Same Coin, Different Sides: Differential Impact of Social Learning on Two Facets of Music Piracy

By: Jingguo Wang, Zhiyong Yang, and Sudip Bhattacharjee

Wang, Jingguo, Zhiyong Yang, and Sudip Bhattacharjee (2011), "Same Coin, Different Sides: Differential Impact of Social Learning on Two Facets of Music Piracy," *Journal of Management Information Systems*, 28(3), 343–384. https://doi.org/10.2753/MIS0742-1222280310

Abstract:

We demonstrate that two intertwined activities of music piracy, *unauthorized obtaining* and *unauthorized sharing*, are differentially influenced by the same social learning environment. We develop a structural model and test it using survey data from a prime demographic set of respondents who engage in music piracy. Considering behavioral heterogeneity, we employ a factor mixture modeling technique to classify respondents into different groups that highlight distinct patterns of social learning influences. We find that the differential effects of social learning factors on obtaining and sharing persist across these groups. We further utilize demographic variables to profile members in each group for segmentation insights. From a theoretical perspective, our findings advance the understanding of music piracy and suggest the importance of separating obtaining from sharing activities when studying piracy. From a managerial perspective, our research provides new avenues for managers and policymakers to design targeted incentives to curtail music piracy.

Keywords: intellectual property infringement | latent class analysis | music piracy | partial least squares regression | social learning theory | unauthorized obtaining | unauthorized sharing

Article:

Rapid advances in Internet connectivity and digital technologies have dramatically increased online downloading and sharing of digital music, shifted the market landscape, and raised important issues on intellectual property rights and loss of sales [14, 17, 31, 32]. Collating separate studies in 16 countries over a three-year period, the International Federation of the Phonographic Industry [54] estimated that more than 40 billion music files were illegally shared over the Internet in 2008. Although some studies do not find significant loss in music sales caused by the prevalence of file sharing [67], many music industrial reports believe that such file availability and consumer activity have been damaging for music industry investments as well as artist careers. The Institute for Policy Innovation, for example, reports that music piracy costs the

United States $12.5 billion annually [82]. Bhattacharjee et al. [16] also find evidence of "lost sales" due to piracy over peer-to-peer (P2P) networks. The damage is primarily on low-ranking albums, while the top-ranking albums tend to remain immune to illegal sharing [18].

In response to such behavior brought on by technological changes, most research has focused on investigating the sociopsychological motives of music piracy. These studies primarily focus on how individual characteristics (e.g., gender, income, music cost, willingness to pay, personal value, morality, and ethics) and legal sanctions affect the tendency or behavior of obtaining unauthorized music (e.g., downloading music files on the Internet) [25, 30 , 34, 43, 58, 81], or unauthorized music sharing [15, 80]. However, little is known about the role of social environment in shaping individuals' music pirating behavior, though researchers value its importance [21, 33]. Condry [33] argues that the culture of music piracy is difficult to change through lawsuits or technologies alone because the social dynamics that drive the interest in music depend on word-of-mouth discussions, friend-to-friend sharing, and convenience in music access. Hence, it is important to understand the social motives and drivers that significantly impact unauthorized obtaining and sharing behavior. An investigation into the effects of social learning is a fruitful way to advance our understanding of music piracy, and helps to develop effective strategies to reduce this behavior.

In this study, we extend social learning theory [3] to understand two intertwined aspects of music piracy behavior, *unauthorized obtaining* and *unauthorized sharing.*[1] *Unauthorized obtaining* is defined as the extent to which an individual engages in acquiring unauthorized music (e.g., copying unauthorized music files from peers, downloading unauthorized music files on the Internet, or buying pirated CDs), whereas *unauthorized sharing* is the extent to which an individual engages in sharing music with others without authorization (e.g., sharing music files in a P2P network, uploading music files to Web sites, or letting peers copy music files). While acknowledging that unauthorized obtaining and sharing are often intertwined, we argue that these two aspects have distinct motives. We posit that obtaining is primarily driven by personal economic benefits/losses, whereas sharing is mainly determined by social benefits/losses.

Our research contributes to the understanding of music piracy behavior in two important areas. First, we simultaneously examine the effects of four major social learning factors [3]—namely, differential association, definitions of music piracy, differential reinforcement, and imitation—on potential consumers' unauthorized obtaining and sharing activities. We use a structural model to identify and compare the relative importance of each social learning factor. We find empirical support for the differential effects of social learning factors on the two types of unauthorized behavior. Note that our study does not identify obtainers and sharers according to their level of obtaining and sharing. We take the position that individuals may engage in both aspects, potentially at varying levels; however, these two aspects (of the same individual) are simultaneously and differentially affected by the same social learning environment. Second, we incorporate individuals' heterogeneity in their responsiveness to social learning factors as a moderator in our conceptual model. It is important to take into account such heterogeneity

[1] These two activities have been termed as "music piracy behavior" under certain legal environments. In subsequent discussion, we use the term to signify either or both activities. However, we do not pass any ethical judgment on the consumers who undertake such activity, as we argue later that consumers may not view legal and ethical actions as congruent.

because respondents differ in their sensitivity to socialization agents (which may be due to individual difference in personal values [90], lifestyles [61], or music prices elasticity [46, 60]). A traditional approach widely used in examining social learning influences involves data analysis at an aggregate level. This assumes that all individuals are homogeneous in the structure of relationships. However, that can be misleading if considerable variation exists with respect to the magnitude or pattern of the regression coefficients [11]. Following Ramaswamy et al.'s [74] approach, we use a factor mixture modeling technique to classify respondents into groups based on their responsiveness to different social learning factors. These groups exhibit distinct magnitudes and patterns of social learning influences. The differential effects of social learning factors on obtaining and sharing persist across these groups. Follow-up analyses indicate that demographic variables can be used to profile members in each group to provide valuable segmentation insights.

To summarize, this paper contributes important elements to the extant literature. It highlights the distinction between unauthorized obtaining and sharing, and shows how these two aspects of music piracy are affected by social learning variables in varying degrees. A better understanding of such a distinction would aid policymakers to develop targeted strategies to curtail different aspects of music piracy. The study further suggests that intervention and prevention programs may be more effective when combined with consumer segmentation strategies.

The paper is organized as follows. The next section introduces the theoretical background of the study, followed by the conceptual model and hypotheses. We then describe data collection procedures, survey instrument validation, and model testing using partial least squares (PLS) regression, followed by a latent class analysis to disentangle the unobserved heterogeneity in the sample. Finally, we discuss theoretical implications of the study and propose some measures aimed at preventing or reducing unauthorized obtaining and sharing.

Theory and Hypothesis Development

Social Learning Theory

Social learning theory [3] is widely used to explain different types of deviant behavior, such as academic dishonesty, substance abuse, and domestic violence. It suggests that one's behavior is shaped by social interactions and expected consequences, and that the probability of committing a crime or deviance is a function of the balance of these influences. Specifically, individuals are more likely to engage in deviant behavior and less likely to conform to the norms in one or more of the following situations: (1) they differentially associate with others who engage in such behavior; (2) they define the behavior as desirable or justified in a situation that discriminates against such behavior; (3) they have received a relatively greater reward than punishment for their behavior, and anticipate the same in the current or future periods; and (4) they are relatively more exposed in-person or symbolically to salient deviant models [3]. These situations reflect four major explanatory social learning concepts, namely, differential association, definitions, differential reinforcement, and imitation, respectively.

Differential association refers to the direct association and interaction with others who engage in certain types of behavior or express norms, values, and attitudes supporting such behavior, as well as the indirect association and identification with more distant reference groups [4]. It provides a social context where techniques, attitudes, and rationalizations for behaving in certain ways are learned and internalized. The more a person is exposed to deviant behavior and attitudes (in terms of duration, frequency, intensity, and priority), the greater the probability of engaging in deviant or criminal behavior.

Definitions are one's intrinsic or internal attitudes toward and beliefs about a specific behavior, including orientations, rationalizations, justifications, and excuses [4]. A person's definitions on an activity reflect the attitudes toward and beliefs on the commission of an act as relatively more right or wrong, good or bad, acceptable or unacceptable, and justified or unjustified. For example, if a person defines unauthorized music obtaining as a smart way to acquire free music, or unauthorized music sharing as an easy avenue to make friends, it demonstrates a positive attitude toward music piracy and a divergence between the legal and the ethical/economic justifications of the activity. As individuals start to define such behavior as good (positive definition) or at least justified (neutralizing definition) rather than as undesirable (negative definition), they will be more likely to engage in it. Definitions provide a mind-set, making an individual more cognitively willing to commit an act, and serve as internal discriminative stimuli that behaviorally affect the commission of such an act (which may be termed *illegal*).

Differential reinforcement refers to the balance of rewards and punishments attached to a behavior [4]. Whether individuals will refrain from or commit a deviance depends on the balance of past, present, and anticipated future rewards and punishments for their actions. The more severe the punishment for deviant behavior and greater the likelihood for punishment, the less likely that the behavior will occur and be repeated. Reinforcers and punishers may be nonsocial, such as the direct physical effects of drugs and alcohol. But the theory posits that principal behavioral effects come from the interaction within groups that comprise or control the individual's major sources of reinforcement [22]. The concept of social reinforcement includes the whole range of various rewards or punishments from society or subgroups. The balance of reinforcement may motivate individuals to commit deviant acts even in the presence of their own definitions unfavorable to those acts.

Imitation refers to the engagement in a behavior after direct or indirect (e.g., in media depictions) observation of the similar behavior by others [4]. The characteristics of the models, the behavior observed, and the observed consequences of the behavior may affect the imitation of a behavior [8]. Imitation is more important in the initial acquisition and performance of novel behavior than in the maintenance of a behavioral pattern once established.

The process of social learning is complex, and the theory defines these four concepts as a set of variables that are part of the same underlying learning process. The influence of these variables produces deviant or conforming behavior (see [4] for a review of empirical support for social learning theory). In this study, we use these four social learning variables to understand the role of social learning in consumer behavior toward unauthorized music obtaining and sharing.

Unauthorized Obtaining and Unauthorized Sharing

Prior studies mainly focus on one aspect of music piracy at a time—obtaining (most often) [25, 30, 34, 43, 58, 81] or sharing [15, 80]. Some consider unauthorized obtaining and sharing as intertwined behaviors (i.e., examining music piracy in general, without differentiating between obtaining and sharing). We provide a more fine-grained analysis of music piracy through a simultaneous examination of unauthorized obtaining and sharing for the same individual. Individuals may engage in these behaviors at the same time for different reasons: obtaining may be mainly driven by economic needs, whereas sharing may be largely driven by social needs.

Consistent with this reasoning, Cenite et al. [24] find that the motivation for content downloading in a P2P network is driven by the desire to find something that is hard to locate by others, to avoid a long waiting time, and to sample entertainment content, as well as convenience and cost considerations. Other personal variables that have been associated with music downloading include income, price, willingness to pay, personal value, morality, ethics, and perceived legal sanction risk [13, 25, 30, 34, 43, 58, 81]. At the same time, music sharing is mainly affected by social activities, friendship, and self-identity [21]. Echoing these arguments, prior studies find that file contribution behavior in P2P networks is driven by reciprocity, fame, social capital, avoidance of punishment, recognition from friends, and network externalities [12, 24, 64, 77]. Nandi and Rochelandet [64] report that the motivation for file sharing is poorly determined by rational, self-interested behavior.

Two issues need to be emphasized here. First, in P2P networks, many sharers are also downloaders, and vice versa. As indicated earlier, we do not classify downloaders and sharers into different categories. Instead, we examine the same individual's different roles at the same time. We argue that for the same individual, the motives underlying his or her obtaining behavior differ from those underlying his or her sharing behavior. Because of such differences, social learning factors exert differential effects on these two aspects of music piracy. Second, sharing may contain two forms, including both passive sharing (i.e., sharing for the sake of downloading, such as in BitTorrent) and proactive sharing (e.g., using a personal computer as an active seed to share music files through P2P software, not for the purpose of downloading). In our framework, only the proactive form is treated as sharing.

Hypothesis Development

Figure 1 presents our conceptual model, where the four social learning factors are specified as predictors of the two facets of music piracy. The unobserved heterogeneity moderates individuals' responsiveness to the effects of social learning.

Effect of Differential Association on Obtaining and Sharing

We expect that differential association would be positively related to both obtaining and sharing. Music piracy requires individuals not only to learn ways to upload, download, or convert/compress CDs into smaller digital files but also to identify reliable sources and communities for obtaining and sharing. Peer groups serve as an important social context for individuals to learn such skills and knowledge, and undoubtedly have a great impact. Friends, for instance, can be a reliable source for the newest songs and the latest techniques for downloading/uploading music files from/to networks. They can also suggest reliable communities for swapping music files [21, 33]. Most importantly, the peer group exposes the individual to the various norms and values related to music piracy. Individuals who interact with peer groups become exposed to, and ultimately learn, normative definitions (e.g., motives, drives, rationalizations, and attitudes) favorable and unfavorable to music piracy. Individuals may be more likely to be reinforced to engage in music piracy, and otherwise pressured or enticed if they associate with pirating peers [3, 89]. This is consistent with prior research showing that differential association exerts a strong influence not only on software piracy intention [47] but also on computer-related deviant behaviors such as computer crime [78, 83], and MP3 file downloading [48]. Therefore, we hypothesize:

Hypothesis 1: Differential association has a positive effect on (a) unauthorized obtaining and (b) unauthorized sharing.

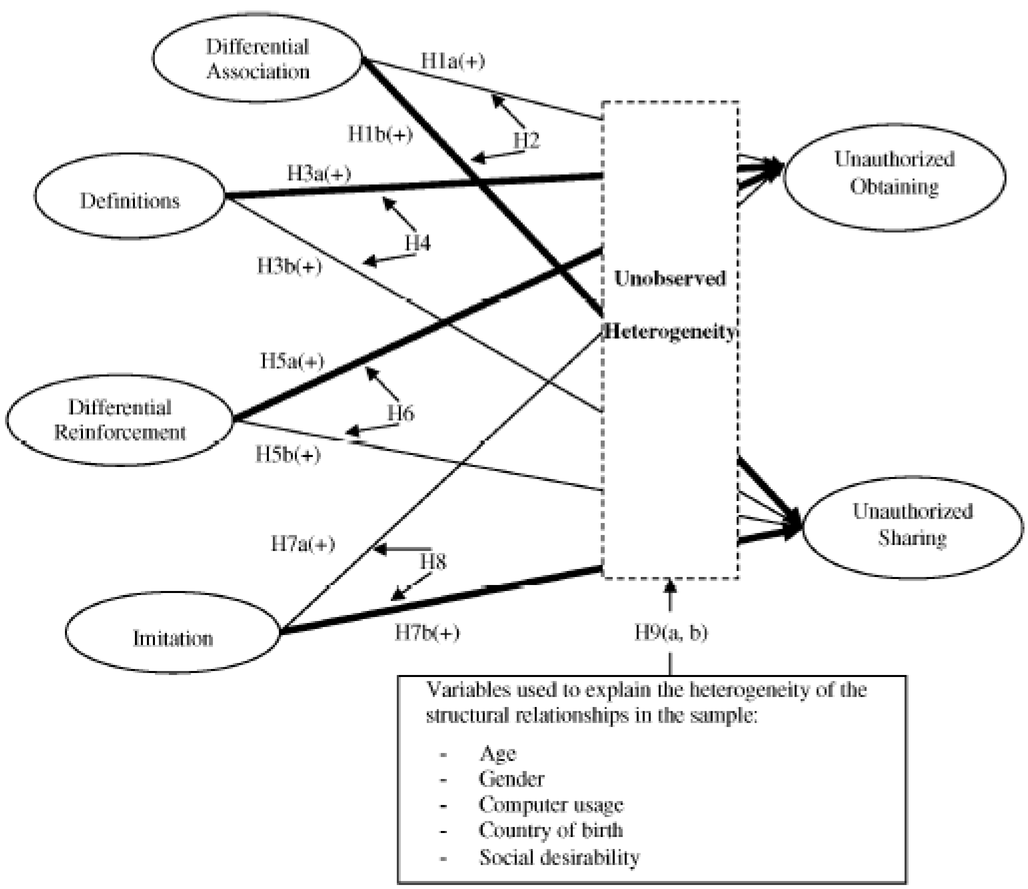

Figure 1. Conceptual Model of Differential Effects of Social Learning Variables on Unauthorized Obtaining and Unauthorized Sharing

Note: For H2, H4, H6, and H8, the heavier line is hypothesized as having a stronger impact than the lighter line.

We expect that the effect of differential association on sharing will be stronger than on obtaining. Sharing is chiefly driven by social activities and friendship [21], which are directly related to differential association. Recognition from friends increases one's involvement in sharing but not in downloading [12, 24, 64, 77]. Proactively engaging in sharing helps maintain and strengthen the relationship with other users on the network, as the viability of a P2P network critically depends on the proportion of sharers to downloaders. An increased set of sharers creates a thriving network. Free riders (obtaining without sharing files in the network) may run a risk of being expulsed from the group [12]. Further, as discussed above, obtaining is substantially affected by economic motives, which may moderate its social norms. Consequently, indirect reciprocity was found to be a social norm that is voluntarily enforced by contributors in a music sharing network [44]. Therefore, we hypothesize:

> *Hypothesis 2: The effect of differential association is stronger for unauthorized sharing than for unauthorized obtaining.*

Effect of Definitions of Music Piracy on Obtaining and Sharing

Digital music is a form of intellectual property [13], and legal statutes define music piracy as an illegal conduct, such as that specified in U.S. Copyright Law (Title 17 U.S.C. Section 101 et seq., Title 18 U.S.C. Section 2319). It seems logical that individuals should hold unfavorable definitions on music piracy. However, this is not always the case. Social groups (e.g., friends or online buddies) may alter individuals' definitions of music piracy by distinguishing between legal and ethical/economic acceptability, generating positive attitudes toward it (e.g., "music pirating is wise") and/or neutralizing it using techniques such as denial of responsibility, denial of injury/ denial of victim, condemnation of the condemners, and appeal to higher loyalties that rationalize the piracy activities [85]. Those who associate with delinquent peers are more likely to be taught beliefs favorable to a deviant behavior [3, 89]. Further, individuals' law-abiding attitude may also affect their definitions of the behavior [5]. Recent research has shown that individuals' definitions of computer crime [78, 83] and MP3 downloading [48] are significantly related to their own engagement in such behavior. Similarly, attitudes toward software piracy positively correlate with software piracy intentions [47, 70]. Greater acceptance of neutralization techniques increases MP3 downloading [49]. Therefore, we hypothesize:

> *Hypothesis 3: Favorable definitions of music piracy behavior increase (a) unauthorized obtaining and (b) unauthorized sharing.*

Definitions of music piracy provide a mind-set that makes an individual more likely to engage in piracy, and serve as internal discriminative stimuli that behaviorally affect the commission of piracy. Individuals' behavior toward obtaining may be more sensitive to their definitions on music piracy than their sharing behavior. As we posited, obtaining unauthorized music is mainly driven by personal and internal needs (e.g., enjoyment of a variety of free music), whereas sharing unauthorized music is mainly driven by social and external environment (e.g., peer pressure). Let's take negative definitions as an example (with the same logic applying to positive definitions). Negative definitions of music piracy are likely to suppress both obtaining and sharing motivations, as put forth in H3. However, as internal discriminative stimuli, negative definitions may restrain behavior toward obtaining more than sharing because it might be easier to overcome personal and internal needs that drive obtaining behavior than to overcome the effect of the social and external environment that drives sharing behavior. Therefore, we hypothesize:

Hypothesis 4: The effect of definitions of music piracy is stronger for unauthorized obtaining than for unauthorized sharing.

Effect of Differential Reinforcement on Obtaining and Sharing

Social learning theory suggests that acquisition and repetition of music piracy behavior depends on differential reinforcement/punishment toward the behavior. We anticipate that reinforcement affects both unauthorized obtaining and sharing behavior. Reinforcement comprises gains/losses in both economic and social aspects. From an economic perspective, an individual's tendency to engage in music piracy depends on the balance of past, present, and anticipated future rewards (e.g., saving money) and punishments (e.g., a fine if caught). From a social perspective, the concept of social reinforcement includes a range of rewards (e.g., recognition from friends) or punishments from society or subgroups (e.g., being expelled from groups) [21]. Previous studies have shown that formal social deterrence is an effective measure to reduce software piracy [42, 70] and music piracy [30]. Therefore, we hypothesize:

Hypothesis 5: Positive differential reinforcement increases (a) unauthorized obtaining and (b) unauthorized sharing.

Obtaining leads to the economic benefit of saving money and immediate gratification. Relative to such direct, immediate, or obvious personal benefits from obtaining, social benefits derived by sharing are indirect. When reinforcement (punishment or reward) is present, individuals tend to assign priority to the actions with direct benefits rather than those with indirect benefits [75]. Hence, we anticipate a stronger effect of differential reinforcement on obtaining than on sharing. Therefore, we hypothesize:

Hypothesis 6: The effect of differential reinforcement is stronger for unauthorized obtaining than for unauthorized sharing.

Effect of Imitation on Obtaining and Sharing

Behavior could be learned at the cognitive level through observing others' actions [39]. Sources of imitation may come from social groups (e.g., peers, family members, and teachers) or from media (e.g., television, movie, magazines, books, and the Internet) [3]. Individuals may engage in music piracy by imitating others. Individuals not only acquire the initial necessary knowledge but also experience the culture and learn the definitions of music piracy from these sources. Once the behavior is learned, it may be reinforced by the consequences it generates. Notably, the above reasoning is in line with the recent finding that parental smoking and peer smoking are the two most important factors that affect teen smoking initiation and progression [92]. According to Yang and Schaninger [92], a core mechanism underlying such effects is that parents and friends serve as role models for substance use. Imitation's effect is not temporary; on the contrary, it has a long-lasting effect on a child's smoking trajectory over a wide range of developmental periods (over a course of eight years in [92]). Therefore, we hypothesize:

Hypothesis 7: Imitation has a positive effect on (a) unauthorized obtaining and (b) unauthorized sharing.

The effect of imitation is anticipated to be stronger for sharing than for obtaining. While both activities are termed *illegal,* for practical purposes it is more feasible to track unauthorized sharing than unauthorized obtaining. This is one reason the music industry has purposefully focused on punishing unauthorized sharers as opposed to unauthorized downloaders. Imitation exerts a greater influence on unauthorized sharing because it may help sharers discount the perceived risk of engaging in this behavior. Consistent with this reasoning, previous research shows that imitation is driven by a desire not only to be accepted by others but also to be safe [20]. Information cascades, which occur when individuals follow others' behavior and disregard their own information [9, 19], is especially apparent when individuals face an uncertain environment such as music sharing [19]. Hence, we contend that sharing unauthorized music is by nature a riskier behavior than unauthorized obtaining, and chances of getting caught are higher [77]. Imitation is more likely to reduce one's safety concerns on sharing rather than on obtaining. Therefore, we hypothesize:

> *Hypothesis 8: The effect of imitation is stronger for unauthorized sharing than for unauthorized obtaining.*

Heterogeneity in Responsiveness to Social Learning Variables

Individuals learn continuously and learn different things at different times in their lives, and their responsiveness to social learning variables may be a function of demographic and sociocultural variables. The unobserved heterogeneity may come from one or more of the following sources. First, behavioral heterogeneity may be a result of differences in personal values [90]. Some individuals engage in music piracy because they are more susceptible to peer influence or value social status in a group more than others. Second, behavioral heterogeneity may also result from the difference in individual lifestyles [61]. Third, behavioral heterogeneity may be driven by individual differences in elasticity, that is, the relative change in demand in response to the changes of music price or other marketing instruments. According to previous researchers [46, 60], elasticity is the most commonly cited normative ideal base for market segmentation. Difference in individuals' elasticity may result in heterogeneous propensities to engage in piracy behavior. Therefore, we hypothesize:

> *Hypothesis 9a: Unobserved heterogeneity exists in the sample, reflecting individuals' sensitivity to social learning variables.*

> *Hypothesis 9b: Respondents' sensitivity to social learning variables can be explained by demographic variables such as age, gender, country of birth, social desirability, and computer usage.*

Research Methodology and Results

Measurement Development

We adopted measurement items from existing literature and made necessary adaptations to fit them in the context of music piracy. We constructed an initial set of items by analyzing the literature and reflecting on the proposed theory. The survey protocol was pretested by a group of faculty members, doctoral students, undergraduate students, and university administrative staff before the actual data collection. In addition to the pretest, a pilot study was carried out with 298 students. Minor changes were made in the survey protocol following the feedback gathered from the pretest and the pilot study. In the survey instrument, music piracy was defined as the illegal duplication and distribution of sound recordings. Appendix A presents the final measurement items for the main constructs of the model.

Following prior studies [5, 48, 49, 62], we used multifaceted measures to assess both unauthorized obtaining and unauthorized sharing. Each behavior is a second-order reflective construct, and has three first-order confirmative constructs, measuring intensity, frequency, and amount of the behavior from different channels. Unauthorized obtaining comprises three channels, whereas unauthorized sharing involves four, as shown in Appendix A . For cases when both downloading and sharing were concurrent (e.g., Bit-Torrent), the behavior was completely or partially classified as one of these behaviors by the participants themselves, based on whether their intention was to download or to proactively share.

Following Akers et al. [5], we measured *differential association* using a formative construct with two dimensions: peer piracy norm (i.e., respondents' perception of the approving-disapproving attitudes toward music piracy held by their peers) and differential peer association. Differential peer association was assessed by a reflective second-order construct. It has three first-order reflective constructs, gauging differential association from three aspects, including downloading, uploading, and letting friends copy. Each of these first-order constructs has three items adapted from Akers et al. [5] and Skinner and Fream [83].

Definitions of music piracy was measured by a formative construct with three dimensions: negative definition, law-abiding attitude, and techniques of neutralization, following Akers et al. [5]. Negative definitions of music piracy is a first-order reflective construct with three items measuring an individual's own approval or disapproval of music piracy adapted from Chiou et al. [30]. Law-abiding attitude is a first-order reflective construct with one item measuring obedient or defying attitudes toward the law in general, following Akers et al. [5]. Neutralization is a second-order formative construct composed of four techniques of neutralizations: denial of responsibility, denial of injury/denial of victim, condemnation of the condemners, and appeal to higher loyalties [85]. These four dimensions were measured using reflective constructs with items adopted from Ingram and Hinduja [49].

Differential reinforcement was gauged by a second-order formative construct with four dimensions: personal gain, peer reinforcement, formal social sanction risk, and formal social sanction severity, following the work of Akers et al. [5]. Personal gain is a reflective construct with two items measuring nonsocial rewards. Peer reinforcement is a reflective construct with two items measuring a respondent's report of anticipated or actual positive or negative sanction of friends to one's music piracy behavior. We also included two items each for social sanction risk and social sanction severity as in prior studies [30, 70, 83].

Imitation was assessed using a first-order formative construct with items from Akers et al. [5] and Skinner and Fream [83]. We followed the guidelines suggested by Jarvis et al. [51] and

Petter et al. [71] to determine the reflective and formative nature of a construct. The use of formative constructs for social learning variables enhances parsimony through the substitution of a single construct in place of multiple indicators within a theoretical model [23].

We developed two versions of the questionnaire to check whether the order of questions may create additional noise in the results, following prior studies (e.g., [93]). The items in the two versions are identical, but the order of questions is reversed. In the questionnaire, we also introduced several reverse-coded items to reduce acquiescence problems and to control common method bias [55]. We included "power" [6] as a marker variable in the survey to test the potential threat of common method bias [72]. It has eight items (e.g., "I can get people to listen to what I say") directly adopted from Anderson and Galinsky [6].

Survey Administration

The survey was carried out with a group of undergraduate students at a major university in southern United States. Students in college campuses are significant consumers of music, and account for a sizable level of unauthorized obtaining and sharing [13, 86]. This has led the Recording Industry Association of America (RIAA) to focus on college campuses for its antipiracy effort [50, 63]. Hence, our sample focuses on a prime demographic that engages in the activity being studied.

The survey invitation was posted in public areas of the university and distributed to over 2,000 students taking business, engineering, or science courses. Participation was voluntary, and each participant received a $6 gift certificate as a token of appreciation. The data were gathered through a self-administered paper-and-pencil survey. In the survey session, a principal investigator explained that this is a study to understand unauthorized music obtaining and sharing among college students. As music piracy is a sensitive topic, we were careful to ensure that respondents would provide accurate information reflecting their true beliefs and behavior. We promised that all information would remain strictly anonymous and confidential, and no information related to identity (such as name or ID) would be collected. These procedural remedies are also recommended for controlling common method bias [72].

A total of 665 valid responses were collected, with 429 using one version of the questionnaire and 236 using the other version (with the order of questions reversed). To test whether the order of questions would create variances in our criterion variables, we coded survey version as a binary variable and treated it as a covariate in the model following Zhou et al. [93]. Its main effects, as well as interactions with social learning variables, were not found to affect obtaining or sharing (all $p > 0.25$). Therefore, this variable was dropped from the model and the data from both versions were pooled together. As shown in Table 1, we have more male respondents (56 percent) than female respondents (44 percent). About 70 percent were junior and senior students. Approximately 55 percent were between the ages of 21 and 25. A majority (93 percent) spent at least 5 hours using a computer per week, and 87 percent of them were fulltime students.

Table 2 summarizes the percentage of participants who engaged in unauthorized obtaining and sharing. Only 3.76 percent of participants did not engage in either behavior, whereas 82.71

percent engaged in both behaviors. A large portion (86.77 percent) of participants engaged in some level of obtaining, and 92.18 percent engaged in some level of sharing.

Table 1. Summary of Sample Demographics (n = 665)

Gender	
Male	375
Female	286
Missing	4
Age	
16–20 years	145
21–25 years	369
26–30 years	82
> 30 years	62
Missing	7
Ethnic heritage	
Caucasian	256
Others	409
Missing	3
Year in college	
Freshman	47
Sophomore	81
Junior	248
Senior	220
Fifth year	64
Missing	5
Computer use per week	
Less than 5 hours	43
5–10 hours	105
10–15 hours	124
15–20 hours	114
More than 20 hours	275
Missing	4
Full-time student	
Yes	580
No	81
Missing	4

Table 2. Participants Who Engaged in Obtaining and Sharing

	No obtaining	**Some level of obtaining**	**Total**
No sharing	25 (3.76)	27 (4.06)	52 (7.82)
Some level of sharing	63 (9.47)	550 (82.71)	613 (92.18)
Total	88 (13.23)	577 (86.77)	665 (100)

Note: Percentages are shown in parentheses.

Data Analysis and Results

The measurement model and the full structural model were tested using PLS regression. PLS can test complex relationships by avoiding inadmissible solutions and factor indeterminacy, and provides the ability to model latent constructs even under conditions of nonnormality with small to medium-sized samples [27]. However, one potential disadvantage of PLS is its tendency to underestimate path coefficients and overestimate loadings. As a result, the significant results of a PLS analysis can be given more credence because the test is more conservative [7]. Another limitation is that jackknife or bootstrap procedures are needed to obtain standard errors of the parameter estimates. Because PLS is a limited-information estimation method, its estimates are not as efficient as full-information estimates [7, 40].

We estimated the high-order factor structure using the repeated indicators method based on the hierarchical component model [29, 56, 91]. We used a molecular approximation in which a high-order construct is specified to lead to its corresponding low-order constructs if it is reflective, and its corresponding low-order constructs are specified to lead to a high-order construct if it is formative [28]. The SmartPLS 2.0 software [76] was employed in the PLS analysis, and the bootstrap procedure was used to estimate the significance of the path coefficients.

Measurement Validation

We analyzed the measurement model by testing its construct reliability, convergent validity, and discriminant validity [41]. The descriptive statistics for the principal constructs and their correlations are shown in Table B1 in Appendix B. Cronbach's alphas for all first-order reflective constructs were at or above 0.73, exceeding the suggested threshold of 0.60, and composite reliabilities were all well above the suggested 0.70 level [65]. These results show that the constructs are internally consistent. We assessed convergent and discriminant validity of the first-order reflective constructs in the model using the following four methods: (1) the square roots of the average variance extracted (AVE) of all the constructs were much larger than all the other cross-correlations; (2) all the AVEs were well above 0.50, suggesting that the constructs capture much higher construct-related variance than error variance; (3) the correlations among all the constructs were all well below the 0.90 threshold, suggesting that all the constructs are distinct from each other; and (4) all the items loaded highest on their intended constructs with all factor loadings greater than 0.70 (all *t*-values are significant) (see Table B2 in Appendix B for item loadings and cross-loadings). These results suggest that the constructs have adequate convergent and discriminant validity.

For the second-order reflective construct of obtaining, the structural coefficients of obtaining-amount (0.90), obtaining-frequency (0.85), and obtaining-intensity (0.82) were considerably higher than the recommended value of 0.70 [26]. The intercorrelations among these first-order constructs (obtaining-amount and obtaining-frequency: 0.66; obtaining-amount and obtaining-intensity: 0.65; obtaining-intensity and obtaining-frequency: 0.50) were considerably lower than the structural coefficients. For the second-order reflective construct of sharing, the structural coefficients of sharing-amount (0.94), sharing-frequency (0.89), and sharing-intensity (0.89) were higher than 0.70. The intercorrelations among these first-order constructs (sharing-amount and sharing-frequency: 0.78; sharing-amount and sharing-intensity: 0.80; sharing-intensity and sharing-frequency: 0.65) were lower than the structural coefficients.

Figure C1 in Appendix C illustrates the principal formative constructs. To assess the reliability of formative constructs (first-order or higher), we used multicollinearity assessments based on the variance inflation factor (VIF) [71]. We found that the VIFs for the formative constructs were all well below 3.3 [36, 71], indicating that the formative measures are not highly correlated. We also examined the weights of the formative measures. All the measures were significant at the 0.001 level, except for law-abiding attitude in the construct definitions and 13 (or item 3) and 16 (or item 6) in the construct of imitation. We therefore removed these items that were not significant in our subsequent PLS analyses [37].

Common method bias is a valid concern in survey-based research. We used the following three approaches to evaluate the extent of common method bias in our data. The first approach was Harman's single-factor test [72]. If our data has a substantial amount of common method variance, a single factor will emerge and/or one general factor will account for the majority of the covariance among the measures. A principal component analysis of our data extracted 18 factors with eigenvalues greater than 1. These 18 factors together accounted for 67.6 percent of the variance, and the first factor accounted for 17.0 percent. Since no single factor emerged, and one general factor did not account for the majority of the variance, we did not observe substantial common method bias in the data. The second approach was to examine the correlation matrix to identify highly correlated factors. Common method bias likely exists when there are extremely high correlations ($r > 0.90$) [69]. Table B1 in Appendix B did not reveal such evidence. We used a third approach and incorporated a theoretically unrelated variable (i.e., "marker") into our model [6]. If common method bias exists in the data, we would expect the marker variable to be significantly related to other constructs in the model. In our analysis, we used the construct of power [72] as the marker variable and examined structural parameters by comparing the model with this marker variable and the other without. The results showed that the marker variable was not statistically significant to any of the model constructs. In addition, adding the power construct did not alter any of the path coefficients, in terms of sign, magnitude, or significance levels. Taken together, all three approaches consistently suggest that our data did not suffer from substantial common method bias.

Testing the Structural Model

Table 3 presents the standardized PL S path coefficients of the principal constructs for the model. In the regression we also introduced *gender* (0 = male, 1 = female), *age, computer usage* (i.e., length of time participants spent on computer per week*), not U.S. born* (0 = the participant was born in United States, 1 = otherwise), and *social desirability* [35] as control variables. We measured *social desirability* using a short version of the Marlowe–Crowne social desirability scale [84]. We found that *gender* ($\beta = -0.08$, $p < 0.01$), *age* ($\beta = -0.06$, $p < 0.01$), *computer usage* ($\beta = 0.07$, $p < 0.01$), and *not U.S. born* ($\beta = 0.06$, $p < 0.05$) significantly affect unauthorized obtaining, whereas only *not U.S. born* ($\beta = 0.10$, $p < 0.01$) significantly affects unauthorized sharing.

Table 3. PLS Path Coefficients and Invariance Tests: Testing for Hypotheses 1–8

	Obtaining	**Test for**	**Sharing**	**Test for**	**Invariance test**	**Test for**
Differential association	0.23***	H1a	0.29***	H1b	$\chi^2 = 2.14$, df = 1, $p = 0.14$	H2
Definitions	0.27***	H3a	0.05	H3b	$\chi^2 = 29.97$, df = 1, $p < 0.001$	H4
Differential reinforcement	0.23***	H5a	0.05	H5b	$\chi^2 = 19.50$, df = 1, $p < 0.001$	H6
Imitation	0.14***	H7a	0.22***	H7b	$\chi^2 = 4.92$, df = 1, $p = 0.03$	H8
R^2 (percent)	44.8		22.1			

*** Significant at the 0.001 level.

Differential association has a significant positive effect on both obtaining ($\beta = 0.23$, $p < 0.001$) and sharing ($\beta = 0.29$, $p < 0.001$), supporting H1a and H1b, respectively. Although the impact of differential association on sharing is higher than that on obtaining, which is in the hypothesized direction, the *p*-value of the invariance test is greater than 0.10, thus not supporting H2. Definitions of music piracy have a significant positive influence on obtaining (β = 0.27, $p < 0.001$), but not on sharing (β = 0.05, $p > 0.10$), validating H3a but rejecting H3b. A follow-up invariance test shows that the effect of definitions on obtaining is greater than that on sharing ($\chi 2 = 29.97$, $p < 0.001$). Therefore, H4 is supported. Differential reinforcement has a significant effect on obtaining (β = 0.23, $p < 0.001$) but not on sharing (β = 0.05, $p > 0.10$), providing support for H5a but not for H5b. The results of an invariance test supported H6. These results indicate that differential reinforcement primarily affects direct benefits and concerns. Imitation has a significant positive effect on both obtaining (β = 0.14, $p < 0.001$) and sharing (β = 0.22, $p < 0.001$), supporting H7a and H 7b, respectively. Consistent with H8, the follow-up invariance test showed that the impact of imitation on sharing is stronger than obtaining.

Explanatory Power of the Model

The explanatory power of the model in PLS analysis is reported as *R*2 in Table 3 [10, 26]. The model can be considered as a satisfactory and substantive model because it accounts for 44.8 percent of the variance in obtaining and 22.1 percent in sharing, which are considerably greater than 10 percent (a suggested cut-off value [38]). We also tested an alternate model, based on two theories used by prior researchers to explain music piracy behavior: general deterrence theory [68, 73, 87] and the theory of reasoned action [1, 2]. In the alternate model, we specified peer norm, attitude toward music piracy (i.e., negative definition on music piracy), formal social sanction (including sanction risk and severity) to be the antecedents of obtaining and sharing. Further, the same set of control variables was included in the alternate model. As shown in Table 4, this alternate model accounts for 32.5 percent of the variance in obtaining and 9.3 percent in sharing. Hence, the explanatory power of our original model is considerably greater. We can also see from the alternate model that peer norm and attitudes toward music piracy play important roles in explaining obtaining and sharing, and their differential effects on these two intertwined activities are largely consistent with those of differential association and definitions (see Table 3). Our alternate model indicates that formal social sanction does not significantly affect obtaining or sharing. This indicates that formal penalties seem to have little direct deterrent effect on individuals' piracy behavior. It echoes prior arguments that legal restrictions do not always inhibit illegal file swapping [81]. Personal gain and peer reinforcement may play a more important role in reinforcing one's piracy behavior.

Table 4. PLS Path Coefficients of the Alternate Model

Variables	Obtaining	Sharing
Peer norm	0.13**	0.08*
Attitudes toward music piracy	0.42***	0.19***
Formal social sanction risk	–0.02	0.05
R^2 (percent)	32.5	9.0

* Significant at the 0.05 level; ** significant at the 0.01 level; *** significant at the 0.001 level.

Heterogeneity in Responsiveness to Social Learning Variables

Latent class analysis was used to test H9a to extract the potential unobserved heterogeneity in the sample, based on the inferred relationships between social learning variables and unauthorized obtaining and sharing behavior. Latent class analysis deals with unobserved heterogeneity in the parameters of a certain model across the population by imposing a "mixing distribution" on the parameters of that model, which is different from conventional clustering methods that segment individuals based on observed attributes. The observations in a sample are assumed to arise from two or more groups that are mixed in unknown proportions. In this study, we used the latent class model introduced by Lubke and Muthén [57], which classifies the participants into groups with similar response patterns, and estimates the path coefficients within each segment simultaneously. The segments were formed on the basis of the proposed relationships between social learning variables and the two aspects of music piracy. Following the work of Lubke and Muthén [57], we allowed path coefficients of the four variables to vary across segments while keeping other parameters (e.g., item loadings or weights) fixed in the analysis. H9a would be supported if the data best fit with more than one group.

We evaluated different numbers of clusters (denoted by *K*) for the data as shown in Table 5. Prior studies [66, 88] suggest sample-size-adjusted BIC (Bayes's information criterion) as the best of the information criterion indices. Table 5 indicates that sample-size-adjusted BIC is minimized for $K = 3$. The result suggests that three latent classes adequately describe the data. These three segments account for 71.88 percent, 20.45 percent, and 7.67 percent of the entire sample, respectively. Therefore, H9a is supported.

Table 5. Model Selection: Testing for Hypothesis 9a

Number of clusters	Log likelihood	AIC	BIC	Adjusted BIC	EN
Aggregate ($K = 1$)	–1,491.24	3,008.48	3,066.98	3,025.71	1.00
$K = 2$	–1,385.50	2,818.99	2,926.99	2,850.79	0.86
$K = 3$	–1,333.83	2,737.67	2,895.16**	2,784.03***	0.73
$K = 4$	–1,316.87	2,725.74*	2,932.73	2,786.68	0.73

Notes: AIC = Akaike's information criterion; BIC = Bayes's information criterion; EN = entropy statistic.
* Minimum AIC; ** minimum BIC; *** minimum sample-size-adjusted BIC.

Table 6. Analysis of Posterior Probabilities (Standardized Coefficients): Testing for Hypothesis 9b

	U.S. born, light computer users (segment 1)	Older, light computer users (segment 2)	Younger male, not U.S. born, heavy computer users (segment 3)
Age	0.05	–0.08**	–0.10***
Gender	0.05	0.05	–0.08**
U.S. born	–0.10***	–0.04	0.13***
Computer usage	–0.07*	–0.07*	0.11***
Social desirability	–0.02	0.01	0.01
R^2 (percent)	13.6	11.9	20.7

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

To test H9b, the membership probability is calculated for each individual in each segment given $K = 3$. Following Ramaswamy et al.'s [74] approach, standardized posterior probability scores of each segment were used as the dependent variable, while participants' *age, gender, U.S. born, computer usage,* and *social desirability* were introduced as independent variables. Theoretically, this approach gives the profile of each segment using observable variables (demographics in this case). The results in Table 6 suggest that the first segment is more likely to be U.S. born ($\beta = -0.10$, $p < 0.01$) and light computer users ($\beta = 0.07$, $p < 0.10$), whereas the second segment contains older ($\beta = 0.08$, $p < 0.05$), light computer users ($\beta = -0.07$, $p < 0.10$). The last group tends to be younger (β = –0.10, $p < 0.01$), male (β = –0.08, $p < 0.05$), not U.S. born (β = 0.13, $p < 0.01$), and heavy computer users (β = 0.11, $p < 0.01$). Taken together, H9b is supported.

Table 7 presents the path coefficients for each of the three segments. For segment 1 (U.S. born, light computer users), our model accounts for 41.9 percent of the variance in unauthorized obtaining and 22.2 percent in sharing. The variance explained changes to 64.5 percent and 74.2 percent, respectively, for segment 2 (older, light computer users), and 63.3 percent and 77.2 percent for segment 3 (younger, not U.S. born males who spent more time on computers). Across all segments, while sharing behavior is mainly driven by differential association and imitation (supporting H1b and H 7b), the motives for obtaining vary across different segments. For U.S. born, light computer users, obtaining is affected by all four social learning variables, thereby supporting H1a, H3a, H5a, and H 7a. The obtaining behavior of older, light computer users is primarily driven by differential association (β = 0.27, $p < 0.01$), definitions (β = 0.41, $p < 0.001$), and reinforcement (β = 0.30, $p < 0.01$), but not driven by imitation ($p > 0.15$). These results support H1a, H3a, and H5a for this group, respectively. The obtaining behavior of younger, not U.S. born male, heavy computer users is mainly influenced by reinforcement (β = 0.58, $p < 0.001$), and imitation (β = 0.36, $p < 0.001$). Therefore, H5a and H7a are supported for this segment.

Table 7. Disaggregated Results for Heterogeneous Sample: Three-Segment Solution

	U.S. born, light computer users (segment 1)		**Older, light computer users (segment 2)**		**Younger male, not U.S. born, heavy computer users (segment 3)**	
	Obtaining	**Sharing**	**Obtaining**	**Sharing**	**Obtaining**	**Sharing**
Differential association	0.21***	0.16***	0.27**	0.40***	–0.14	0.58***
Definitions	0.26***	0.07*	0.41***	0.18*	0.31	0.06
Differential reinforcement	0.15**	0.01	0.30**	0.00	0.53***	0.00
Imitation	0.07*	0.06*	0.11	0.34***	0.44***	0.36***
R^2 (percent)	41.9	22.2	64.5	74.2	63.3	77.2
Sample percent	71.88		20.45		7.67	

* Significant at the 0.05 level; ** significant at the 0.01 level; *** significant at the 0.001 level.

The invariance tests for each segment provide additional evidence of the differential effects of social learning variables on obtaining versus sharing. In the last two segments, differential association exerts a stronger impact on sharing than it does on obtaining, supporting H2. In contrast, definitions of music piracy affect sharing more weakly than it affects obtaining for the first two segments, supporting H4. For all three segments, differential reinforcement shows a stronger impact on obtaining than on sharing, supporting H6. In addition, imitation has a weaker influence on obtaining than on sharing in the second segment, supporting H8. These results substantiate our theory that for the same individual, obtaining is primarily driven by economic needs, whereas sharing is mainly determined by social needs.

Self-Selection Bias

Given that participation in our survey is voluntary (as required by the Institutional Review Board at the University of Texas at Arlington for survey studies), such a sampling may result in self-selection bias. To overcome this concern, our study used a relatively large sample size ($n = 665$) compared to most other survey studies in information systems (where sample sizes are usually between 200 and 300). The use of a large sample is suggested to be an effective approach to remedy potential selection bias [45, 52]. In addition, the levels of reported sharing and obtaining (92.2 percent and 86.8 percent, respectively, see Table 2) are comparable with those in Sabbagh [79], which shows that illegal copying in some form is undertaken by 96 percent of 18- to 24-year-olds surveyed. Note that our study took considerations of multiple forms of music piracy in measuring unauthorized obtaining and sharing (see Appendix A). If we consider only piracy over the Internet (i.e., count "using your computer as an active seed to share music files through P2P software" and "proactively uploading music files to Web sites to share with others" for unauthorized sharing, and "downloading unauthorized digital music files from the Internet" for unauthorized obtaining), the level of piracy in our sample (see Table 8) is comparable with that reported in Madden and Lenhart [59] given consideration of the demographic set our study focuses on. Hence, self-selection bias does not pose significant threats to our results.

Table 8. Participants Who Engaged in Internet-Based Obtaining and Sharing

	No obtaining	**Some level of obtaining**	**Total**
No sharing	185 (28)	192 (29)	377 (57)
Some level of sharing	46 (7)	242 (36)	288 (43)
Total	231 (35)	434 (65)	665 (100)

Note: Percentages are shown in parentheses.

Discussion and Conclusion

The paper examines two distinct aspects of music piracy—namely, unauthorized obtaining and unauthorized sharing—from a social learning perspective, and explores how the social context may exert simultaneous but distinct effects on each of these two activities of an individual. As summarized in Table 9, all four social learning variables (differential association, definitions of music piracy, differential reinforcement, and imitation) have significant impact on unauthorized obtaining as predicted by social learning theory, while only two (differential association and imitation) exert significant influence on unauthorized sharing. More importantly, the impact of definitions and differential reinforcement on obtaining are significantly larger than that on sharing, whereas the reverse pattern holds for the effects of imitation and differential association. These findings are largely replicated even after extracting the unobserved behavioral heterogeneity in the sample. From a theoretical perspective, our study extends the domain of research from the examination of one aspect of music piracy at a time, or music piracy in general, to a more fine-grained understanding of music piracy through a simultaneous examination of unauthorized obtaining and sharing for the same individual. A conceptual distinction between unauthorized obtaining and unauthorized sharing is important, as it advances our understanding of the differential motives underlying each aspect of music piracy and provides a solid foundation for researchers and managers to develop appropriate strategies to address different aspects of music piracy.

Theoretical and Methodological Contributions

Our findings suggest an important, but overlooked, nuance in the literature: unauthorized obtaining and unauthorized sharing are shaped differently by the same set of social learning variables. Our framework offers a theoretical explanation on why policymakers have difficulty in counteracting piracy on university campuses through primarily enforcing legal sanctions and technology [33]. We find that differential reinforcement is an important preventive mechanism of illegal obtaining; however, it barely affects music sharing. One's sharing behavior is more likely to be shaped via differential association with peers who engage in music piracy and imitation of their behavior. When the norms of piracy are established in peer groups and internalized in individuals' value systems, the effect of legal deterrence diminishes dramatically.

These findings enrich our understanding of music piracy and set up a new foundation for future research. Based on our findings, future studies can seek the distinct social precursors and internalization processes for obtaining and sharing. The difference in social influence mechanisms for unauthorized obtaining and sharing could also be explored. For example, susceptibility to peer influence may be a key underlying process through which sharing (but not obtaining) is affected in social contexts.

In addition, our research contributes to the literature from a methodological perspective. We show the importance of disentangling behavioral heterogeneity when explaining piracy behavior so that proper inferences can be drawn for different segments. Our findings suggest that latent class analysis can be used in future studies on piracy. Researchers and marketing practitioners may classify music pirates into different groups and develop customized intervention programs to effectively counter piracy, using more observable demographic variables to reflect unobserved heterogeneity in piracy.

Practical Implications

The findings of this study indicate the significance of developing diverse strategies to curtail distinct aspects of music piracy. Since sharing is mainly driven by imitation and differential association, we should focus on these two aspects to reduce individuals' tendency to engage in sharing. One approach is to set up good examples among college students for them to follow. Exemplar figures can be established through advertising in college newspapers to show that a good citizen on campus is the one who keeps away from file sharing. Another strategy is to take specific measures to break individuals' association with pirating peers. For example, successful counseling and intervention strategies could be developed to prevent students from associating with music pirating groups.

Unlike music sharing, obtaining is primarily motivated through the realization of personal benefits or avoidance of personal losses. As a result, it is greatly affected by definitions of music piracy and differential reinforcement. Armed with this information, effective educational programs could be developed to change individuals' definitions of music piracy, shape their conceptions of morality and legitimacy regarding music piracy, and successively create a normative culture among groups where each person feels individually and socially bound to abide by those legal standards. Through such programs, we may remove excuses and induce guilt and shame for engaging in unauthorized obtaining. Further, policymakers and managers could devise more cost-effective business models so that the perceived benefits of obtaining unauthorized music are reduced, and user-friendly shopping experience for music could be offered to enhance the benefit of "not pirating."

Table 9. Summary of the Model's Hypotheses and Results

Hypotheses		Aggregate	Incorporating heterogeneity in social learning: U.S. born, light computer users (segment 1)	Older, light computer users (segment 2)	Younger male, not U.S. born, heavy computer users (segment 3)
H1a	Differential association has a positive effect on unauthorized obtaining.	Supported	Supported	Supported	Not supported
H1b	Differential association has a positive effect on unauthorized sharing.	Supported	Supported	Supported	Supported
H2	The effect of differential association is stronger for unauthorized sharing than for unauthorized obtaining.	Not supported	Not supported	Supported	Supported
H3a	Favorable definitions of music piracy behavior increase unauthorized obtaining.	Supported	Supported	Supported	Not supported
H3b	Favorable definitions of music piracy behavior increase unauthorized sharing.	Not supported	Supported	Not supported	Not supported
H4	The effect of definitions of music piracy is stronger for unauthorized obtaining than for unauthorized sharing.	Supported	Supported	Supported	Not supported
H5a	Positive differential reinforcement increases unauthorized obtaining.	Supported	Supported	Supported	Supported
H5b	Positive differential reinforcement increases unauthorized sharing.	Not supported	Not supported	Not supported	Not supported
H6	The effect of differential reinforcement is stronger for unauthorized obtaining than for unauthorized sharing.	Supported	Supported	Supported	Supported
H7a	Imitation has a positive effect on unauthorized obtaining.	Supported	Supported	Not supported	Supported
H7b	Imitation has a positive effect on unauthorized sharing.	Supported	Supported	Supported	Supported
H8	The effect of imitation is stronger for unauthorized sharing than for unauthorized obtaining.	Supported	Not supported	Supported	Not supported
H9a	Unobserved heterogeneity exists in the sample, reflecting individuals' sensitivity to social learning variables.	Supported	—	—	—
H9b	Respondents' sensitivity to social learning variables can be explained by such demographic variables as age, gender, country of birth, social desirability, and computer usage.	Supported	—	—	—

All of these piracy-combating strategies need to be developed in combination with effective segmentation approaches to enhance its effectiveness. For U.S. born, light computer users, all social learning variables affect both obtaining and sharing, with differential association and definitions being the two more important predictors. Therefore, prevention programs that focus on effectively dealing with peer influence and recognize the detrimental effects of piracy tend to be effective for this group. For older, light computer users, however, the more important predictors of obtaining are definitions and differential reinforcement, whereas sharing is mostly affected by differential association and imitation. As a result, deterrent approaches such as lawsuits, and good examples from peers may be more effective for this group. The obtaining behavior of young, non-U.S. born, male heavy computer users is affected by differential reinforcement and imitation, while their sharing behavior is affected by differential association and imitation. Consequently, educational intervention programs should be designed to create a normative culture among the high-pirating group, so that they feel individually and socially obliged to abide by those legal standards.

Limitations and Future Research

The results have to be interpreted in the context of the study limitations. First, all of the measures in our model are self-reported without actual behavioral data. Although common method bias was not found to be a threat to the internal validity of our findings, some behavioral measures can be used in future research. Second, although surveys have been used as a major research methodology to apply social learning theory for understanding various deviant behavior (see, e.g., [5]; see also [4] for a review on relevant empirical studies), such a method may not be able to fully capture the complex and dynamic process of social learning. Third, we did not ask whether participants obtained the music for sampling or pure piracy. Future research could explore the robustness of our model after sampling behavior is controlled.

Fourth, our research used survey data from university students. Although we are confident that our sample is representative of university students' music piracy, piracy behavior among older adults is underrepresented in this study. As shown in Table 1, we had a relatively small percentage of participants (9.32 percent) who reported their age over 30. Future research could employ a more representative sample from the general population so that older adults' piracy behavior could be represented. In addition, compared to the general population, a higher percentage of university students are online, and more likely to engage in music sharing and downloading [53]. That is a major reason why RIAA targeted college campuses for antipiracy efforts [50, 63]. Although we believe that the use of a heavy piracy sample is unlikely to pose significant threats to the core thesis of our paper (i.e., social learning variables exert differential effects on unauthorized obtaining versus sharing), future research could use a more representative sample to test the rigor of our theory.

Future research could also investigate whether the influence of virtual and real social peer groups differ. Our framework could also be tested for other types of digital products that face a piracy environment, such as movies and software. A deeper understanding of the underlying social influence mechanism may also be a fruitful direction for future research.

Acknowledgments: The authors gratefully acknowledge the University of Texas at Arlington (UTA) for financial support for this study, the UTA Marketing Department for the data support through the Research Experience Program, the Connecticut Information Technology Institute (CITI), and the Gladstein Endowed MIS Research Lab. The authors thank the editor and three reviewers for many constructive suggestions. The usual disclaimer applies.

References

1. Ajzen, I. *Attitudes, Personality, and Behavior.* Chicago: Dorsey Press, 1988.
2. Ajzen, I., and Fishbein, M. *Understanding Attitudes and Predicting Social Behavior.* Englewood Cliffs, NJ: Prentice Hall, 1980.
3. Akers, R.L. *Social Learning and Social Structure: A General Theory of Crime and Deviance.* Boston: Northeastern University Press, 1998.
4. Akers, R.L., and Jensen, G.F. The empirical status of social learning theory of crime and deviance: The past, present, and future. In F. Cullen, J. Wright, and K. Blevins (eds.), *Taking Stock: The Status of Criminological Theory.* New Brunswick, NJ: Transaction, 2006, pp. 37–76.
5. Akers, R.L.; Krohn, M.D.; Lanza-Kaduce, L.; and Radosevich, M. Social learning and deviant behavior: A specific test of a general theory. *American Sociological Review, 44,* 4 (1979), 636–655.
6. Anderson, C., and Galinsky, A.D. Power, optimism, and risk-taking. *European Journal of Social Psychology, 36,* 4 (2006), 511–536.
7. Bagozzi, R.P., and Yi, Y. Advanced topics in structural equation models. In R.P. Bagozzi (ed.), *Advanced Methods of Marketing Research.* Cambridge, MA: Blackwell, 1994, pp. 1–52.
8. Bandura, A. *Social Learning Theory.* Englewood Cliffs, NJ: Prentice Hall, 1977.
9. Banerjee, A. A simple model of herd behavior. *Quarterly Journal of Economics, 107,* 3 (1992), 797–817.
10. Barclay, D.; Higgins, C.; and Thompson, R. The partial least squares approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies, 2,* 2 (1995), 285–309.
11. Bass, F.M.; Cattin, P.; and Wittink, D.R. Firm effects and industry effects in the analysis of industry structure and profitability. *Journal of Marketing Research, 15,* 1 (February 1978), 3–10.
12. Becker, J.U., and Clement, M. Dynamics of illegal participation in peer-to-peer networks—Why do people illegally share media files? *Journal of Media Economics, 19,* 1 (2006), 7–32.
13. Bhattacharjee, S.; Gopal, R.D.; and Sanders, G.L. Digital music and online sharing: Software piracy 2.0? *Communications of the ACM, 46,* 7 (2003), 107–111.
14. Bhattacharjee, S.; Gopal, R.D.; Lertwachara, K.; and Marsden, J.R. Consumer search and retailer strategies in the presence of online music sharing. *Journal of Management Information Systems, 23,* 1 (Summer 2006), 129–159.
15. Bhattacharjee, S.; Gopal, R.D.; Lertwachara, K.; and Marsden, J.R. Impact of legal threats on online music sharing activity: An analysis of music industry legal actions. *Journal of Law and Economics, 49,* 1 (2006), 91–114.

16. Bhattacharjee, S.; Gopal, R.D.; Lertwachara, K.; and Marsden, J.R. Whatever happened to payola? An empirical analysis of online music sharing. *Decision Support Systems, 42,* 1 (2006), 104–120.
17. Bhattacharjee, S.; Gopal, R.D.; Marsden, J.R.; and Sankaranarayanan, R. Re-tuning the music industry—Can they re-attain business resonance? *Communications of the ACM, 52,* 6 (2009), 136–140.
18. Bhattacharjee, S.; Gopal, R.D.; Lertwachara, K.; Marsden, J.R.; and Telang, R. The effect of digital sharing technologies on music markets: A survival analysis of albums on ranking charts. *Management Science, 53,* 9 (2007), 1359–1374.
19. Bikhchandani, S.; Hirschleifer, D.; and Welch, I. A theory of fads, fashion, custom, and cultural change in informational cascades. *Journal of Political Economy, 100,* 5 (1992), 992–1026.
20. Bonabeau, E. The perils of the imitation age. *Harvard Business Review, 82,* 6 (2004), 99–104.
21. Brown, B.; Sellen, A.J.; and Geelhoed, E. Music sharing as a computer supported collaborative application. In W. Prinz, M. Jarke, Y. Rogers, K. Schmidt, and V. Wulf (ed.), *Proceedings of the Seventh European Conference on Computer Supported Cooperative Work.* Norwell, MA: Kluwer, 2001, pp. 179–198.
22. Burgess, R.L., and Akers, R.L. A differential association-reinforcement theory of criminal behavior. *Social Problems, 14,* 2 (1966), 128–147.
23. Cenfetelli, R.T., and Bassellier, G. Interpretation of formative measurement in information systems research. *MIS Quarterly, 33,* 4 (2009), 689–707.
24. Cenite, M.; Wang, M.W.; Chong, P.; and Chan, G.S. More than just free content: Motivations of peer-to-peer file sharers. *Journal of Communication Inquiry, 33,* 3 (2009), 206–221.
25. Chen, Y.-C.; Shang, R.-A.; and Lin, A.-K. The intention to download music files in a P2P environment: Consumption value, fashion, and ethical decision perspectives. *Electronic Commerce Research and Applications, 7,* 4 (2008), 411–422.
26. Chin, W.W. The partial least squares approach for structural equation modeling. In G.A. Marcoulides (ed.), *Modern Methods for Business Research.* Mahwah, NJ: Lawrence Erlbaum, 1998, pp. 295–336.
27. Chin, W.W. Issues and opinion on structural equation modeling. *MIS Quarterly, 22,* 1 (1998), vii–xvi.
28. Chin, W.W., and Gopal, A. Adoption intention in GSS: Relative importance of beliefs. *Data Base for Advances in Information Systems, 26,* 2–3 (1995), 42–63.
29. Chin, W.W.; Marcolin, B.L.; and Newsted, P.R. A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14,* 2 (2003), 189–217.
30. Chiou, J.-S.; Huang, C.-y.; and Lee, H.-h. The antecedents of music piracy attitudes and intentions. *Journal of Business Ethics, 57,* 2 (2005), 161–174.
31. Chircu, A.M., and Kauffman, R.J. Special section: Competitive strategy, economics, and the Internet. *Journal of Management Information Systems, 19,* 3 (Winter 2002–3), 11–16.
32. Clemons, E.K.; Gu, B.; and Lang, K.R. Newly vulnerable markets in an age of pure information products: An analysis of online music and online news. *Journal of Management Information Systems, 19,* 3 (Winter 2002–3), 17–41.

33. Condry, I. Cultures of music piracy: An ethnographic comparison of the U.S. and Japan. *International Journal of Cultural Studies, 7,* 3 (2004), 343–363.
34. Coyle, J.R.; Gould, S.J.; Gupta, P.; and Gupta, R. "To buy or to pirate": The matrix of music consumers' acquisition-mode decision-making. *Journal of Business Research, 62,* 10 (2009), 1031–1037.
35. Crowne, D.P., and Marlowe, D. *The Approval Motive.* New York: John Wiley & Sons, 1964.
36. Diamantopoulos, A., and Siguaw, J.A. Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management Science, 17,* 4 (2006), 263–282.
37. Diamantopoulos, A., and Winklhofer, H.M. Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research, 38,* 2 (2001), 259–277.
38. Falk, R.F., and Miller, N.B. *A Primer for Soft Modeling.* Akron, OH: University of Akron Press, 1992.
39. Feldman, P. *The Psychology of Crime: A Social Science Textbook.* Cambridge: Cambridge University Press, 1993.
40. Fornell, C., and Bookstein, F.L. Two structural equation models: LISREL and PL S applied to consumer exit-voice theory. *Journal of Marketing Research, 19,* 4 (1982), 440-452.
41. Fornell, C., and Larcker, D.F. Structural equation models with unobservable variables and measurement errors. *Journal of Marketing Research, 18,* 3 (1981), 39–50.
42. Gopal, R.D., and Sanders, G.L. Preventive and deterrent controls for software piracy. *Journal of Management Information Systems, 13,* 4 (Spring 1997), 29–47.
43. Gopal, R.D.; Sanders, G.L.; Bhattacharjee, S.; Agrawal, M.; and Wagner, S.C. A behavioral model of digital music piracy. *Journal of Organizational Computing and Electronic Commerce, 14,* 2 (2004), 89–105.
44. Gu, B.; Huang, Y.; Duan, W.; and Whinston, A.B. Indirect reciprocity in contributions to a peer-to-peer music sharing network—An empirical analysis of individual level data. Paper presented at the 2008 International Conference on Information Systems, Paris, December 2008 (available at http://aisel.aisnet.org/icis2008/158/).
45. Guy, D.; Carmichael, D.; and Whittington, O. *Practitioner's Guide to Audit Sampling.* New York: John Wiley & Sons, 1998.
46. Haley, R.I. Benefit segmentation: A decision-oriented research tool. *Journal of Marketing, 32,* 3 (1968), 30–35.
47. Higgins, G.E., and Makin, D.A. Does social learning theory condition the effects of low self-control on college students' software piracy? *Journal of Economic Crime Management, 2,* 2 (2004), 1–22.
48. Hinduja, S. *Music Piracy and Crime Theory.* New York: LFB Scholarly Publishing, 2006. 49. Ingram, J.R., and Hinduja, S. Neutralizing music piracy: An empirical examination. *Deviant Behavior, 29,* 4 (2008), 334–366.
49. Jardin, X. RIAA focuses on colleges for anti-piracy efforts. NPR, March 1, 2007 (available at www.npr.org/templates/story/story.php?storyId=7667058/).
50. Jarvis, C.B.; MacKenzie, S.B.; and Podsakoff, P.M. A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research, 30,* 2 (2003), 199–218.
51. Jones, P. *Statistical Sampling and Risk Analysis in Auditing.* Hampshire, UK: Gower, 1999.
52. Jones, S. The Internet goes to college: How students are living in the future with today's technology. Pew Internet & American Life Project, Washington, DC, 2002.

53. Kennedy, J. IFPI digital music report 2009. International Federation of the Phonographic Industry, London, 2009 (available at www.ifpi.org/content/library/dmr2009.pdf).
54. Lindell, M.K., and Whitney, D.J. Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86,* 1 (2001), 114–121.
55. Lohmöller, J.-B. *Latent Variable Path Modeling with Partial Least Squares.* Heidelberg: Physica-Verlag, 1989.
56. Lubke, G.H., and Muthén, B. Investigating population heterogeneity with factor mixture models. *Psychological Methods, 10,* 1 (2005), 21–39.
57. Lysonski, S., and Durvasula, S. Digital piracy of MP3s: Consumer and ethical predispositions. *Journal of Consumer Marketing, 25,* 3 (2008), 167–178.
58. Madden, M., and Lenhart, A. Music downloading, file-sharing and copyright. Pew Internet & American Life Project, Washington, DC, 2003.
59. Massy, W.F., and Frank, R.E. Short term price and dealing effects in selected market segments. *Journal of Marketing Research, 2,* 2 (1965), 171–185.
60. Mitchell, A. *The Nine American Life-Styles.* New York: Warner, 1983.
61. Moores, T.T., and Chang, J.C.-J. Ethical decision making in software piracy: Initial development and test of a four-component model. *MIS Quarterly, 30,* 1 (2006), 167–180.
62. Musgrove, M. Music industry tightens squeeze on students; Campus network access targeted. *Washington Post* (March 9, 2007), D3.
63. Nandi, T.K., and Rochelandet, F. The incentives for contributing digital contents over P2P networks: An empirical investigation. *Review of Economic Research on Copyright Issues, 5,* 2 (2008), 19–35.
64. Nunnally, J.C. *Psychometric Theory.* New York: McGraw-Hill, 1978.
65. Nylund, K.L.; Asparouhov, A.; and Muthén, B. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling, 14,* 4 (2007), 535–569.
66. Oberholzer-Gee, F., and Strumpf, K. The effect of file sharing on record sales: An empirical analysis. *Journal of Political Economy, 115,* 6 (2007), 1–42.
67. Paternoster, R. The deterrent effect of the perceived certainty and severity of punishment: A review of the evidence and issues. *Justice Quarterly, 4,* 2 (1987), 173–217.
68. Pavlou, P.A.; Liang, H.; and Xue, Y. Understanding and mitigating uncertainty in online exchange relationships: A principle–agent perspective. *MIS Quarterly, 31,* 1 (2007), 105–136.
69. Peace, A.; Galletta, D.; and Thong, J. Software piracy in the workplace: A model and empirical test. *Journal of Management Information Systems, 20,* 1 (Summer 2003), 153–177.
70. Petter, S.; Straub, D., and Rai, A. Specifying formative constructs in information systems research. *MIS Quarterly, 31,* 4 (2007), 623–656.
71. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; and Podsakoff, N.P. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88,* 5 (2003), 879–903.
72. Pratt, T.C.; Cullen, F.T.; Blevins, K.R.; Daigle, L.E.; and Madensen, T.D. The empirical status of deterrence theory: A meta-analysis. In F.T. Cullen, J.P. Wright, and K.R. Blevins (ed.), *Taking Stock: The Status of Criminological Theory.* New Brunswick, NJ: Transaction, 2006, pp. 37–76.

73. Ramaswamy, V.; DeSarbo, W.S.; Reibstein, D.J.; and Robinson, W.T. An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science, 12,* 1 (1993), 103–124.
74. Reb, J., and Connolly, T. Myopic regret avoidance: Feedback avoidance and learning in repeated decision making. *Organizational Behavior and Human Decision Processes, 109,* 2 (2009), 182–189.
75. Ringle, C.M.; Wende, S.; and Will, S. SmartPLS 2.0 (M3) Beta. Hamburg, 2005 (available at www.smartpls.de).
76. Ripeanu, M.; Mowbray, M.; Andrade, N.; and Lima, A. Gifting technologies: A BitTorrent case study. Technical Report HPL-2007-26, Enterprise Systems and Software Laboratory, HP Laboratories, Bristol, UK, 2007 (available at www.hpl.hp.com/techreports/2007/HPL-2007-26.pdf).
77. Rogers, M.K. A social learning theory and moral disengagement analysis of criminal computer behavior: An exploratory study. Ph.D. dissertation, University of Manitoba, Winnipeg, 2001.
78. Sabbagh, D. Average teenager's iPod has 800 illegal music tracks. *The Times* (June 16, 2008) (available at http://technology.timesonline.co.uk/tol/news/tech_and_web/personal_tech/article4144585.ece/).
79. Shang, R.-A.; Chen, Y.-C.; and Chen, P.-C. Ethical decisions about sharing music files in the P2P environment. *Journal of Business Ethics, 80,* 2 (2008), 349–365.
80. Sinha, R.K., and Mandel, N. Preventing digital music piracy: The carrot or the stick? *Journal of Marketing, 72,* 1 (2008), 1–15.
81. Siwek, S.E. The true cost of sound recording piracy to the U.S. economy. Policy Report no. 188, Institute for Policy Innovation, Lewisville, TX, 2007.
82. Skinner, W.F., and Fream, A.M. A social learning theory analysis of computer crime among college students. *Journal of Research in Crime and Delinquency, 34,* 4 (1997), 495–518.
83. Strahan, R., and Gerbasi, K.C. Short, homogeneous versions of the Marlowe–Crowne social desirability scale. *Journal of Clinical Psychology, 28,* 2 (1972), 191–193.
84. Sykes, G., and Matza, D. Techniques of neutralization: A theory of delinquency. *American Sociological Review, 22,* 6 (1957), 664–670.
85. Taylor, R. Piracy on campus: An overview of the problem and a look at emerging best practices to reduce online theft of copyrighted works. Testimony before the Subcommittee on Courts, the Internet, and Intellectual Property, House Judiciary Committee, Washington, DC, 2005.
86. Tittle, C.R. *Sanctions and Social Deviance: The Question of Deterrence.* New York: Praeger, 1980.
87. Tofighi, D., and Enders, C.K. Identifying the correct number of classes in a growth mixture models. In G.R. Hancock and K.M. Samuelson (ed.), *Advances in Latent Variable Mixture Models.* Greenwich, CT: Information Age, 2007, pp. 317–341.
88. Warr, M. *Companions in Crime: The Social Aspects of Criminal Conduct.* Cambridge: Cambridge University Press, 2002.
89. Wedel, M., and Kamakura, W.A. *Market Segmentation: Conceptual and Methodological Foundations.* Norwell, MA: Kluwer Academic, 2000.

90. Wold, H. Soft modeling: The basic design and some extensions. In K.G. Jöreskog and H. Wold (ed.), *Systems Under Indirect Observation: Causality, Structure and Prediction, Part II.* Amsterdam: North-Holland, 1982, pp. 1–53.
91. Yang, Z., and Schaninger, C.M. The impact of parenting strategies on child smoking behavior: The role of child self-esteem trajectory. *Journal of Public Policy & Marketing, 29,* 2 (2010), 232–247.
92. Zhou, L.; Yang, Z.; and Hui, M.K. Non-local or local brands? A multi-level investigation into confidence in brand origin identification and its strategic implications. *Journal of the Academy of Marketing Science, 38,* 3 (2010), 202–218.

Appendix A: Measurement Items for the Main Constructs

Unauthorized Obtaining

Frequency

How often do you do the following things? (never, a few times a year, 2–3 times per month, once a week, 2–3 times per week, 4–5 times per week, every day)

1. Download unauthorized digital music files from the Internet (e.g., BitTorrent, Pirate Bay, Gnutella, eDonkey).
2. Copy unauthorized music files from friends or relatives.
3. Buy unauthorized/pirate music CDs.

Amount

In the past year, how many songs in total were involved in your following activities? (0 songs, 1–10 songs,11–100 songs, 101–200 songs, 201–400 songs, 401–600 songs, more than 600 songs)

1. Download unauthorized digital music files from the Internet (e.g., BitTorrent, Pirate Bay, Gnutella, eDonkey).
2. Copy unauthorized music files from friends or relatives.
3. Buy unauthorized/pirate music CDs.

Intensity

On average, how many songs each time were involved in your following activities in the past year? (0 songs, 1–5 songs, 6–10 songs, 11–15 songs, 16–20 songs, 21–25 songs, more than 25 songs)

1. Download unauthorized digital music files from the Internet (e.g., BitTorrent, Pirate Bay, Gnutella, eDonkey).
2. Copy unauthorized music files from friends or relatives.
3. Buy unauthorized/pirate music CDs.

Unauthorized Sharing

Frequency

How often do you do the following things related to unauthorized music-sharing with others? (never, a few times a year, 2–3 times per month, once a week, 2–3 times per week, 4–5 times per week, every day)

1. Use your computer as an active seed to share music files through P2P software (to help others download).
2. Proactively upload music files to Web sites to share with others.
3. Let friends or relatives copy the music files that you have.
4. Lend music CDs to friends or relatives.

Amount

In the past year, how many songs in total were involved in your following activities? (0 songs, 1–10 songs, 11–100 songs, 101–200 songs, 201–400 songs, 401–600 songs, more than 600 songs)

1. Use your computer as an active seed to share music files through P2P software (to help others download).
2. Proactively upload music files to Web sites to share with others.
3. Let friends or relatives copy the music files that you have.
4. Lend music CDs to friends or relatives.

Intensity

On average, how many songs each time were involved in your following activities in the past year? (0 songs, 1–5 songs, 6–10 songs, 11–15 songs, 16–20 songs, 21–25 songs, more than 25 songs)

1. Use your computer as an active seed to share music files through P2P software (to help others download).
2. Proactively upload music files to Web sites to share with others.
3. Let friends or relatives copy the music files that you have.
4. Lend music CDs to friends or relatives.

Differential Association—Peer Norm

1. People who are important to you think that music piracy is 1 = bad/7 = good.
2. People who influence your behavior think that music piracy is
   1 = foolish/7 = good.
3. People whose opinions you value think that music piracy is
   1 = unattractive/7 = attractive.

Differential Association—Differential Peer Association

1. How many of your friends that you have known for the longest time have engaged in the following activities? (none of them, a few of them, some of them, half of them, more than half, most of them, all of them)

   Obtain: Downloaded unauthorized digital music from the Internet.
   Let copy: Asked you to let them copy the music that you had.
   Upload: Proactively uploaded music to Web sites to share with others.

2. How many of your friends with whom you associate most often have engaged in the following activities? (none of them, a few of them, some of them, half of them, more than half, most of them, all of them)

   Obtain: Downloaded unauthorized digital music from the Internet.
   Let copy: Asked you to let them copy the music that you had.
   Upload: Proactively uploaded music to Web sites to share with others.

3. How many of your best friends have engaged in the following activities? (none of them, a few of them, some of them, half of them, more than half, most of them, all of them)

   Obtain: Downloaded unauthorized digital music from the Internet.
   Let copy: Asked you to let them copy the music that you had.
   Upload: Proactively uploaded music to Web sites to share with others.

Definitions—Negative

1. To me, the act of unauthorized downloading or sharing of music is
   1 = unacceptable/7 = acceptable.
2. To me, the act of unauthorized downloading or sharing of music is
   1 = bad/7 = good.
3. To me, the act of unauthorized downloading or sharing of music is
   1 = foolish/7 = wise.

Definitions—Neutralization

I would be more likely to download or share unauthorized music, if…

Denial of Responsibility

1. I could not afford the purchase price of the music on CD.
2. Numerous sources offering MP3s for free download are readily available online.
3. There are no clear-cut rules, laws, regulations, or even guidelines when it comes to MP3 file exchanges.

Denial of Injury/Victim

4. It was known that the recording industry “could afford it” and would never miss the tiny amount of proceeds lost.
5. It was known that law enforcement agencies, universities, and authorities could not care less about MP3 file exchanges.
6. It was known that no one is really getting hurt from such activity.

Condemnation of Condemners

7. It was known that the music industry deserves to have their music distributed freely online considering the fact that they rip off consumers.

Appeal to Higher Loyalties

8. A family member, friend, or significant other needed the music.
9. The music will be used to complete a project for school or work.

Definitions—Law-Abiding

1. We all have a moral duty to obey the law. (1= strongly disagree/7 = strongly agree)

Differential Reinforcement—Personal Gain

1. Unauthorized downloading or sharing of music saves my money for music. (1 = strongly disagree/7 = strongly agree)
2. Unauthorized downloading or sharing of music allows me to listen to a greater variety of music. (1 = strongly disagree/7 = strongly agree)

Differential Reinforcement—Peer Reinforcement

1. Unauthorized downloading or sharing of music helps me fit into the group better. (1 = strongly disagree/7 = strongly agree)
2. Unauthorized downloading or sharing of music enhances my image. (1 = strongly disagree/7 = strongly agree)

Differential Reinforcement—Perceived Sanction Risk

1. If I obtain or share music without authorization, the probability that I would be caught is 1 = very low/7 = very high.
2. If I obtain or share music without authorization, I would probably be caught. (1 = strongly disagree/7 = strongly agree)

Differential Reinforcement—Perceived Sanction Severity

1. If I were caught obtaining or sharing music without authorization, I think the punishment would be 1 = very low/7 = very high.

2. If I were caught obtaining or sharing music without authorization, I would be severely punished. (1 = strongly disagree/7 = strongly agree)

Imitation

How much knowledge about unauthorized downloading or sharing of music (e.g., where to download unauthorized music files, how to share music files) have you learned from the following sources? (learned nothing, learned a little, learned some, learned a lot, earned everything)

1. Teachers
2. Family
3. Books or magazines
4. Friends
5. Internet and computer bulletin board
6. Television and movies

Appendix B

Table B1. Descriptive Statistics, Correlations, and Average Variance Extracted

Constructs	Mean (SD)	CR	α^2	1	2	3	4	5	6	7	8	9	10	11	12
1. Obtaining	1.97 (0.72)	—	—	—											
2. Obtaining-amount	1.98 (0.81)	—	—	0.90	—										
3. Obtaining-frequency	1.90 (0.74)	—	—	0.85	0.66	—									
4. Obtaining-intensity	2.12 (1.09)	—	—	0.82	0.65	0.50	—								
5. Sharing	2.01 (0.88)	—	—	0.64	0.58	0.55	0.49	—							
6. Sharing amount	1.87 (0.86)	—	—	0.61	0.60	0.53	0.43	0.94	—						
7. Sharing-frequency	1.98 (0.96)	—	—	0.54	0.47	0.55	0.33	0.89	0.78	—					
8. Sharing-intensity	1.97 (1.09)	—	—	0.59	0.51	0.43	0.56	0.89	0.80	0.65	—				
9. Differential association	3.52 (1.32)	—	—	0.55	0.47	0.47	0.46	0.42	0.38	0.36	0.39	—			
10. Peer association	3.43 (1.47)	0.94	0.92	0.52	0.45	0.45	0.42	0.43	0.39	0.37	0.39	0.98	**0.79**		
11. Association-peer norm	3.79 (1.43)	0.93	0.88	0.39	0.32	0.32	0.38	0.19	0.15	0.14	0.20	0.63	0.45	**0.90**	
12. Definitions	4.05 (1.34)	—	—	0.56	0.49	0.47	0.50	0.28	0.25	0.22	0.27	0.52	0.45	0.52	—
13. Definitions-negative	3.49 (1.39)	0.92	0.86	0.52	0.46	0.43	0.45	0.24	0.23	0.21	0.23	0.51	0.41	0.61	0.75
14. Definitions-neutralization	4.35 (1.43)	—	—	0.49	0.41	0.40	0.44	0.24	0.22	0.18	0.25	0.44	0.40	0.40	0.96
15. Denial of responsibility	4.67 (1.58)	0.85	0.73	0.44	0.37	0.35	0.41	0.20	0.18	0.14	0.21	0.37	0.33	0.33	0.81
16. Denial of injury/victim	4.14 (1.71)	0.91	0.86	0.41	0.35	0.34	0.36	0.22	0.18	0.18	0.22	0.38	0.34	0.35	0.86
17. Condemnation	3.80 (1.95)	1	1	0.32	0.27	0.29	0.27	0.16	0.15	0.15	0.14	0.27	0.25	0.23	0.69
18. Appeal	4.49 (1.71)	0.91	0.80	0.41	0.34	0.34	0.38	0.22	0.21	0.14	0.23	0.41	0.36	0.38	0.76
19. Differential reinforcement	2.70 (7.65)	—	—	0.55	0.47	0.49	0.45	0.28	0.26	0.25	0.27	0.55	0.49	0.53	0.61
20. Personal gain	4.84 (1.94)	0.92	0.83	0.53	0.45	0.46	0.46	0.24	0.21	0.19	0.26	0.50	0.44	0.50	0.66
21. Peer reinforcement	2.16 (1.37)	0.90	0.79	0.43	0.38	0.36	0.35	0.33	0.30	0.32	0.30	0.36	0.33	0.28	0.33
22. Sanction risk	3.15 (1.73)	0.92	0.82	–0.18	–0.15	–0.18	–0.13	0.00	0.00	0.00	0.01	–0.27	–0.23	–0.31	–0.26
23. Sanction severity	4.25 (1.79)	0.91	0.81	–0.08	–0.07	–0.09	–0.05	–0.04	–0.05	–0.04	–0.02	–0.15	–0.13	–0.16	–0.09
24. Imitation	2.51 (0.75)	—	—	0.33	0.28	0.29	0.28	0.35	0.31	0.34	0.28	0.35	0.37	0.11	0.20

Table B1. Continued

Constructs	**Mean (SD)**	**CR**	**α²**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1. Obtaining	1.97 (0.72)	—	—												
2. Obtaining-amount	1.98 (0.81)	—	—												
3. Obtaining-frequency	1.90 (0.74)	—	—												
4. Obtaining-intensity	2.12 (1.09)	—	—												
5. Sharing	2.01 (0.88)	—	—												
6. Sharing amount	1.87 (0.86)	—	—												
7. Sharing-frequency	1.98 (0.96)	—	—												
8. Sharing-intensity	1.97 (1.09)	—	—												
9. Differential association	3.52 (1.32)	—	—												
10. Peer association	3.43 (1.47)	0.94	0.92												
11. Association-peer norm	3.79 (1.43)	0.93	0.88												
12. Definitions	4.05 (1.34)	—	—												
13. Definitions-negative	3.49 (1.39)	0.92	0.86	**0.89**											
14. Definitions-neutralization	4.35 (1.43)	—	—	0.52	—										
15. Denial of responsibility	4.67 (1.58)	0.85	0.73	0.43	0.86	**0.81**									
16. Denial of injury/victim	4.14 (1.71)	0.91	0.86	0.45	0.91	0.67	**0.88**								
17. Condemnation	3.80 (1.95)	1	1	0.41	0.71	0.49	0.64	**1**							
18. Appeal	4.49 (1.71)	0.91	0.80	0.44	0.77	0.58	0.56	0.43	**0.91**						
19. Differential reinforcement	2.70 (7.65)	—	—	0.60	0.51	0.45	0.43	0.32	0.44	—					
20. Personal gain	4.84 (1.94)	0.92	0.83	0.58	0.60	0.57	0.50	0.39	0.50	0.74	**0.93**				
21. Peer reinforcement	2.16 (1.37)	0.90	0.79	0.33	0.28	0.23	0.23	0.23	0.23	0.63	0.32	**0.91**			
22. Sanction risk	3.15 (1.73)	0.92	0.82	–0.32	–0.18	–0.14	–0.17	–0.06	–0.19	–0.61	–0.21	–0.02	**0.91**		
23. Sanction severity	4.25 (1.79)	0.91	0.81	–0.16	–0.04	–0.03	–0.03	0.04	–0.07	–0.50	–0.02	–0.07	0.61	**0.92**	
24. Imitation	2.51 (0.75)	—	—	0.18	0.18	0.13	0.14	0.15	0.17	0.20	0.20	0.26	0.02	0.05	—

Notes: SD = standard deviation; CR = composite reliability. a Cronbach's alpha. The diagonal values (in boldface) represent the square root of AVE.

Table B2. Item Loadings and Cross-Loadings

	Peer association	Association-peer norm	Definitions-negative	Denial of responsibility	Denial of injury/victim	Appeal	Personal gain	Peer reinforcement	Sanction risk	Sanction severity
ASDL01	**0.79**	0.46	0.42	0.33	0.34	0.33	0.45	0.21	–0.28	–0.07
ASDL02	**0.80**	0.46	0.40	0.31	0.33	0.33	0.44	0.24	–0.26	–0.11
ASDL03	**0.79**	0.45	0.40	0.34	0.34	0.32	0.44	0.25	–0.27	–0.09
ASSH01	**0.79**	0.34	0.33	0.33	0.32	0.33	0.40	0.27	–0.16	–0.08
ASSH02	0.82	0.34	0.34	0.31	0.29	0.33	0.36	0.28	–0.12	–0.08
ASSH03	**0.82**	0.34	0.35	0.32	0.28	0.33	0.39	0.27	–0.19	–0.10
ASUP01	**0.74**	0.25	0.20	0.14	0.16	0.21	0.18	0.26	–0.11	–0.11
ASUP02	**0.76**	0.26	0.23	0.12	0.14	0.20	0.18	0.29	–0.11	–0.14
ASUP03	**0.76**	0.27	0.24	0.15	0.15	0.20	0.21	0.28	–0.11	–0.13
ASST01	0.45	**0.88**	0.56	0.29	0.31	0.33	0.44	0.23	–0.26	–0.12
ASST02	0.44	**0.92**	0.55	0.30	0.33	0.37	0.48	0.26	–0.29	–0.14
ASST03	0.42	**0.90**	0.54	0.30	0.32	0.33	0.43	0.26	–0.29	–0.18
DFNG01	0.45	0.55	**0.90**	0.44	0.46	0.44	0.57	0.32	–0.32	–0.13
DFNG02	0.36	0.54	**0.88**	0.34	0.37	0.34	0.46	0.29	–0.27	–0.17
DFNG03	0.33	0.53	**0.88**	0.35	0.37	0.37	0.48	0.26	–0.26	–0.12
DFNT01	0.25	0.25	0.38	**0.77**	0.46	0.47	0.49	0.19	–0.11	–0.02
DFNT02	0.32	0.27	0.39	**0.81**	0.51	0.46	0.49	0.22	–0.11	0.01
DFNT03	0.27	0.28	0.28	**0.83**	0.63	0.47	0.40	0.15	–0.13	–0.06
DFNT04	0.30	0.32	0.41	0.57	**0.88**	0.47	0.43	0.27	–0.17	–0.04
DFNT05	0.34	0.30	0.38	0.61	**0.88**	0.51	0.42	0.17	–0.19	–0.03
DFNT06	0.31	0.31	0.41	0.58	**0.88**	0.51	0.46	0.17	–0.11	0.00
DFNT08	0.32	0.35	0.41	0.53	0.51	**0.91**	0.48	0.27	–0.17	–0.08
DFNT09	0.30	0.35	0.38	0.52	0.52	**0.91**	0.43	0.15	–0.18	–0.05
REIN01	0.43	0.45	0.50	0.53	0.46	0.46	**0.92**	0.30	–0.16	–0.01
REIN02	0.45	0.48	0.57	0.52	0.46	0.47	**0.93**	0.29	–0.23	–0.03
REIN03	0.25	0.26	0.29	0.24	0.21	0.23	0.29	**0.90**	0.00	–0.04
REIN04	0.20	0.24	0.31	0.18	0.21	0.19	0.30	**0.91**	–0.03	–0.08
REPB01	–0.25	–0.31	–0.30	–0.11	–0.15	–0.17	–0.17	–0.01	**0.92**	0.57
REPB02	–0.28	–0.27	–0.29	–0.15	–0.17	–0.18	–0.21	–0.02	**0.93**	0.55
REPN01	–0.11	–0.16	–0.17	–0.01	–0.02	–0.08	–0.02	–0.06	0.63	**0.93**
REPN02	–0.06	–0.14	–0.12	–0.05	–0.03	–0.05	–0.01	–0.06	0.48	**0.91**

Note: Boldface values represent item loadings on their intended construct.

Appendix C: Measures of Main Constructs

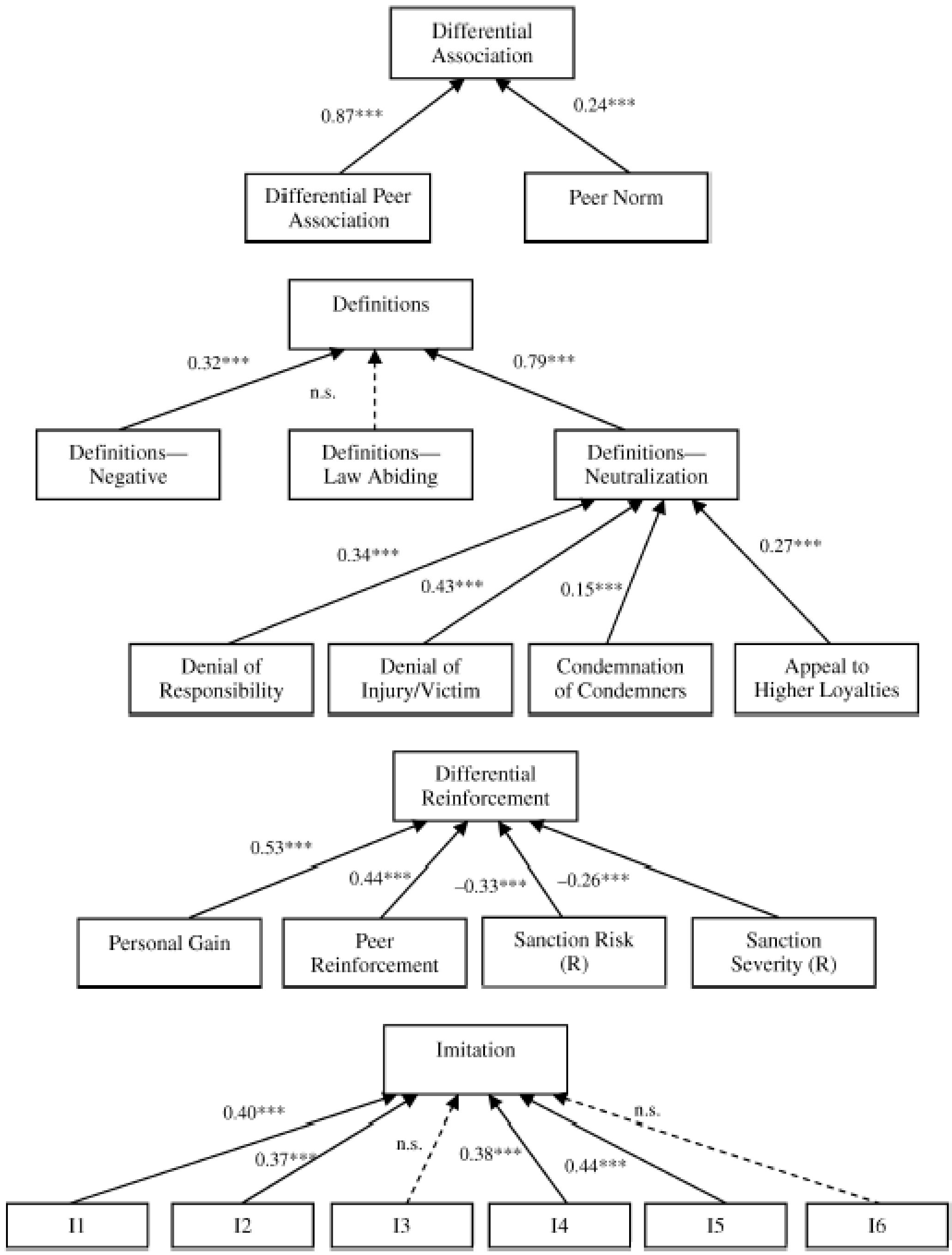

Figure C1. Principal Formative Constructs
Notes: R = reverse coded. *** Significant at the 0.001 level; n.s. = not significant.