

9-11-2023

A Segmentation Study of Digital Pirates and Understanding the Effectiveness of Targeted Anti-Piracy Communication

Bong-Keun Jeong
Coastal Carolina University

Sarah S. Khan
North Carolina State University

Bomi Kang
Coastal Carolina University

Follow this and additional works at: <https://digitalcommons.coastal.edu/management>



Part of the [Management Information Systems Commons](#)

Recommended Citation

Jeong, B.-K., Khan, S.S., & Kang, B. (2023). A Segmentation Study of Digital Pirates and Understanding the Effectiveness of Targeted Anti-Piracy Communication. *J. Theor. Appl. Electron. Commer. Res.*, 18, 1560-1579. <https://doi.org/10.3390/jtaer18030079>. Available at <https://digitalcommons.coastal.edu/management/2/>.

This Article is brought to you for free and open access by the College of Business at CCU Digital Commons. It has been accepted for inclusion in Management and Decision Sciences by an authorized administrator of CCU Digital Commons. For more information, please contact commons@coastal.edu.



Article

A Segmentation Study of Digital Pirates and Understanding the Effectiveness of Targeted Anti-Piracy Communication

Bong-Keun Jeong ^{1,*}, Sarah S. Khan ² and Bomi Kang ¹

¹ Coastal Carolina University, Conway, SC 29528, USA; bkang@coastal.edu

² Department of Business Management, Poole College of Management, North Carolina State University, Raleigh, NC 27695, USA; sskhan@ncsu.edu

* Correspondence: bjeong@coastal.edu

Abstract: The objective of this study is to improve the effectiveness of anti-piracy educational strategies by identifying unique digital pirate segments and delivering personalized campaign messages to the target audiences. In the first study, we introduced a segmentation study of digital pirates based on different types of risks involved in pirating activities. We identify four digital pirate segments (anti-pirates, hard-core pirates, performance-sensitive pirates, and finance-sensitive pirates), each demonstrating distinctive characteristics. Further profiling of the segments revealed different risk perceptions regarding gender and piracy experience. In the second study, we conduct an experiment to test the effects of targeted campaign messages for the newly identified pirating segments. Our results show that targeted piracy campaign messages have a significantly higher message persuasiveness, while they damage the attitude towards piracy. However, we found that the targeted piracy campaign messages have a marginal effect on changing the intention to pirate. Findings from this study offer useful implications for the design and implementation of anti-piracy educational campaigns.

Keywords: digital piracy; anti-piracy; communication; segmentation perceived risk



Citation: Jeong, B.-K.; Khan, S.S.; Kang, B. A Segmentation Study of Digital Pirates and Understanding the Effectiveness of Targeted Anti-Piracy Communication. *J. Theor. Appl. Electron. Commer. Res.* **2023**, *18*, 1560–1579. <https://doi.org/10.3390/jtaer18030079>

Academic Editor: Xuefeng Zhang

Received: 29 June 2023

Revised: 3 September 2023

Accepted: 7 September 2023

Published: 11 September 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The unauthorized use of copyrighted content is a continuing and serious problem in digital goods industries such as software, music, and movies. Advances in file-sharing and streaming technologies provide a greater opportunity for consumers to have access to free content than ever before. Internet users visited piracy sites 182 billion times in 2021, a 15.2% increase when compared to 2020. Illegal downloading and streaming of TV shows was the most popular pirated content, accounting over 50% of all piracy traffic. Publishing piracy (e.g., books, magazines) was the second-most pirated content, followed film, music, and software [1].

Governments and industries have employed a number of different anti-piracy strategies including technological prevention, legal prosecution, and educational deterrence. Through these approaches, they aim to prevent consumers from accessing illegal content, protect intellectual property, and increase legitimate sales. However, evidence indicating the success of these strategies in decreasing piracy is mixed [2–4]. For example, technological preventive controls using digital rights management have been implemented; however, they have limited success due to technical drawbacks. Furthermore, they often lead to customer dissatisfaction as they impose unfair restrictions, such as limiting the number of times content can be copied, installed, or printed. Legal prosecutions initiated by digital goods industries have successfully shut down some well-known file sharing websites (e.g., Megaupload and RapidShare). Industries have also taken actions against individual pirates in which violators are subject to fines and potential jail time. The average settlement accused of illegal downloads ranges from USD 2000 to 5000 [5]. However, one study

showed that the traffic volume on Peer-to-Peer (P2P) sites did not decrease significantly even after the legal threats, and the total number of files shared continued to increase [6].

Recently, educational deterrence efforts have gained increasing attention in efforts to curtail digital piracy. Organizations such as Universal Music Group (UMG), Motion Picture Association of America (MPAA), and Software Alliance (BSA) have designed and executed public anti-piracy educational campaigns attempting to educate consumers about the risks of copyright infringement and the benefits of legally purchased digital products and services. Through this educational approach, organizations encourage consumers to think critically about how they acquire software, music, and other forms of intellectual property [7–9]. Prior studies suggest that anti-piracy educational campaigns are an effective way to dissuade users from downloading illegal content [9–12]. However, even with the clear articulation of digital copyright laws and educational campaigns, changing consumers' attitude towards piracy has been challenging due to the difficulty and high costs associated with increasing consumers' awareness about the subject.

One way to improve the effectiveness of anti-piracy educational strategies is identifying and marketing towards target audiences. Understanding the target audiences can facilitate successful campaigns, as the message may appeal to the right people. Digital pirates consist of a heterogeneous population, and each group (cluster) demonstrates unique characteristics. Some anti-piracy approaches may not appeal to a specific group of pirates with a certain type of piracy perception. Hence, a segmentation study of digital pirates should be undertaken to better understand the pirating population and identify distinctive subgroups. A few studies have examined how to classify digital pirates using ethical, behavioral, and descriptive measures [11,13,14]. However, no attempts have been made to identify pirating segments based on different types of piracy risk perceptions. Furthermore, different segments identified in prior studies are mostly based on the magnitude of piracy level (e.g., ethical/unethical or principled/suspicious/corrupt), which does not provide behavioral insights. Identifying the source of ethical ambiguity is the first step towards taking measures to curtail unethical behavior. Previous research has shown that risk perceptions have significant effects on piracy intentions and behaviors [15–17]. However, our understanding is limited on the details of perceived risks among pirates, especially from segmentation perspective. We postulate pirating segments based on consumer piracy risk perception. Various risk dimensions including psychological, social, prosecution, financial, performance, time, and privacy risk have been measured to identify clusters of pirates who share similar risk perception. This segmentation approach can offer more meaningful information about the unique characteristics of each segment, which can be used to improve educational deterrence efforts.

Additionally, we develop and test targeted campaign messages that may appeal to specific pirating segments identified in the first study. In the second study, we use a mixed experimental design to examine the effects of educational campaigns that highlight specific types of piracy risk on the perceived message effectiveness, attitude towards piracy, and piracy intention. Our findings can offer a better understanding of heterogeneity in the pirating segments, and how they respond differently to targeted anti-piracy educational campaigns. The rest of this paper is organized as follows. Section 2 provides the theoretical foundation for our research. Section 3 presents the segmentation framework and the results of cluster analysis. Section 4 provides the experiment design and the results of the second study that examines the effectiveness of targeted anti-piracy message on different pirating segments. Lastly, Sections 5 and 6 discuss the implications, conclusions, and directions for future research.

2. Literature Review

2.1. Piracy Risk Perception

Several theoretical models have been proposed to understand consumer piracy behavior, including ethical decision-making theory [18,19], theory of planned behavior [20], deterrence theory [21], and perceived risk theory [22]. Different from most theories that

focus on explaining the motivation behind individuals’ decisions to engage in digital piracy, perceived risk theory is more relevant to the cognitive appraisal of consumer piracy risk [23]. It captures different components of piracy risk holistically, and provides insights regarding the relationships among risk components.

Perceived risk is commonly modeled as a two-dimensional construct (uncertainty and consequences) or a multi-dimensional construct (e.g., social, psychological, performance, financial, and physical risk). For example, Pham et al. proposed an integrated model to explore the factors affecting digital piracy behavior: subjective norm, attitude, perceived behavioral control, moral obligation, perceived risk (prosecution), and technology development [17]. They found that the perceived prosecution risk has a significant influence on perceived behavioral control and attitude towards piracy. Tan considered the effects of performance, prosecution, financial, and social risk on the intention to purchase pirated software [24]. The results indicate that those four components have a significant relationship with purchase intention. In addition, several studies have shown that the perceived prosecution risk has a significant influence on attitude towards e-book and software piracy [16,25,26].

In this study, we adopted a piracy risk model developed by Jeong, Zhao, and Khouja [23]. As a higher-order construct, they proposed seven sub-constructs for perceived piracy risk: performance risk, financial risk, time risk, social risk, psychological risk, privacy risk, and prosecution risk. This multi-dimensional risk approach provides useful information about different types of risks involved in pirating activities, and the relative importance of each risk dimension. A summary of these seven risk components is shown in Table 1.

Table 1. Consumer piracy risk dimensions.

Dimensions	Description
Performance risk	The risk that pirating activities will cause a loss due to malfunctioning and not performing as designed
Financial risk	The risk that pirating activities will cause a monetary loss due to re-installment of computer system and data recovery
Time risk	The risk that pirating activities will cause potential time and effort loss
Social risk	The risk that pirating activities will cause potential loss of status in one’s social group such as family, peers, and colleagues
Psychological risk	The risk that pirating activities will cause unwanted anxiety, tension, discomfort, and loss of self-image
Privacy risk	The risk that pirating activities will cause a loss of private and confidential information
Prosecution risk	The risk that pirating activities will cause a legal prosecution

2.2. Segmentation Study

Customer segmentation (also known as market segmentation) is a process of dividing heterogeneous customers into homogenous subgroups based on behavioral, demographic, geographic, or psychographic traits [27]. While smaller segments are distinguished by different characteristics, customers in each subgroup share similar needs and behaviors. Information from the segmentation can be used to develop a campaign suited to the unique needs and characteristics of target segments. Customer segmentation can be conducted either a priori or posteriori [28,29]. In a priori segmentation, the researcher defines a basis for segmenting the market, and uses pre-defined cluster descriptors. It is not derived from customer data but is based on popular variables or a classification scheme (e.g., demographic data such as age, gender, education, or income). The posteriori segmentation approach is empirically derived from data collected through a market survey. Once the data are collected, the researcher uses multivariate analysis (i.e., cluster analysis) to identify groups of respondents who provide similar answers, and profile the respondents

into segments. The posteriori segmentation is especially useful when the number, size and market structure are unknown [27,30].

Customer segmentation has been considered as one of the most effective tools to identify target markets and to develop tailored marketing messages. The segmentation approach has been used extensively in consumer behavior [31–34], tourism [35,36] and promotions [37–39]. For instance, Tran [40] developed a comprehensive model that captures the effects of perceived personalized ads on Facebook on customer attitudinal and behavioral reactions. The author found that the personalized ads have a significant impact on ad credibility, ad avoidance, ad skepticism, ad attitude, and purchase intention. In addition, three different types of market segments were discovered, including ad lovers, ad accommodators, and ad haters. Semerádová and Weinlich [41] examined the relationship between ad personalization level and user reactance using the hyper-targeting (also called microtargeting) tool called Facebook Lookalike Audiences. Facebook Lookalike Audiences utilizes in-depth customer information and marketing automation to deliver tailored and highly personalized messages. They found that ads with a medium level of personalization actually performed better than ads with the highest hyper-targeting rates. That is, hyper-targeting may not yield only positive outcomes, and it could be essential to identify the optimal level of advertising details customized for particular customer segments.

However, there are a limited number of studies that have applied the segmentation method to digital piracy and consumer ethics. Ho and Weinberg (2011) segmented digital pirates into four groups (hardcopy only pirates, softcopy only pirates, dual channel pirates, non-pirates) using the channels of acquisition. The study examined how different segments react to pricing, product availability, and viewing channels. They found that “hardcopy only pirates” are more sensitive to price than other segments, and “dual channel pirates” are not as interested as non-pirates in immediate movie consumption and theatrical experiences [14]. Based on age and the trait of opportunism, one study classified internet users into four segments—pirates, mercenaries, scouts, and saints [13]. The results showed that there is a significant gender difference between pirates and the remainder of internet users. The “pirates” segment exhibited the lowest propensity to pay for digital content, and the “saints” segment presented with the greatest propensity to pay. While the findings from the two studies above are helpful for understanding the nature of pirate segments and developing marketing strategies, both studies used the a priori segmentation method. Since the segments are pre-defined, they do not explore other potential segments that could be more meaningful.

A few empirical studies have segmented consumer ethics with the posteriori segmentation approach. For example, Arli proposed three unique ethical consumer segments (good Samaritans, mainstream ethical consumers, unethical consumers) using consumer ethics scales developed by Vitell and Muncy [27]. A study by Al-Khatib et al. used Machiavellianism, ethical orientation, opportunism, and trust to segment consumers in the Gulf market [42]. The analysis resulted in three distinct clusters (principled purchasers, suspicious shoppers, and corrupt consumers), and each segment presented unique characteristics and behaviors. However, consumer ethics scales measure more general consumer attitudes towards unethical practices. Therefore, some dimensions and questionnaires are not directly related or specific to digital piracy (e.g., recycling, environmental awareness, returning damaged merchandise, using an expired coupon). Furthermore, Al-Khatib et al.’s study limits the generalizability, as their findings only represent the Gulf market (Saudi Arabia, Oman and Kuwait). Corte and Kenhove proposed a psychographic segmentation of digital pirates [11]. Subjective norms, self-efficacy, habit, perceived harm, and deontological and teleological orientation are used to segment digital pirates into four segments (anti-pirates, conflicted pirates, cavalier pirates, die-hard pirates). The authors also investigated how the segments respond differently to piracy-combating measures (legal vs. educational). They found that the educational strategy is more effective than the legal strategy in lowering piracy intention in conflicted and cavalier pirates. Our approach is different from that of Corte and Kenhove because we use different components of consumer piracy risk (pros-

education, financial, performance, time, privacy, social, and psychological risk) to classify digital pirates, while their study focused on ethical, behavioral, and descriptive measures. As suggested by Kumar and Nagpal, the choice of segmentation basis is the most crucial factor in the segmentation study [43]. We present select literature on the segmentation of digital piracy and consumer ethics in Table 2.

Table 2. Selected literature on the segmentation of digital pirates and consumer ethics.

Authors	Segmentation Approach	Variables Used	Segments
[42]	posteriori	ethical beliefs, Machiavellianism, ethical orientation, opportunism, trust	principled purchasers, suspicious shoppers, corrupt consumers
[27]	posteriori	consumer ethics scale	good Samaritans, mainstream ethical consumers, unethical consumers
[28]	posteriori	consumer ethics scale, Machiavellianism, religiosity	religious millennials, lukewarm millennials, least religious millennials
[11]	posteriori	subjective norms, self-efficacy, habit, perceived harm, deontological and teleological orientation	anti-pirates, conflicted pirates, cavalier pirates, die-hard pirates
[14]	a priori	prices, product availability, viewing channels	hardcopy only pirates, softcopy only pirates, dual channel pirates, non-pirates.
[13]	a priori	opportunism, age	pirates, mercenaries, scouts, and saints

3. Study 1: The Segmentation Study of Digital Pirates

3.1. Data Collection and Sample

We used a self-administered survey to examine how consumers perceive piracy risk associated with digital piracy. We compiled a group of questions to represent each risk dimension presented in Appendix A. All survey instruments were adapted from the literature, and the wording was slightly modified to fit the context of digital piracy [24,44–46]. A five-point Likert scale (1 = strongly disagree to 5 = strongly agree) was used to measure the items. The respondents were asked to indicate their assessment of the magnitude of perceived risk. The validity of the questionnaire was tested before we administered the actual survey. Three IS professionals went through an iterative review process to maximize content validity and revise any poorly worded items. Twenty-five items were selected for the components of piracy risk in the survey instrument. We included the items in a random order, and some items were reversed to establish internal consistency. We also collected other descriptive information, such as gender, age, digital piracy experience (Yes/No), and digital piracy experience in years (less than 1 year, 1–4 years, more than 4 years).

The subjects for this study were undergraduate students in major universities. The literature suggests that younger populations are more likely to be exposed and engaged in pirating activities [47,48]. Furthermore, students as subjects have been widely used in previous piracy studies [23,49,50]. Students enrolled in business courses were invited to fill out a web-based survey at the end of the semester. Participation was entirely voluntary, and there was no penalty for non-participation. The confidentiality of responses was assured, and the subjects did not identify themselves on the questionnaires. We took these extra measures to ensure truthful responses regarding this sensitive topic. Of 828 subjects, 476 subjects returned fully completed questionnaires, yielding a response rate of 57.5 percent. Table 3 presents descriptive statistics on the demographic profiles of subjects.

Table 3. Demographic information.

Gender	Male	245
	Female	224
Age	18–20	122
	21–30	314
	31–40	29
	Above 40	9
Digital Piracy Experience (Y/N)	Yes	404
	No	66
Digital Piracy Experience in Years	less than 1 year	145
	1–4 years	106
	more than 4 years	152

Note: The numbers in Table 3 may be different in relation to the total number of subjects that participated in the survey, since some participants did not provide their demographic information.

3.2. Instrument Measures

Principal component analysis with Varimax rotation was used to test the initial survey items’ loading on the different factors (see Table 4). Most items were loaded on their respective constructs. However, one item in psychological risk (PSY4) and one item in financial risk (FIN2) were dropped because the factor loadings were less than 0.5, or they were loaded on another construct.

Table 4. Results of principal component analysis.

Construct	Item	1	2	3	4	5	6	7
Social Risk	SOC1	0.867						
	SOC2	0.850						
	SOC3	0.772						
	SOC4	0.843						
Psychological Risk	PSY1		0.628					
	PSY2		0.769					
	PSY3		0.734					
Time Risk	TIM1			0.734				
	TIM2			0.686				
	TIM3			0.835				
	TIM4			0.789				
Performance Risk	PER1				0.760			
	PER2				0.864			
	PER3				0.839			
	PER4				0.795			
Prosecution Risk	PRO1					0.713		
	PRO2					0.856		
	PRO3					0.664		
Financial Risk	FIN1						0.835	
	FIN3						0.803	
Privacy Risk	PRI1							0.819
	PRI2							0.845
	PRI3							0.725

We also conducted reliability, convergent, and discriminant validity tests. Reliability was evaluated by computing Cronbach’s alpha. As shown in Table 5, all the measures were well above the cut-off level of 0.7, indicating excellent internal consistency [51,52]. Convergent validity can be assessed by examining average variance extracted (AVE) and composite reliability (CR). The acceptable value for AVE and CR is 0.5 and 0.7, respectively [53]. All the

items met this requirement, suggesting the adequate convergence validity of the measurements. Lastly, the items also showed excellent discriminant validity [54]. Table 6 presents that all the square roots of AVE values on the main diagonal were greater than the pair-wise correlations between the constructs on the off diagonal. This indicates discriminant validity among the variables.

Table 5. Assessment of reliability and convergent validity.

Construct	Number of Items	AVE	Composite Reliability	Cronbach’s Alpha
Social	4	0.695	0.901	0.899
Psychological	3	0.508	0.755	0.841
Time	4	0.582	0.847	0.864
Performance	4	0.665	0.888	0.896
Prosecution	3	0.561	0.791	0.803
Financial	2	0.671	0.803	0.790
Privacy	3	0.637	0.840	0.853

Table 6. Pair-wise correlations: assessment of discriminant validity.

	PER	PRO	SOC	PSY	PRI	TIM	FIN
Performance	0.815						
Prosecution	0.314	0.815					
Social	0.282	0.357	0.834				
Psychological	0.344	0.547	0.674	0.713			
Privacy	0.442	0.391	0.287	0.414	0.798		
Time	0.570	0.231	0.368	0.427	0.457	0.763	
Financial	0.203	0.515	0.381	0.545	0.403	0.237	0.819

3.3. Analysis Results

We used SPSS Statistics 28 for the cluster analysis and further profiling of the segments. The K-means clustering algorithm was chosen for the cluster analysis. The K-means clustering algorithm classifies objects based on attributes/features into *k* (positive integer) number of groups by minimizing the sum of squares of distances between data and the corresponding cluster centroid [55]. Although the K-means algorithm is popular and is relatively fast and efficient, it has a major weakness, which is that the number of clusters (*k*) must be specified in advance. To determine the best number of clusters, we computed the silhouette coefficient (SC), Bayesian information criterion (BIC), and Akaike information criterion (AIC). The silhouette coefficient is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation). In a good cluster solution, the cohesion is small and the separation is large, resulting in a silhouette measure close to the maximum value of one [56]. The silhouette index ranges from −1 to +1, and greater than 0.0 is recommended for the within-cluster distance and the between-cluster distance [27,28]. The Bayesian information criterion and Akaike information criterion are well-known information criteria used in model selection. They are commonly used to determine the best number of clusters with the lowest BIC and AIC [11].

Based on three index values as well as a visual assessment of cluster composition, a four-cluster solution was accepted as the optimal segmentation (see Table 7). Compared with two-, three-, five-, and six-cluster solutions, the four-cluster model showed the highest SC (0.4) and the lowest BIC (1742.732) values. A five-cluster solution had slightly lower AIC, but further examination suggested that one cluster was a variation of an existing cluster. Furthermore, two clusters contained less than 10% of the sample, hence making it difficult to interpret the composition of these clusters. We labeled the four digital pirate segments as follows: hard-core pirates, finance-sensitive pirates, performance-sensitive pirates, and anti-pirates. Table 8 presents an overview of cluster composition.

Table 7. Overview of cluster models.

	Silhouette Coefficient (SC)	Bayesian Information Criterion (BIC)	Akaike Information Criterion (AIC)
2-cluster	0.4	1913.067	1796.435
3-cluster	0.4	1802.220	1627.272
4-cluster	0.4	1737.757	1504.494
5-cluster	0.3	1742.732	1451.153
6-cluster	0.3	1773.278	1423.383

Table 8. Cluster means of digital pirate segments.

Risk	Cluster				Post Hoc Test ($p < 0.05$)
	1 Hard-Core Pirates	2 Finance-Sensitive Pirates	3 Performance-Sensitive Pirates	4 Anti-Pirates	
Prosecution	1.96	3.22	2.32	3.64	1 < 2, 1 < 3, 1 < 4, 3 < 2, 2 < 4, 3 < 4
Financial	1.61	2.80	1.82	3.30	1 < 2, 1 < 4, 2 < 3, 2 < 4, 3 < 4
Performance	1.92	2.44	3.78	3.52	1 < 2, 1 < 3, 1 < 4, 2 < 3, 2 < 4, 4 < 3
Time	1.64	2.11	3.25	3.16	1 < 2, 1 < 3, 1 < 4, 2 < 3, 2 < 4
Privacy	2.17	3.23	3.35	3.79	1 < 2, 1 < 3, 1 < 4, 2 < 4, 3 < 4
Social	1.41	1.73	1.67	2.62	1 < 2, 1 < 3, 1 < 4, 2 < 4, 3 < 4
Psychological	1.49	2.00	1.80	3.18	1 < 2, 1 < 3, 1 < 4, 2 < 4, 3 < 4

Hard-core pirates present the minimal amount of risk on all dimensions of risk perception scales. Consumers in this segment do not worry about the loss of respect, negative image, or negative social status as a consequence of pirating behavior, and show the least amount of psychological tension and guilt. They are likely to show little fear of legal consequences even when digital goods industries file a large number of lawsuits against individuals for copyright infringement. Hard-core pirates may become skilled and knowledgeable, as they are constantly engaged in pirating activities. It requires little effort to obtain pirated content because knowledge and frequent practice decrease the time needed to locate illegal copies [23]. Therefore, performance risk and time risk are also low in this segment. Hard-core pirates are more likely to be male (69.6%), and, as expected, have extensive digital piracy experience (93.9%).

Performance-sensitive pirates present a high risk perception in relation to performance and time risk, and are thus named performance-sensitive pirates. Consumers in this segment are particularly concerned about the risk that pirated content may not function as well as a legitimate product, or as it was designed. Studies show that more than 50 percent of popular songs available on a popular P2P network were polluted, and less than 10 percent of music files were considered high or near-CD quality [6,57]. Digital goods industries intentionally create and disseminate polluted versions of files on P2P networks so that it becomes difficult for users to download an original copy and decreases the popularity of files [58]. In this pirating segment, the fear of content pollution and the inferior quality of pirated content have a significant impact on their intention to engage in digital piracy. Performance-sensitive pirates are also concerned about the risk that pirating activities will cause potential time and effort losses. Some people stop using or decrease the use of P2P applications because they often cannot find files that they would like to

download [59]. Users must navigate a complex P2P environment to locate the content (time spent looking for illegal copies). Large volumes of polluted or corrupted content have been published in file-sharing systems. Therefore, it takes a substantial amount of time to distinguish such content from the original content they seek [60]. In this segment, the numbers of females (51.8%) and males (48.2%) are similar, and digital piracy experience in years (less than 1 year—35.8%, 1–4 years—30.3%, more than 4 years—33.9%) is also closely distributed.

Finance-sensitive pirates present a high risk perception in relation to financial and prosecution risk. They are mainly concerned that pirating activities will cause monetary losses, such as related to the re-installment of software and data recovery due to viruses and malwares. P2P networks have been known to be vulnerable to computer infections and security attacks, as some P2P applications generate revenue from third parties by embedding spyware and malware [60]. Studies show that 68% of all downloadable responses in LimeWire contained malware, and 44% of the 4778 executable files downloaded through a KaZaA client application included viruses and Trojan horses [61,62]. Many mp3 files that are being shared contain a Trojan horse program that attacked over half a million computers in a week [63]. In this segment, the fear of financial loss due to viruses and malwares significantly influences their decision to engage in digital piracy. Finance-sensitive pirates are also conscious about the risk of legal prosecution. A consumer survey by IFPI reports that 50% of respondents stopped or reduced downloading music files from P2P networks due to fear of legal consequences [59]. More than 30,000 people in the United States have been sued for downloading music illegally, and the average settlement ranges from USD 2000 to 5000 for accusations of illegal BitTorrent use [5,64]. Unlike performance-sensitive pirates and hard-core pirates, the punishment (lawsuit or fine) for copyright infringement is especially important in relation to their intention to engage in digital piracy. Similar to finance-sensitive pirates, the numbers of females (53.2%) and males (46.8%) and digital piracy experience in years are closely distributed (less than 1 year—37.0%, 1–4 years—27.2%, more than 4 years—35.8%).

Anti-pirates perceive high risk in all dimensions compared with the other segments. They consider pirating behavior unethical; they are self-conscious about their image and have a desire to be identified with a certain social group. A follow-up contrast analysis showed that anti-pirates report the highest perceptions of privacy, financial, social, and psychological risk. Compared with the rest, anti-pirates also perceive high risk in terms of time and performance. In this segment, the numbers of females (54.6%) and males (46.4%) are similar, and most people have no or little digital piracy experience (82%).

We performed a further profiling of the segments based on gender, piracy experience (Y/N), and piracy experience in years. First, as shown in Table 9, females display a higher risk perception on all dimensions, and the difference is statistically significant. This is consistent with previous findings that females have higher risk perceptions and willingness-to-pay for legal alternatives compared with males [65]. Studies suggest that males and females have different perceptions of and attitudes towards piracy due to their differences in socialization. Higher levels of self-control can reduce the gender gap, while it is not possible to eliminate the gender difference in digital piracy [66,67].

We also found that people with no prior digital piracy experience perceive a significantly higher risk on all dimensions except for performance risk (See Table 10). It is worth noting that performance risk is actually higher for people with prior experience, although this is not statistically significant. One possible explanation is that consumers with no piracy experience would not be able to explain how much time and effort they have to spend searching for files in P2P systems. Analysis of variance (ANOVA) was performed for digital piracy experience in years. There was a significant difference regarding piracy risk between less than 1-year and more than 4-years. However, no difference was found between 1–4 years and more than 4 years. This suggests that the risk perception seems to decrease as one continuously engages in digital piracy and gains more experience.

Table 9. Gender difference in risk perception.

	Gender	Mean	SD	t Value	Significance
Performance Risk	Male	2.821	1.052	3.664 ***	0.000
	Female	3.162	0.957		
Prosecution Risk	Male	2.683	0.990	3.638 ***	0.000
	Female	3.010	0.955		
Social Risk	Male	1.854	0.801	1.941 *	0.050
	Female	2.003	0.864		
Psychological Risk	Male	2.100	0.885	2.661 **	0.008
	Female	2.324	0.935		
Privacy Risk	Male	3.057	0.986	3.053 **	0.002
	Female	3.321	0.877		
Time Risk	Male	2.439	0.970	3.577 ***	0.000
	Female	2.762	0.980		
Financial Risk	Male	2.330	0.999	2.494 *	0.013
	Female	2.564	1.032		

*** Significant at 0.001 level, ** significant at 0.01 level, * significant at 0.05 level.

Table 10. Piracy experience difference in risk perception.

	Experience	Mean	SD	t Value	Significance
Performance Risk	Yes	3.155	0.990	-1.445	0.149
	No	2.959	1.027		
Prosecution Risk	Yes	2.754	0.972	-4.781 ***	0.000
	No	3.368	0.939		
Social Risk	Yes	1.816	0.741	-7.072 ***	0.000
	No	2.556	1.032		
Psychological Risk	Yes	2.080	0.829	-7.955 ***	0.000
	No	2.989	1.032		
Privacy Risk	Yes	3.143	0.942	-2.723 *	0.007
	No	3.484	0.952		
Time Risk	Yes	2.498	0.963	-5.351 ***	0.000
	No	3.181	0.954		
Financial Risk	Yes	2.381	1.007	-3.391 **	0.001
	No	2.840	1.099		

*** Significant at 0.001 level, ** significant at 0.01 level, * significant at 0.05 level.

4. Study 2: The Effectiveness of Targeted Anti-Piracy Campaigns on Pirate Segments

Previous literature shows that copyright enforcement regimes do not necessarily increase compliance and lower digital piracy rates. Rigid copyright enforcement regimes such as legal sanctions do not increase the profit of legal providers [68], nor prevent consumers from continuing using pirated content [69], at least in a significant proportion [70]. Meocevic (2022) concluded that institutional designs trigger indignation and subsequently a reactance response by some consumers. The results of his study indicate that emotional appraisals drive engagement with digital piracy, not ethical, deterrence, or rational choices [71]. A study by Miceli and Castelfranchi (2019) also showed that indignation creates harm towards the wrongdoer through reactance in both tight and loose scenarios of copyright enforcement [72]. Therefore, a copyright enforcement regime cannot be the most effective way to battle the issues of illegal digital activities.

We believe the cognitive appraisal of risk perception and targeted educational programs could represent an alternative to the negative emotional responses of those who engaged in digital piracy. Prior studies also suggest that educational deterrence efforts

are an effective way to dissuade consumers from downloading and streaming illegal content [9,73]. In the second study, we developed targeted anti-piracy campaign messages appealing to the specific pirating segments, and examined whether and how four pirating segments respond to these educational campaigns. Two campaign messages that highlight (1) time and performance risk (performance-focused message), and (2) financial and legal risk (finance-focused message) were designed to examine the effects of educational campaigns on the perceived effectiveness of the anti-piracy message, attitude towards piracy, and piracy intention. A mixed experimental design of 2 (between subjects: finance-focused message vs. performance-focused message) \times 4 (between subjects: anti-pirates, performance-sensitive pirates, finance-sensitive pirates, hard-core pirates) \times 2 (within-subjects: before vs. after the manipulation) was used. The data were analyzed using repeated measures ANOVA.

4.1. Data Collection and Samples

Before we introduced anti-piracy campaign messages, participants self-reported their attitude towards piracy and piracy intention (before the manipulation) using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Questionnaires for the attitude towards piracy and piracy intention were adapted from prior literature and slightly modified to fit the context of digital piracy [20,74–76]. We also measured the same segmentation items (piracy risk perception) from study 1 to determine the clusters afterwards and collected descriptive information. Then, participants were randomly assigned to either a finance-focused message or a performance-focused message. For the finance-focused message, we included statements such as “*exposed to the danger of lawsuit,*” and “*lead to a significant financial loss due to hardware or system re-installment, or data recovery,*” to highlight the financial risks of engaging in digital piracy. For the performance-focused message, we used statements such as “*wasting your time because most pirated contents from the Internet are polluted or corrupted,*” and “*lead to a significant time and effort loss,*” to emphasize the performance- and time-related risks of digital piracy (see Appendices A and B for a complete list of campaign messages and survey questionnaires).

We developed anti-piracy messages based on Facebook’s “No Piracy” initiative and the Microsoft piracy website (www.microsoft.com/piracy) to keep the manipulation and educational campaigns as realistic as possible. The effectiveness of the message can be enhanced by including statistical evidence [73,77,78]. Prior studies showed that statistical evidence is effective since statistics provide a logical explanation and systematically represent a larger population. In the anti-piracy campaign messages, we included statistical information such as “*the average settlement for the accused of illegal downloads ranges from \$2000 to \$5000,*” and “*68% of all downloadable files in LimeWire are corrupted,*” retrieved from other studies [5,62]. After reading the message, participants were asked to evaluate the perceived effectiveness of the educational campaign message. We also measured the attitude towards piracy and piracy intention once again (after the manipulation). A total of 983 responses were collected and used for the analysis.

4.2. Analysis Results

To check the priming manipulation, participants were asked to rate the extent to which the message emphasizes financial-related risk or performance-related risk. T-test analysis showed that participants exposed to the finance-focused message thought the message conveyed information about the financial risks of digital piracy, $M_{\text{finance}} = 4.13$ vs. $M_{\text{performance}} = 3.62$, $t(495) = 10.88$, $p < 0.001$. On the other hand, participants exposed to the performance-focused message believed that the message highlighted performance and time-related risks of digital piracy, $M_{\text{performance}} = 4.07$ vs. $M_{\text{finance}} = 3.48$, $t(486) = 10.85$, $p < 0.001$. We ran a K-means cluster analysis to determine cluster memberships and found the same four cluster segments replicating the findings from study 1.

Tables 11 and 12 present changes in attitude towards piracy and piracy intention among pirating segments for two different types of campaign messages. A finance-focused

educational campaign decreases attitude towards piracy in all segments, but a significant drop was only observed in the finance-sensitive pirates ($p < 0.05$). Furthermore, we found that the finance-focused educational campaign was marginally effective in changing piracy intention for the finance-sensitive pirates, while it did not significantly lower pirating intentions in any segment. Interestingly, it actually increased pirating intentions for the performance-sensitive pirates and hard-core pirates. We suspect that although attitude is an antecedent of behavioral intention [74,79], other factors such as subjective norms and behavioral control that may influence the intention to pirate need to be examined. A performance-focused educational campaign showed similar results (Table 12). We found a significant decrease in attitude towards piracy and a marginal decrease in piracy intention for the performance-sensitive pirates. However, other segments did not differ in terms of attitude towards piracy and piracy intention.

Table 11. Changes in attitude towards piracy and piracy intention among pirating segments: finance-focused message.

Cluster	Attitude Towards Piracy			Piracy Intention		
	Pre-Test M	Post-Test M	Significance	Pre-Test M	Post-Test M	Significance
Anti-Pirates	2.22	2.14	0.273	1.73	1.73	0.939
Finance-Sensitive Pirates	2.64	2.51	0.030 *	2.25	2.14	0.079
Performance-Sensitive Pirates	2.67	2.59	0.186	2.14	2.16	0.839
Hard-Core Pirates	2.75	2.74	0.966	2.37	2.43	0.531

* Significant at 0.05 level.

Table 12. Changes in attitude towards piracy and piracy intention among pirating segments: performance-focused message.

Cluster	Attitude Towards Piracy			Piracy Intention		
	Pre-Test M	Post-Test M	Significance	Pre-Test M	Post-Test M	Significance
Anti-Pirates	2.33	2.34	0.978	1.86	1.93	0.273
Finance-Sensitive Pirates	2.67	2.58	0.181	2.28	2.32	0.500
Performance-Sensitive Pirates	2.66	2.44	0.034 *	2.38	2.19	0.061
Hard-Core Pirates	2.66	2.61	0.599	2.41	2.54	0.167

* Significant at 0.05 level.

We also asked participants directly to evaluate the message persuasiveness (e.g., persuasive, convincing, and credible) after reading the educational campaign message. An ANOVA test was conducted for statistical analysis, and we found significant differences on both messages: a finance-focused message, $F(3, 487) = 26.311, p < 0.001$ and a performance-focused message, $F(3, 496) = 32.131, p < 0.001$. As shown in Table 13, not surprisingly, anti-pirates rated the campaign message persuasiveness significantly higher than other segments. Follow-up contrast analysis also indicated that finance-sensitive pirates found a finance-focused message more persuasive than performance-sensitive pirates and hard-core pirates. For a performance-focused message, performance-sensitive pirates rated a significantly higher message persuasiveness compared to the hard-core pirates, but a marginal difference was found between finance-sensitive pirates.

Table 13. Comparison of campaign message persuasiveness among pirating segments.

	Finance-Focused Message			Performance-Focused Message		
	M	SD	Post Hoc ($p < 0.01$)	M	SD	Post Hoc ($p < 0.01$)
1. Anti-Pirates	4.19	0.70	2 < 1, 3 < 1, 4 < 1	4.12	0.84	2 < 1, 3 < 1, 4 < 1
2. Finance-Sensitive Pirates	3.74	0.65	2 < 1, 3 < 2, 4 < 2	3.45	0.59	2 < 1
3. Performance-Sensitive Pirates	3.36	0.59	3 < 1, 3 < 2	3.74	0.53	3 < 1, 4 < 3
4. Hard-Core Pirates	3.34	1.04	4 < 1, 4 < 2	3.35	1.04	4 < 1, 4 < 3

5. Discussion

According to Grolleau and Meunier (2022), anti-piracy messages can be counter-productive, but “tailoring them to the targeted subgroups” can make the messaging more effective than using the more-is-better approach [80]. However, it remains a challenge to effectively identify digital pirate segments for the purpose and to create targeted messaging. We build on previous works on anti-piracy campaigns’ effectiveness [73,81] by profiling digital pirates based on their risk perception, and then testing targeted educational campaigns among the segments to see the campaign message effectiveness. We provide further evidence for the importance of identifying digital pirate segments and designing targeted messaging for the increased effectiveness of the anti-piracy campaign. While the segmentation of digital pirates has been proposed previously [11,14,27,28], using piracy risk perception to classify digital pirates has not been considered.

Based on risk perceptions, we have identified four digital pirate segments, each possessing a unique profile. The largest segment was the anti-pirates presenting aversion to risk on all seven risk characteristics considered. This finding indicates that the anti-pirates segment possess certain risk perceptions, along with other characteristics identified by previous studies, which may help us understand this segment better. For example, Arli (2017) identified good Samaritans using the consumer ethics scale. Corte and Kenhove (2015) identified anti-pirates using various variables, including, but not limited to, subjective norms, self-efficacy, habit, perceived harm, and deontological and teleological orientation. Ho and Weinberg (2011) identified non-pirates using prices, product availability, and viewing channels. Massad and Risch (2013) called their segment saints, who were identified using opportunism and age variables. Once observed from the risk perception lens, we found that anti-pirates have a higher risk perception on risk dimensions including privacy, financial, social, and psychological risk compared with the other segments. They consider pirating behavior unethical, and they are self-conscious about their image and have a desire to be identified with a certain social group. Compared with the rest of the segments, anti-pirates also present a substantial risk on time and performance. This segment is also gender-dominant for females, with little to no piracy experience.

Another segment we discovered based on the risk perception was hard-core pirates. Like anti-pirates, this segment is also not new. Previously, this segment has been identified as corrupt consumers [42], unethical consumers [27], least religious consumers [28], and die-hard pirates [11] using varying characteristics. We found that hard-core pirates have extensive digital experience, and their piracy skills increased as they engaged in piracy activities on a regular basis, leading to lower performance and time risk. They are not concerned about loss of respect, negative image, and negative social status because of pirating behavior, and show the least amount of psychological tension and guilt. They also show little fear of legal consequences even when digital goods industries file a large number of lawsuits against individuals for copyright infringement. This segment is also gender-dominant for males.

We found two new segments, i.e., performance-sensitive and finance-sensitive segments, demonstrating varying behaviors on the seven risk dimensions we have considered. Performance-sensitive pirates are particularly concerned about the performance of the pirated product, the wastage of time and effort associated with finding content of interest,

and increased chances of finding an inferior-quality product, which affects their intention to pirate. On the other hand, the finance-sensitive segment is more worried about the financial loss and prosecution risk associated with piracy activities. They weigh the monetary loss associated with the increased vulnerability of their computer systems. In addition, they are concerned about the legal and prosecution risk, which is unique to this segment. We found that, for both finance-sensitive and performance-sensitive segments, piracy experience and gender do not discriminate among these segments significantly.

In the second study, we developed and tested two different anti-piracy campaign messages among the identified four piracy segments. One message focused on the time and performance risk (performance-focused message), and the other focused on the financial and legal risk (finance-focused message). We measured the effects of these messages on the message persuasiveness, attitude towards piracy, and piracy intention among all four segments. The results indicate that not all messages resonate with all segments equally. More specifically, the finance-focused message was most effective for finance-sensitive pirates. They found the finance-focused message more persuasive, and it significantly reduced their attitude towards piracy. However, the effect of this message on their intention to pirate was marginal. As discussed before, there are several factors, such as subjective norms and behavioral control, that may influence the piracy intention. Hence, it needs to be examined further. Interestingly, the finance-focused campaign message increased piracy intention in performance-sensitive pirates and hard-core pirates. It makes sense in the case of hard-core pirates since they have the most experience in digital piracy, with the least sensitivity towards the consequences of digital piracy, whereas the performance-focused message was most effective among performance-sensitive pirates in decreasing their attitude towards piracy, and they found this message more persuasive. Again, the intention to pirate was not affected by the message within this segment.

Overall, anti-pirates perceived both finance- and performance-focused messages persuasive. Given the risk profile of anti-pirates in terms of the risk perception and experience, this result makes sense. Anti-pirates have less experience in digital piracy relative to other segments, and they have higher perceived risk in all risk categories except for performance risk. Furthermore, gender has a role to play in determining the risk perception towards piracy, where females have a higher risk perception towards piracy than males. This result is consistent with previous findings that females are more likely to be risk-averse than males [65]. Experience is also closely related to piracy risk perception. Less experienced pirates report higher perceived risk in all categories except performance risk. Hence, early intervention among pirate segments may increase the effectiveness of anti-piracy campaigns, which is consistent with the finding of Jeong and Khouja (2013). This also calls for testing innovative ways to address the issue of digital piracy in segments like hard-core pirates.

Our findings provide several practical implications for strategizing and designing anti-piracy educational campaign messages. Major piracy campaign themes mostly focus on the financial risks of digital piracy. For instance, Creative Content Australia (CCA) launched a new campaign called *"Piracy. You're Exposed"* to educate consumers regarding how pirating activities are linked to fraud, malware, and viruses that result in financial loss [82]. The Premier League also launched the second season of the *"Boot Out Piracy"* campaign aiming to raise awareness of the dangers of pirate content. The campaign specifically highlights the risks of malicious malware or ransomware when using unauthorized websites or streaming services [83]. While these campaigns are effective in changing attitudes towards piracy among anti-pirates and finance-sensitive pirates, they may not be persuasive for performance-sensitive pirates as they are not overly concerned about monetary loss, and the risk of legal prosecution is less likely to change their behaviors. Currently, there are only a few anti-piracy campaigns highlighting performance- and time-related risk. We suggest that campaign-makers develop more targeted campaigns that appeal to the performance-sensitive segment. For this segment, the campaign message would be more effective if it emphasized a loss due to poor performance or the substantial waste of time. For example,

a message like “90% of music files available on popular P2P networks are not the same as the quality of audio CDs. A pirated copy does not function as well as a legitimate product or as it was designed to function,” or “47% of active pirates reported that they have encountered blocked sites. Site blocking makes it more difficult to find pirated content online. You can spend hours and hours on social media and search engines, but you will not be able to find content you are looking for,” can be a better way of persuading performance-sensitive pirates.

6. Conclusions

In this study, we presented a segmentation analysis focusing on digital pirates and their involvement in various piracy-related risks. The analysis led us to identify four distinct categories of digital pirates: anti-pirates, hard-core pirates, performance-sensitive pirates, and finance-sensitive pirates. These segments exhibited unique traits that set them apart from one another. The subsequent profiling of these segments also unveiled disparities in how they perceive risks, particularly in relation to factors such as gender and their experiences with piracy. We also conducted an experiment aimed at assessing the impact of tailored campaign messages on the identified segments of digital pirates. Our findings indicate that these targeted anti-piracy campaign messages exhibit significantly increased persuasiveness, concurrently leading to a reduction in the overall favorable attitude towards piracy. However, it is worth noting that the effects of these targeted campaign messages on altering the intention to engage in piracy were only slightly discernible.

Several limitations apply to this study, and provide avenues for future research. Firstly, we only consider the risk perception to segment digital pirates in this study. Human beings are behaviorally complex, whereby other factors may influence their piracy behavior besides risk perception. From the previous literature, we can infer that pirates can be segmented using multiple variables. In addition, some pirate segments are found consistently across the board, i.e., anti-pirates and hard-core pirates. We recommend studying these known segmentation factors together, as this can help refine pirate segments' profiles and get a better understanding of not only the existing segments, but also ways in which segmentation is possible among pirates. We also recommend exploring other factor that may facilitate a deeper understanding of digital pirate segments, which have not been considered previously. Secondly, our sample was restricted demographically. Expanding the sample across different cultures will also allow us to enrich the digital pirates' segments since piracy behaviors vary across the globe. In addition, a future study needs to include a more representative sample from the general population, since participants here were mostly undergraduate students. Thirdly, we tested only two types of anti-piracy campaign messages in this study. There is room to create and test different types of campaign messages that may have better appeal to digital pirates. For example, it might be interesting to examine the effects of reward-based campaign messages (e.g., report piracy to be eligible for a cash reward) among pirate segments. This step can be facilitated by looking at the pirate segments holistically through known segmentation factors to date. Lastly, we did not consider the timing of intervention among pirate segments, since the experience plays a significant role in decreasing piracy risk perception over time. Also, human behavior changes over time. Hence, testing the timing of anti-piracy campaign messaging can be worth exploring.

Author Contributions: Conceptualization, B.-K.J.; methodology, B.-K.J.; software, B.-K.J.; validation, B.-K.J., S.S.K. and B.K.; formal analysis, B.-K.J.; investigation, B.-K.J.; resources, S.S.K. and B.K.; writing—original draft preparation, B.-K.J., S.S.K. and B.K.; writing—review and editing, B.-K.J., S.S.K. and B.K.; supervision, B.-K.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding. The APC was funded by Coastal Carolina University.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of Coastal Carolina University (protocol code #2021.162 and 4/13/2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Survey Questionnaires

Definition

Digital Piracy is “The unlawful (unauthorized) reproduction, distribution, or use of any copyrighted digital contents. This can be done with music files, videos and movies, e-books, software, and other materials.”

Intellectual Property Rights are “Legally recognized exclusive rights. Under intellectual property law, owners are granted certain exclusive rights to a variety of intangible assets such as musical, literary, artistic works, inventions, and designs. Common types of intellectual property rights include copyright, trademarks, and patents.”

Risk Perception

Downloading illegal content from the Internet:

1. makes me feel psychologically uncomfortable.
2. gives me a feeling of unwanted anxiety.
3. may cause me to experience unnecessary tension.
4. may negatively affect the way others think of me.
5. may lead to a social loss for me because my friends, family, and colleagues will think less of me.
6. may cause me to be thought of as being foolish by some people whose opinion I value.
7. cause me a concern that I will lose control over the privacy of my information.
8. may lead to a loss of privacy for me because my personal information can be revealed without my knowledge.
9. may lead to a loss of privacy for me because a hacker may access my personal information without my knowledge.
10. may be a waste of time for me because it will take time to set up the required software (e.g., BitTorrent).
11. worries me that I will have to spend too much time learning how to download files.
12. may lead to an inefficient use of my time for searching files, understanding various software packages, and so forth.

As I download illegal content from the Internet:

13. I worry that the pirated content will fail to play like the original one.
14. I worry about whether the pirated content will play the way it is supposed to.
15. I worry that the pirated content will not provide the level of quality like a legitimate copy.
16. I worry that I will be caught for infringement of copyright law.
17. I worry that I will be punished for the infringement of copyright law.
18. I worry that I will have to pay a fine for the infringement of copyright law.
19. I worry that the pirated content will cause damage to my computer due to viruses and malware resulting in a monetary loss.
20. I worry that it may lead to a financial loss for me (e.g., new hard drive, system re-installment, data recovery).

Attitude towards Piracy (before and after the manipulation)

1. I have a positive perception towards digital piracy.
2. I consider that digital piracy is a good idea.
3. Overall, my attitude towards digital piracy is favorable.

Piracy Intention (before and after the manipulation)

1. I intend to pirate digital products in the near future.
2. If I have a chance, I will pirate digital products.
3. I will make an effort to pirate digital products in the near future.

Message Persuasiveness

1. This campaign message is persuasive.
2. This campaign message is convincing.
3. This campaign message is credible.

Manipulation Check

1. This campaign message highlights the financial risks of digital piracy.
2. This campaign message is focused on the risk of lawsuits in digital piracy.
3. This campaign message highlights the risks of downloading corrupted or inferior quality content through digital piracy.
4. This campaign message is focused on the loss of time and effort related to digital piracy.

Appendix B. Campaign Messages in the Experiment***Finance-focused Message*****DID YOU KNOW?**

- If you engage in digital piracy, you are exposed to the danger of lawsuits. According to the statistics issued by Institute for Policy Innovation (IFPI), more than 30,000 people in the United States have been sued for illegal music downloading since the year 2000. The average settlement for the accused of illegal downloads ranges from \$2000 to \$5000.
- Downloading illegal content from the Internet can lead to a significant financial loss. A recent survey by Microsoft shows that 73% of pirated software contains viruses and malwares that make your computer defenseless against malicious threats. This may result in a substantial monetary loss due to hardware or system re-installment, or data recovery.
- To find out more about the RISKS of violating intellectual property rights, visit <http://www.bsa.org/anti-piracy>.

Performance-focused Message**DID YOU KNOW?**

- If you engage in digital piracy, you are simply wasting your time. According to the Institute for Policy Innovation (IFPI), more than 70% of the songs available on popular Peer-to-Peer networks were polluted, while only less than 10% of the music files were considered as decent or near the quality of original content. You will not find the content you seek while spending a substantial amount of time.
- Downloading illegal content from the Internet can lead to a significant time and effort loss. A recent survey by Microsoft shows that 68% of all downloadable files in Limewire are corrupted. Music and Software industries intentionally create and disseminate polluted versions to make it more difficult for users to download an original copy.
- To find out more about the RISKS of violating intellectual property rights, visit <http://www.bsa.org/anti-piracy>.

References

1. MUSO. 2021 MUSO Discover Piracy by Industry Data Review. 2022. Available online: [/https://f.hubspotusercontent40.net/hubfs/6347345/2021%20MUSO%20Discover%20Piracy%20by%20Industry%20Data%20Review.pdf](https://f.hubspotusercontent40.net/hubfs/6347345/2021%20MUSO%20Discover%20Piracy%20by%20Industry%20Data%20Review.pdf) (accessed on 28 June 2023).
2. Sinha, R.K.; Mandel, N. Preventing Digital Music Piracy: The Carrot or the Stick? *J. Mark.* **2008**, *72*, 1–15. [[CrossRef](#)]
3. Sinha, R.K.; Machado, F.S.; Sellman, C. Don't Think Twice, It's All Right: Music Piracy and Pricing in a DRM-Free Environment. *J. Mark.* **2010**, *74*, 40–54. [[CrossRef](#)]
4. Orme, T. The short- and long-term effectiveness of anti-piracy laws and enforcement actions. *J. Cult. Econ.* **2014**, *38*, 351–368. [[CrossRef](#)]

5. Liebelson, D. Why It's Getting Harder to Sue Illegal Movie Downloaders. Available online: <https://www.motherjones.com/politics/2014/02/bittorrent-illegal-downloads-ip-address-lawsuit/#:~:text=Recently%2C%20several%20federal%20judges%20have,to%20proceed%20with%20the%20lawsuits> (accessed on 3 April 2023).
6. Bhattacharjee, S.; Gopal, R.D.; Lertwachara, K.; Marsden, J.R. Impact of Legal Threats on Online Music Sharing Activity: An Analysis of Music Industry Legal Actions. *J. Law Econ.* **2006**, *49*, 91–114. [[CrossRef](#)]
7. Akman, I.; Mishra, A. Ethical behavior issues in software use: An analysis of public and private sectors. *Comput. Hum. Behav.* **2009**, *25*, 1251–1257. [[CrossRef](#)]
8. Wang, J.; Gwebu, K.; Shanker, M.; Troutt, M.D. An application of agent-based simulation to knowledge sharing. *Decis. Support Syst.* **2009**, *46*, 532–541. [[CrossRef](#)]
9. Jeong, B.K.; Khouja, M. Analysis of the effectiveness of preventive and deterrent piracy control strategies: Agent-based modeling approach. *Comput. Hum. Behav.* **2013**, *29*, 2744–2755. [[CrossRef](#)]
10. Gopal, R.D.; Sanders, G.L. Preventive and deterrent controls for software piracy. *J. Manag. Inf. Syst.* **1997**, *13*, 29–47. [[CrossRef](#)]
11. De Corte, C.E.; Van Kenhove, P. One Sail Fits All? A Psychographic Segmentation of Digital Pirates. *J. Bus. Ethics* **2015**, *143*, 441–465. [[CrossRef](#)]
12. Hashim, M.J.; Kannan, K.N.; Wegener, D.T. Central Role of Moral Obligations in Determining Intentions to Engage in Digital Piracy. *J. Manag. Inf. Syst.* **2018**, *35*, 934–963. [[CrossRef](#)]
13. Massad, V.J.; Risch, B. Pirates, mercenaries, scouts and saints: A segmentation approach to understanding digital downloading. *Int. J. Electron. Cust. Relatsh. Manag.* **2013**, *7*, 87–97. [[CrossRef](#)]
14. Ho, J.; Weinberg, C.B. Segmenting consumers of pirated movies. *J. Consum. Mark.* **2011**, *28*, 252–260. [[CrossRef](#)]
15. Lowry, P.B.; Zhang, J.; Wu, T. Nature or nurture? A meta-analysis of the factors that maximize the prediction of digital piracy by using social cognitive theory as a framework. *Comput. Hum. Behav.* **2017**, *68*, 104–120. [[CrossRef](#)]
16. Akbulut, Y.; Dönmez, O. Predictors of digital piracy among Turkish undergraduate students. *Telemat. Inform.* **2018**, *35*, 1324–1334. [[CrossRef](#)]
17. Pham, Q.T.; Dang, N.M.; Nguyen, D.T. Factors Affecting on the Digital Piracy Behavior: An Empirical Study in Vietnam. *J. Theor. Appl. Electron. Commer. Res.* **2020**, *15*, 122–135. [[CrossRef](#)]
18. Huang, C.-Y. File Sharing as a Form of Music Consumption. *Int. J. Electron. Commer.* **2005**, *9*, 37–55. [[CrossRef](#)]
19. Thong, J.Y.L.; Yap, C.-s. Testing an Ethical Decision-Making Theory: The Case of Softlifting. *J. Manag. Inf. Syst.* **1998**, *15*, 213–237. [[CrossRef](#)]
20. Peace, A.G.; Galletta, D.F.; Thong, J.Y.L. Software Piracy in the Workplace: A Model and Empirical Test. *J. Manag. Inf. Syst.* **2003**, *20*, 153–177.
21. Wolfe, S.; Higgins, G.; Marcum, C. Deterrence and Digital Piracy: A Preliminary Examination of the Role of Viruses. *Soc. Sci. Comput. Rev.* **2008**, *26*, 317–333. [[CrossRef](#)]
22. Liao, C.; Lin, H.-N.; Liu, Y.-P. Predicting the Use of Pirated Software: A Contingency Model Integrating Perceived Risk with the Theory of Planned Behavior. *J. Bus. Ethics* **2010**, *91*, 237–252. [[CrossRef](#)]
23. Jeong, B.K.; Zhao, K.; Khouja, M. Consumer Piracy Risk: Conceptualization and Measurement in Music Sharing. *Int. J. Electron. Commer.* **2012**, *16*, 89–118. [[CrossRef](#)]
24. Tan, B. Understanding consumer ethical decision making with respect to purchase of pirated software. *J. Consum. Mark.* **2002**, *19*, 96–111. [[CrossRef](#)]
25. Lee, B.; Fenoff, R.; Paek, S.Y. Correlates of participation in e-book piracy on campus. *J. Acad. Librariansh.* **2019**, *45*, 299–304. [[CrossRef](#)]
26. Jayasundara, C.C. A Study on the Risk of Prosecution and Perceived Proximity on State University Undergraduates' Behavioural Intention for e-Book Piracy. *New Rev. Acad. Librariansh.* **2021**, *28*, 406–434. [[CrossRef](#)]
27. Arli, D. Investigating consumer ethics: A segmentation study. *J. Consum. Mark.* **2017**, *34*, 636–645. [[CrossRef](#)]
28. Arli, D.; Tkaczynski, A.; Anandya, D. Are religious consumers more ethical and less Machiavellian? A segmentation study of Millennials. *Int. J. Consum. Stud.* **2019**, *43*, 263–276. [[CrossRef](#)]
29. Petrovčič, A.; Slavec, A.; Dolničar, V. The Ten Shades of Silver: Segmentation of Older Adults in the Mobile Phone Market. *Int. J. Hum.-Comput. Interact.* **2018**, *34*, 845–860. [[CrossRef](#)]
30. Dolničar, S. Beyond “Commonsense Segmentation”: A Systematics of Segmentation Approaches in Tourism. *J. Travel Res.* **2004**, *42*, 244–250. [[CrossRef](#)]
31. Paço, A.M.F.d.; Raposo, M.L.B. Green consumer market segmentation: Empirical findings from Portugal. *Int. J. Consum. Stud.* **2010**, *34*, 429–436. [[CrossRef](#)]
32. Straughan, R.D.; Roberts, J.A. Environmental segmentation alternatives: A look at green consumer behavior in the new millennium. *J. Consum. Mark.* **1999**, *16*, 558–575. [[CrossRef](#)]
33. Shavitt, S.; Jiang, D.; Cho, H. Stratification and segmentation: Social class in consumer behavior. *J. Consum. Psychol.* **2016**, *26*, 583–593. [[CrossRef](#)]
34. Rana, J.; Paul, J. Consumer behavior and purchase intention for organic food: A review and research agenda. *J. Retail. Consum. Serv.* **2017**, *38*, 157–165. [[CrossRef](#)]
35. Tkaczynski, A.; Rundle-Thiele, S.R.; Prebensen, N.K. Segmenting potential nature-based tourists based on temporal factors the case of Norway. *J. Travel Res.* **2015**, *54*, 251–265. [[CrossRef](#)]

36. Ritchie, B.W.; Tkaczynski, A.; Faulks, P. Understanding the Motivation and Travel Behavior of Cycle Tourists Using Involvement Profiles. *J. Travel Tour. Mark.* **2010**, *27*, 409–425. [CrossRef]
37. Dietrich, T.; Rundle-Thiele, S.; Leo, C.; Connor, J. One size (never) fits all: Segment differences observed following a school-based alcohol social marketing program. *J. Sch. Health* **2015**, *85*, 251–259. [CrossRef] [PubMed]
38. Tkaczynski, A.; Rundle-Thiele, S. Understanding What Really Motivates Attendance: A Music Festival Segmentation Study. *J. Travel Tour. Mark.* **2013**, *30*, 610–623. [CrossRef]
39. Dietrich, T.; Rundle-Thiele, S.H.; Schuster, L.; Connor, J. Segmenting Australian high school students: Two-step cluster analysis preliminary Results. *Eur. J. Public Health* **2014**, *24*, cku166–067. [CrossRef]
40. Tran, T.P. Personalized ads on Facebook: An effective marketing tool for online marketers. *J. Retail. Consum. Serv.* **2017**, *39*, 230–242. [CrossRef]
41. Semerádová, T.; Weinlich, P. Computer Estimation of Customer Similarity With Facebook Lookalikes: Advantages and Disadvantages of Hyper-Targeting. *IEEE Access* **2019**, *7*, 153365–153377. [CrossRef]
42. Khatib, J.A.A.; Stanton, A.D.A.; Rawwas, M.Y.A. Ethical segmentation of consumers in developing countries: A comparative analysis. *Int. Mark. Rev.* **2005**, *22*, 225–246. [CrossRef]
43. Kumar, V.; Nagpal, A. Segmenting Global Markets: Look Before You Leap. *Mark. Res.* **2001**, *13*, 8–13.
44. Featherman, M.S.; Pavlou, P.A. Predicting e-services adoption: A perceived risk facets perspective. *Int. J. Hum. Comput. Stud.* **2003**, *59*, 451–474. [CrossRef]
45. Stone, R.N.; Gronhaug, K. Perceived Risk: Further Considerations for the Marketing Discipline. *Eur. J. Mark.* **1993**, *27*, 39–50. [CrossRef]
46. Xu, H.; Wang, H.; Teo, H.-H. Predicting the Usage of P2P Sharing Software: The Role of Trust and Perceived Risk. In Proceedings of the 38th Annual Hawaii International Conference on System Sciences, Big Island, HI, USA, 3–6 January 2005; p. 201a.
47. Limayem, M.; Khalifa, M.; Chin, W.W. Factors motivating software piracy: A longitudinal study. *IEEE Trans. Eng. Manag.* **2004**, *51*, 414–425. [CrossRef]
48. Sims, R.R.; Cheng, H.K.; Teegen, H. Toward a Profile of Student Software Pirates. *J. Bus. Ethics* **1996**, *15*, 839–849. [CrossRef]
49. Al-Rafee, S.; Cronan, T.P. Digital Piracy: Factors that Influence Attitude Toward Behavior. *J. Bus. Ethics* **2006**, *63*, 237–259. [CrossRef]
50. Moon, S.-I.; Kim, K.; Feeley, T.H.; Shin, D.-H. A normative approach to reducing illegal music downloading: The persuasive effects of normative message framing. *Telemat. Inform.* **2015**, *32*, 169–179. [CrossRef]
51. Hair, J.F.; Anderson, R.E.; Tatham, R.L.; Black, W.C. *Multivariate Data Analysis: With Readings*, 6th ed.; Prentice Hall: Hoboken, NJ, USA, 2005.
52. Keil, M.; Tan, B.C.Y.; Wei, K.-K.; Saarinen, T.; Tuunainen, V.; Wassenaar, A. A Cross-Cultural Study on Escalation of Commitment Behavior in Software Projects. *Manag. Inf. Syst. Q.* **2000**, *24*, 299–325. [CrossRef]
53. Fornell, C.; Larcker, D.F. Structural equation models with unobservable variables and measurement error: Algebra and statistics. *J. Mark. Res.* **1981**, *18*, 382–388. [CrossRef]
54. Chin, W.W. Issues and Opinion on Structural Equation Modeling. *MIS Q.* **1998**, *22*, 7–16.
55. Park, S.; Suresh, N.C.; Jeong, B.-K. Sequence-based clustering for Web usage mining: A new experimental framework and ANN-enhanced K-means algorithm. *Data Knowl. Eng.* **2008**, *65*, 512–543. [CrossRef]
56. Liu, Y.; Li, Z.; Xiong, H.; Gao, X.; Wu, J. Understanding of Internal Clustering Validation Measures. In Proceedings of the IEEE International Conference on Data Mining, Sydney, NSW, Australia, 13–17 December 2010.
57. Liang, J.; Kumar, R.; Xi, Y.; Ross, K.W. Pollution in P2P File Sharing Systems. In Proceedings of the IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies, Miami, FL, USA, 13–17 March 2005.
58. Benevenuto, F.; Costa, C.; Vasconcelos, M.; Almeida, V.; Almeida, J.; Mowbray, M. Impact of Peer Incentives on the Dissemination of Polluted Content. In Proceedings of the 2006 ACM symposium on Applied computing, Dijon, France, 23–27 April 2006; pp. 1875–1879.
59. IFPI. *The Recording Industry 2006 Piracy Report: Protecting Creativity in Music*; International Federation of the Phonographic Industry: London, UK, 2006.
60. Christin, N.; Weigend, A.S.; Chuang, J. Content Availability, Pollution and Poisoning in File Sharing PeertoPeer Networks. In Proceedings of the Proceedings of the 6th ACM conference on Electronic commerce, Vancouver, BC, Canada, 5–8 June 2005; pp. 68–77.
61. Shin, S.; Jung, J.; Balakrishnan, H. Malware prevalence in the KaZaA file-sharing network. In Proceedings of the 6th ACM SIGCOMM conference on Internet measurement Rio de Janeiro, Rio de Janeiro, Brazil, 25–27 October 2006; pp. 333–338.
62. Kalafut, A.; Acharya, A.; Gupta, M. A Study of Malware in Peer-to-Peer Networks. In Proceedings of the Proceedings of the 6th ACM SIGCOMM conference on Internet measurement, Rio de Janeiro, Brazil, 25–27 October 2006; pp. 327–332.
63. Null, C. *Fake, Infected Media File Attacks Half a Million Victims in a Week*; Yahoo! Tech: Sunnyvale, CA, USA, 2008.
64. Kravets, D. File Sharing Lawsuits at a Crossroads, After 5 Years of RIAA Litigation. 2008. Available online: <https://www.wired.com/2008/09/proving-file-sh/> (accessed on 28 June 2023).
65. Chiang, E.P.; Assane, D. Music piracy among students on the university campus: Do males and females react differently? *J. Socio-Econ.* **2008**, *37*, 1371–1380. [CrossRef]
66. Kim, J.E.; Kim, J. Software Piracy among Korean Adolescents: Lessons from Panel Data. *Deviant Behav.* **2015**, *36*, 705–724. [CrossRef]

67. Higgins, G.E. Gender Differences in Software Piracy: The Mediating Roles of Self-Control Theory and Social Learning Theory. *J. Econ. Crime Manag.* **2006**, *4*, 1–30.
68. Tunca, T.I.; Wu, Q. Fighting Fire with Fire: Commercial Piracy and the Role of File Sharing on Copyright Protection Policy for Digital Goods. *Inf. Syst. Res.* **2013**, *24*, 436–453. [[CrossRef](#)]
69. Aguiar, L.; Claussen, J.; Peukert, C. Catch me if you can: Effectiveness and consequences of online copyright enforcement. *Inf. Syst. Res.* **2018**, *29*, 525–777. [[CrossRef](#)]
70. McKenzie, J.; Crosby, P.; Cox, J.; Collins, A. Experimental evidence on demand for “on-demand” entertainment. *J. Econ. Behav. Organ.* **2019**, *161*, 98–113. [[CrossRef](#)]
71. Miocevic, D. Consumers’ responses to opposing copyright enforcement regimes: When cognitive appraisal leads to compliance vs reactance. *Comput. Hum. Behav.* **2022**, *136*, 107380. [[CrossRef](#)]
72. Miceli, M.; Castelfranchi, C. Anger and Its Cousins. *Emot. Rev.* **2019**, *11*, 13–26. [[CrossRef](#)]
73. Jeong, B.K.; Yoon, T.; Khan, S.S. Improving the Effectiveness of Anti-Piracy Educational Deterrence Efforts: The Role of Message Frame, Issue Involvement, Risk Perception, and Message Evidence on Perceived Message Effectiveness. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 298–319. [[CrossRef](#)]
74. Chiou, J.S.; Huang, C.Y.; Lee, H.H. The antecedents of music piracy attitudes and intentions. *J. Bus. Ethics* **2005**, *57*, 161–174. [[CrossRef](#)]
75. Yoon, C. Theory of Planned Behavior and Ethics Theory in Digital Piracy: An Integrated Model. *J. Bus. Ethics* **2011**, *100*, 405–417. [[CrossRef](#)]
76. Liao, C.-H.; Hsieh, I.-Y. Determinants of Consumer’s Willingness to Purchase Gray-Market Smartphones. *J. Bus. Ethics* **2013**, *114*, 409–424. [[CrossRef](#)]
77. Hornikx, J. A review of experimental research on the relative persuasiveness of anecdotal, statistical, causal, and expert evidence. *Stud. Commun. Sci.* **2005**, *5*, 205–216.
78. Hoeken, H.; Hustinx, L. When is Statistical Evidence Superior to Anecdotal Evidence in Supporting Probability Claims? The Role of Argument Type. *Hum. Commun. Res.* **2009**, *35*, 491–510. [[CrossRef](#)]
79. Casidy, R.; Phau, I.; Lwin, M. The role of religious leaders on digital piracy attitude and intention. *J. Retail. Consum. Serv.* **2016**, *32*, 244–252. [[CrossRef](#)]
80. Grolleau, G.; Meunier, L. Doing more with less: Behavioral insights for anti-piracy messages. *Inf. Soc.* **2022**, *38*, 388–393. [[CrossRef](#)]
81. Jeong, B.K.; Kang, B.; Jeong, D.H.; Ji, S.-Y. A Cluster Analysis of Digital Pirates: Multi-Dimensional Piracy Risk Perception Approach. In Proceedings of the Southeast INFORMS, Myrtle Beach, SC, USA, 3–4 October 2019.
82. Keast, J. Creative Content Australia Launches Cyber Security-Focused Anti-Piracy Campaign. Available online: <https://if.com.au/creative-content-australia-launches-cyber-security-focused-piracy-campaign/> (accessed on 3 April 2023).
83. Murphy, D. Premier League Launches ‘Boot Out Piracy’ Campaign in Hong Kong for a Second Year. Available online: <https://mobilemarketingmagazine.com/premier-league-launches-boot-out-piracy-campaign-in-hong-kong-for-a-second-year> (accessed on 15 May 2023).

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.