.949	-2.142	-3.264
Ever received Virus			2.514	1.682	.061
Positive Reinforcement			6.297 (.378)*	5.857 (.352)*	5.849 (.351)*
Imitation					
Learned- Online Friends				.122 (.113)*	.127 (.119)*
Learned- Offline Friends				.038	.019
Learned – Books				-.015	-.017
Learned – TV/ Movies				-.007	.022
Learned - Message Boards				.227 (.103)*	.220 (.146)*
Learned - Streaming Video				-.169	-.164
Learned - Wiki				-.229	-.207
Learned - Directional webpage				.130	.100
Controls					
Internet Use Scale					2.064
Computer Proficiency Scale					.155
Sex					-1.950
Employment Status					3.140
Class Rank					
Sophomore					-5.924
Junior					.590
Senior/ Grad					.997
Model R^2 (Adjusted R^2)	.156 (.151)	.256 (.224)	.322 (.280)	.353 (.291)	.374 (.297)
F Value	26.619	7.942	7.600	5.753	4.808
P Value	.000	.000	.000	.000	.000

*Sig at *p*=.05 level

APPENDIX G

Logistic Regression Tables

Table 31: Music Piracy Involvement Logistic Regression

Variable	Model 1 B (Exp B)	Model 2 B (Exp B)	Model 3 B (Exp B)	Model 4 B (Exp B)	Model 5 B (Exp B)
Differential Association					
Offline	.422 (1.525)*	.376 (1.456)*	.354 (1.425)*	.333 (1.395)*	.335 (1.397)*
Online	.100 (1.106)**	.028	-.025	-.026	-.054
Definitions/ Neutralizations					
Definitions Scale		.273 (1.313)*	.233 (1.262)**	.216	.210
Denial of Injury/ Victim		.068	.053	.055	.031
Denial of Responsibility		-.005	.003	.030	-.013
Condemning		-.617 (.539)*	-.594 (.552)*	-.685 (.504)*	-.686 (503)*
Metaphor of Ledger		-.026	-.098	-.180	-.189
Entitlement		-.170	-.220	-.177	-.222
Normalcy		.300	.275	.405	.473
Buy after Graduation		.318	.177	.034	.009
Will Buy if Like		.390	.603	.532	.531
DRM Defiance		.365 (1.441)**	.238	.227	.299
Differential Reinforcement					
Severity Punishment			-.052	.214	.218
Certainty Punishment			.302	.254	.225
Chances of Virus			-1.198 (.302)*	-1.160 (.313)*	-1.313 (.269)*
Ever received Virus			.428	.461	.453
Positive Reinforcement			.275	.284	.321
Imitation					
Learned- Online Friends				.003	.002
Learned- Offline Friends				.002	.001
Learned – Books				.002	.003
Learned – TV/ Movies				-.022 (.978)**	-.027 (.974)*
Learned - Message Boards				.004	.009
Learned - Streaming Video				.012	.013
Learned - Wiki				-.002	-.006
Learned - Directional webpage				-.022 (.979)**	-.022 (.978)**
Controls					
Internet Use Scale					- .060
Computer Proficiency Scale					-.108
Sex					-.027
Employment Status					.940 (2.560)*
Class Rank					
Sophomore					.481
Junior					.248
Senior/ Grad					-.090
Cox & Snell R^2 (Nagelkerkie R^2)	.262 (.381)	.342 (.498)	.368 (.536)	.391 (.568)	.406 (.591)

*Sig at *p*=.05 level ** Sig at p = .10 level

Table 32: Movie, Game, and Software Piracy Logistic Regression

Variable	Model 1 B (Exp B)	Model 2 B (Exp B)	Model 3 B (Exp B)	Model 4 B (Exp B)	Model 5 B (Exp B)
Differential Association					
Offline	.213 (1.237)*	.136 (1.146)**	.100	.079	-.044
Online	.171 (1.186)*	.096	.022	-.019	-.024
Definitions/ Neutralizations					
Definitions Scale		.323 (1.386)*	.328 (1.388)*	.357 (1.429)*	.685 (1.984)*
Denial of Injury/ Victim		-.195	-.245	-.416 (.660)*	-.647 (.524)*
Denial of Responsibility		-.060	-.103	-.088	-.224
Condemning		-.584 (.558)*	-.526 (.591)*	-.697 (.498)*	-1.302 (.272)*
Metaphor of Ledger		-.422 (.656)**	-.490 (.612)*	-.265	-.215
Entitlement		.102	.114	.182	.138
Normalcy		.564 (1.758)*	.536 (1.709)*	.686 (1.986)*	1.077 (2.936)*
Buy After Graduation		.029	.090	.286	-.166
Will Buy if Liked		1.429 (4.175)*	1.677 (5.349)*	1.764 (5.836)*	1.668 (5.301)*
DRM Defiance		.574 (1.775)*	.480 (1.616)*	.504 (1.654)*	.708 (2.030)*
Differential Reinforcement					
Severity Punishment			-.354	-.583	-.164
Certainty Punishment			-.073	.263	.318
Chances of Virus			-1.277 (.278)*	-1.328 (.265)*	-1.242
Ever received Virus			.456	.270	.584
Positive Reinforcement			.165	.164	.622 (1.863)*
Imitation					
Learned- Online Friends				.009	.012
Learned- Offline Friends				-.008	-.022
Learned – Books				-.019	-.047 (.954)*
Learned – TV/ Movies				.008	.022
Learned - Message Boards				.031 (1.032)*	.024
Learned - Streaming Video				-.010	-.003
Learned - Wiki				-.010	-.005
Learned - Directional webpage				.018	.032 (1.033)*
Controls					
Internet Use Scale					.847 (2.334)*
Computer Proficiency Scale					-.132
Sex					1.767 (5.854)*
Employment Status					-.518
Class Rank					
Sophomore					-.614
Junior					1.463
Senior/ Grad					-.289
Cox & Snell R^2 (Nagelkerkie R^2)	.106 (.191)	.236 (.423)	.257 (.461)	.290 (.520)	.364 (.653)

*Sig at *p*=.05 level ** Sig at p = .10 level